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Optimizing Last-Mile Delivery: A Multi-Criteria Approach with Automated Smart Lockers, Capillary Distribution and Crowdshipping

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Abstract: *Background*: This publication presents a review, multiple criteria optimization models, and a practical example pertaining to the integration of automated smart locker systems, capillary distribution networks, crowdshipping, last-mile delivery and supply chain management. This publication addresses challenges in logistics and transportation, aiming to enhance efficiency, reduce costs and improve customer satisfaction. This study integrates automated smart locker systems, capillary distribution networks, crowdshipping, last-mile delivery and supply chain management. *Methods*: A review of the existing literature synthesizes key concepts, such as facility location problems, vehicle routing problems and the mathematical programming approach, to optimize supply chain operations. Conceptual optimization models are formulated to solve the complex decision-making process involved in last-mile delivery, considering multiple objectives, including cost minimization, delivery time optimization, service level minimization, capacity optimization, vehicle minimization and resource utilization. *Results*: The multiple criteria approaches combine the vehicle routing problem and facility location problem, demonstrating the practical applicability of the proposed methodology in a real-world case study within a logistics company. *Conclusions*: The execution of multi-criteria models optimizes automated smart locker deployment, capillary distribution design, crowdshipping and last-mile delivery strategies, showcasing its effectiveness in the logistics sector.

Keywords: automated smart locker; multiple criteria optimization; facility location problem; vehicle routing problem; capillary distribution; crowdshipping; last-mile delivery; mathematical programming

MSC: 90C90; 90C29; 90B50; 90B06; 68R05

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Citation: Sawik, B. Optimizing Last-Mile Delivery: A Multi-Criteria Approach with Automated Smart Lockers, Capillary Distribution and Crowdshipping. *Logistics* **2024**, *8*, 52. https://doi.org/10.3390/logistics8020052

Academic Editors: Mladen Krstić, Željko Stević and Snežana Tadić

Received: 3 January 2024
Revised: 20 April 2024
Accepted: 1 May 2024
Published: 8 May 2024

1. Introduction

The last mile delivery is frequently referred to as the foremost costly and expensive component of the supply chain [1]. The substantial expenses of the last mile are driven partly by a shortage of the benefits of scale as orders become more fragmented [2].

Last-mile delivery stands out as the most costly and ecologically fragile transportation activity due to its unique challenges. Firstly, the last mile involves delivering goods directly to the end consumer [3], often in urban or suburban areas with dense populations, complex road networks and limited access for large vehicles. This necessitates frequent stops, resulting in increased fuel consumption [4], vehicle wear and tear and labor costs [5]. Moreover, the ecological consequences of delivery over the last mile are substantial [6]. The reliance on fossil fuel-powered vehicles contributes to air pollution and greenhouse gas emissions, exacerbating climate change and posing health risks to populations in urban areas. Additionally, congestion caused by numerous delivery vehicles further intensifies environmental degradation and reduces overall efficiency [7]. Addressing these challenges requires innovative solutions such as alternative fuel vehicles [8], route optimization algorithms [9], and collaborative delivery models [10] to minimize costs and ecological footprints while ensuring timely and sustainable last-mile delivery services [11]. The implementation of smart lockers [12] that function as autonomous pick-up or collecting locations, where the client uses an optional electronic code to access the locker and acquire a package, is one solution offered for lowering the high expenses and incorrect location of inventory in the last mile of business to consumer (B2C) and business to business (B2B) deliveries [13]. An automated smart locker system [14] is a secure storage unit equipped with electronic controls for receiving, storing and dispensing packages or goods. Users receive a notification with a unique code to access their item, enhancing convenience and security for package delivery and pickup [15].

In EU Countries, and especially in Poland, for example, where lockers are widely used, delivering a box from locker-to-locker costs fifteen percent to thirty percent less compared to shipping from a locker to a house, depending on the item size [16].

Alongside their financial advantages [17], the installation of automatic smart lockers helps to build a more environmentally friendly system [18]. As identified by researchers [19], carbon dioxide emitted by transportation vehicles, generated from carbon-based fuel, poses a severe environmental danger. Several academics have researched the GHG emissions and carbon footprint consequences of traditional shopping (customer pickup) versus the delivery of items to the users' location for online shopping [20]. Currently, the majority of vans used for last-mile delivery are electric [21]. For traditional retail purchasing, the buyer picks up the item they bought from the merchant and brings it to their home in the buyer's vehicle. For internet shopping, the product is handed over to the client by the retailer or a courier engaged by the supplier to offer the service of home delivery [22]. Each of these delivery choices damages the environment by producing greenhouse gas (GHG) emissions during the process of the delivery of the bought goods [23].

Numerous researchers have come up with different ideas to tackle these issues (both economic and environmental) via alternative methods such as the so-called 'neighbor relay' [24]. This method consists of compensating neighbors economically in exchange for receiving the failed parcel deliveries due to the 'not at home problem' and then giving the parcel to the customer [25]. However, this kind of study lacks feasibility and can only be applied in certain environments, whereas automated smart lockers are taking on the parcel delivery industry in most European countries and have already evolved into the answer to many challenges of the last-mile delivery problem [26].

The majority of brick-and-mortar distribution systems rely on consumers to handle basic last-mile logistics. The online form of logistics for the last mile differs widely; however, significant issues persist, one of which is theft, notably porch piracy. In reality, millions of parcels the United States of America vanish or become stolen on a daily basis [27]. Taking into account the consumer's option to purchase or not purchase a drop box for the online delivery of packages, it can be called a process of collaborative creation, which is common in both online and traditional commerce, with the consumer's co-creation of supply chain [28]. This study investigates the viability [29,30] of deploying drop boxes, an alternative delivery system, to reduce retailer financial and reputation costs while increasing consumer confidence in direct ordering. It also concludes that such alternative infrastructure may result in an increase in income for online businesses. It also demonstrates that consumers are prepared to pay for such drop boxes while co-creating a range of supply chains [27].

2. Advances to Smart Cities and Sustainable Mobility

As public awareness of the environmental risks posed by our economy grows, so does the popularity of sustainability [31]. Green initiatives have resulted in the emergence of what are known as Smart Cities, which combine economic growth, improved living standards and a reduction in the negative effects caused by commercial activities such as logistics, transportation and city mobility [21]. Furthermore, sustainable mobility is described as the movement or transport of people or objects that is compatible with economic growth, social cohesion [32,33] and environmental protection [34] while incurring low social, environmental and energy costs. Choosing automated smart lockers would have a positive impact on the city's economy and ecology, including the following contributions issued in this study that promotes sustainable mobility in city centers [35]:

For an entire city, our models build a single network of automated smart lockers. This streamlines distribution service management and helps to improve the integrated distribution of many enterprises. The integrated administration of automated smart lockers means that fewer distribution vehicles from different firms are required, reducing the environmental effects [36].

The use of automated smart lockers as an alternative to standard distribution methods offers several advantages. When mobile lockers are explored, which can be erected, disassembled and moved from one location in the city to another, better responsiveness to demand may be accomplished [37].

Take note of the proximity parameter that has been incorporated into the optimization model. This is an effect that mirrors automated smart locker users' behavior, in that the proximity to a locker translates into the ease of picking up parcels, encouraging customers to increase their online buying frequency [38].

In short, last mile delivery confronts five major challenges: workforce aging, costs, sustainability, growing volumes of shipments, and limited operating hours [39]. The path forward to overcome these issues is inextricably linked to the fulfillment of the 2030 Agenda's Sustainable Development Goals [40]. The aging of the metropolitan working population has resulted in a scarcity of physically demanding package delivery personnel. As a result, any increase in distribution activities implies an improvement in working conditions, as sought by Goal 8 of the 2030 Agenda.

In turn, the modernization of the last mile with new parcel delivery alternatives such as collection sites or automated lockers is a step forward for sustainable development, as it is linked to SDG number 9's industry, innovation and infrastructure. Implementing lockers minimizes automobile traffic and hence polluting emissions, improving the social dimension of cities and addressing the needs of the 11th SDG of sustainable cities. To that end, we incorporate new methodologies and approaches, such as the use of system engineering simulations or the ability to obtain visual results in the form of maps to aid in the decision-making and planning processes of urban projects and delivery companies [41].

This contribution emphasizes the distinctive aspects of this research when juxtaposed with prior studies. Firstly, a novel perspective is introduced to the optimization conundrum, rooted in the operational framework of the courier enterprise [42]. Secondly, we harness a more extensive dataset for our case study, culminating in a refined automated smart locker distribution network for parcels and assorted deliveries with clear-cut solutions depicted on maps [43]. Thirdly, we integrate a comprehensive optimization model that tackles both the vehicle routing problem for courier deliveries to automated smart lockers and the facility location problem for locker emplacements [44]. Moreover, we delve into the scalability of the predicament, endeavoring to forge a model adaptable to diverse urban landscapes [45]. In addition, we employ systems engineering principles to devise a groundbreaking e-shopper demand prediction [46]. Furthermore, we incorporate an analysis of the impact of locker proximity on customer behavior, encompassing aspects such as capillary distribution and crowdshipping within the systems engineering model, thus augmenting the efficacy of the methodology [47] and fostering a deeper fusion of the simulation–optimization framework [48,49].

3. Automated Smart Lockers

Automated smart lockers are self-service storage devices that are meant to speed up the delivery and collection of items. They are usually located in easily accessible areas such as shopping malls, office buildings or residential complexes. Users can choose a locker, provide their information and then receive a unique access code or QR code to unlock the given locker. Couriers can leave packages in the lockers, and recipients can pick up their packages whenever they want by entering the code or scanning the QR code. These lockers provide safe and convenient delivery solutions, particularly for online consumers and busy people who may not be available during typical delivery hours [50].

Automated smart lockers offer diverse applications across industries [51]. In retail, they streamline click-and-collect processes, enhancing customer convenience [52]. Within workplaces, they provide secure storage for employees' belongings [53]. Educational institutions can utilize them for contactless book lending or equipment distribution. In healthcare settings, they facilitate medicine pick-ups and secure storage of medical supplies. Smart lockers also serve in the hospitality industry for guest key management and parcel delivery. In residential complexes, they manage package deliveries efficiently. Moreover, they can be integrated into public transportation hubs for temporary luggage storage. Overall, automated smart lockers optimize storage, enhance security, and improve operational efficiency across various sectors.

Automated smart lockers facilitate the delivery of a wide range of items, including parcels, groceries, books, dry cleaning and even prescription medications. They offer a secure and convenient solution for contactless pickup and drop-off services. Businesses can utilize them for e-commerce deliveries, reducing missed deliveries and ensuring package security. Additionally, food delivery services can leverage smart lockers for temperature-controlled storage, maintaining the freshness of perishable goods. These lockers also support the sharing economy by enabling the exchange of goods between individuals. Overall, automated smart lockers enhance efficiency and reliability in delivering various items while providing a seamless user experience. In Figure 1. automated smart parcel lockers from different countries and different companies are shown. Diversified functionality of automated smart lockers are presented in Figure 2.

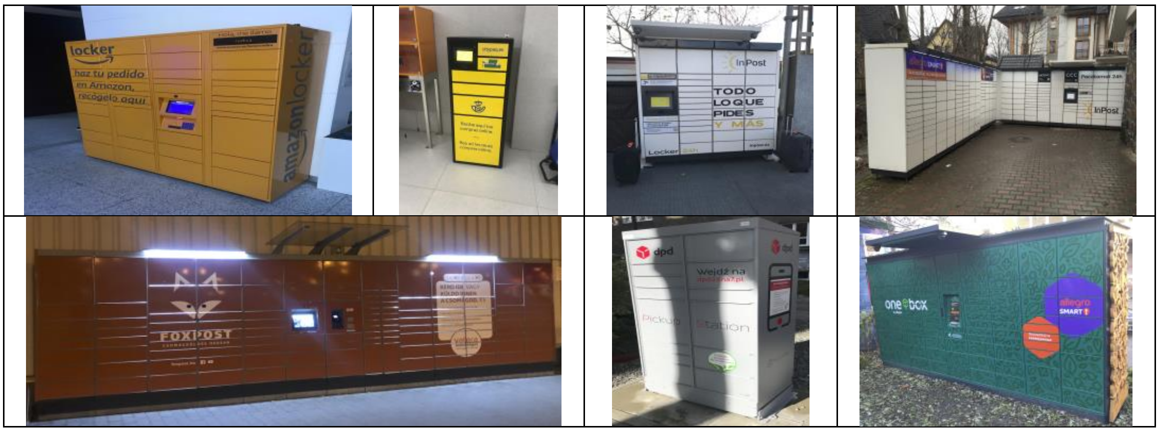

Figure 1. Automated smart lockers for package delivery.

(**a**) books (**b**) flowers (**c**) food (**d**) laundry

Figure 2. Automated smart lockers for: books (**a**), flowers (**b**), food (**c**) and laundry (**d**) delivery.

4. Capillary Distribution

Capillary distribution is a product distribution approach that involves using small-scale, localized channels to reach customers. It is built on the concept of using a network of tiny, interconnected points of sale as opposed to depending primarily on large, centralized distribution centers. This strategy tries to improve accessibility and close the gap between items and consumers. Capillary distribution frequently entails collaborating with local shops or opening pop-up stores in strategic locations. Businesses can expand their market reach and deliver a more personalized shopping experience by leveraging existing infrastructure and engaging with customers on a local level.

Capillary distribution for smart lockers in urban areas involves strategically placing locker units across densely populated regions, ensuring easy accessibility for residents. By leveraging existing infrastructure like public transportation hubs or commercial centers, smart lockers can be installed at convenient locations, reducing last-mile delivery challenges. Integration with mobile apps enables users to locate nearby lockers and schedule deliveries or pickups. This distribution model optimizes space utilization, minimizes delivery distances and reduces traffic congestion. Additionally, it fosters sustainability by encouraging walking or cycling for shorter trips. Overall, capillary distribution enhances the efficiency and effectiveness of smart locker systems in urban environments, catering to diverse needs seamlessly.

5. Crowdshipping

Crowdshipping is a distribution concept that involves a network of volunteers known as "crowdshippers" transporting packages or items from one point to another. It capitalizes on sharing the economy's strength by utilizing the unused capacity in people's vehicles or depending on people who are already driving in the desired direction [54]. Crowdshippers can use a crowdshipping website to sign up and offer to distribute packages along their scheduled routes. Senders can then use the platform to request a delivery, connecting with a crowdshipper who is nearby and travelling in the right direction. Crowdshipping is a low-cost and flexible alternative to traditional courier services, allowing for speedier and more convenient delivery choices, especially for local or short-distance items.

Crowdshipping complements smart locker systems in residential areas by tapping into a network of individuals [55] for package delivery. In big city agglomerations, residents can opt to become crowdshippers, offering to deliver parcels to nearby smart lockers in exchange for incentives. This decentralized approach reduces delivery times and costs while increasing flexibility. Smart lockers serve as centralized pickup points, enhancing security and convenience for both senders and receivers. Mobile apps connect users with crowdshippers, facilitating efficient coordination and tracking. By harnessing the power of the crowd, smart locker systems in residential areas optimize delivery operations, alleviate congestion, and promote community engagement, ultimately enhancing the overall urban logistics ecosystem. This system is at the moment theoretical, but it has roots in car sharing, since car sharing and crowdshipping both leverage underutilized resources in urban areas for efficient transport. Car sharing allows individuals to share vehicles, reducing congestion and pollution. Similarly, crowdshipping harnesses the unused capacity of travelers to deliver goods, optimizing delivery routes and reducing carbon emissions [56]. Both models promote resource sharing, decrease the number of vehicles on the road, and offer sustainable solutions for urban mobility and logistics.

6. Last-Mile Delivery Supply Chain

Last-mile delivery is the final stage of the delivery process in which goods are transferred from a transportation hub or distribution center to the final destination, which is usually a customer's doorstep. It is the most crucial and difficult aspect of the supply chain [57], accounting for a large chunk of the overall delivery cost [58]. Last-mile delivery can be accomplished through a variety of methods, including traditional postal services, courier businesses and developing alternatives such as crowdshipping or self-driving delivery vehicles. To meet consumer expectations, this stage necessitates effective route planning, real-time tracking and prompt delivery. Last-mile delivery is critical to e-commerce success and a significant emphasis area for organizations looking to optimize logistics operations and improve customer happiness.

Optimizing last-mile delivery in urban areas requires a combination of automated smart lockers and efficient vehicle routing. Automated smart lockers act as distribution hubs, reducing delivery distances and improving convenience for recipients. Integrating these lockers with an optimal vehicle routing system addresses the challenges of navigating dense urban environments and managing delivery routes for small trucks and vans.

Firstly, the optimal vehicle routing problem (VRP) considers factors such as delivery time windows, vehicle capacities, and traffic conditions to determine the most efficient routes for each vehicle. Algorithms like genetic algorithms [59] or ant colony optimization can be employed to find near-optimal solutions, minimizing travel distances and time while maximizing delivery capacity.

Secondly, automated smart lockers strategically placed throughout the urban area serve as delivery and pickup points, minimizing the need for direct doorstep deliveries. Delivery vehicles drop off multiple packages at these lockers in a single trip, reducing congestion and carbon emissions associated with individual deliveries.

Thirdly, real-time data and GPS technology enable dynamic route adjustments based on traffic congestion, weather conditions, and delivery demand fluctuations. This flexibility ensures timely deliveries and enhances customer satisfaction.

Furthermore, integrating smart lockers with mobile apps allows recipients to schedule deliveries, select preferred pickup locations, and receive notifications when packages are ready for pickup. This level of customization enhances the overall delivery experience while reducing failed delivery attempts and associated costs.

Overall, the combination of automated smart lockers and optimal vehicle routing addresses the complexities of last-mile delivery in urban areas, resulting in cost savings, reduced environmental impacts and improved service reliability.

7. Horizontal Cooperation in Last-Mile Smart City Supply Chain

Horizontal cooperation in urban last-mile supply chains involves collaborating between various stakeholders, such as delivery services, automated smart locker providers and other delivery points, to streamline package delivery processes [60]. In this system, trucks and vans transport packages to strategically located smart lockers and delivery points across the city [61]. These lockers serve as convenient hubs for recipients to collect their items at their preferred time, reducing the need for multiple individual deliveries to dispersed locations [62]. Additionally, drones can complement traditional delivery methods by swiftly transporting lightweight packages to designated lockers or points, further optimizing delivery efficiency [63]. By integrating these technologies and coordinating efforts horizontally, the last-mile supply chain becomes more agile and responsive to urban demands [64]. Ultimately, this approach enhances the overall efficiency of urban logistics, reduces congestion, and minimizes environmental impact, contributing to the development of smarter and more sustainable cities [65].

8. Supply Chain for Automated Smart Lockers for Parcels

By providing a simple and secure solution for package delivery and collection, automated smart parcel lockers play an important role in the supply chain [66]. These lockers are strategically placed throughout various neighborhoods and public spaces, making them accessible to both shops and customers. The supply chain for automated smart lockers for packages and other items is comprised of several steps, beginning with the cooperation of retailers and logistics suppliers [67]. Packages are delivered by retailers to distribution facilities, where they are sorted and assigned to individual lockers based on their destination and consumer preferences [68,69]. Once the packages have been assigned, logistics providers transfer them to the appropriate lockers, assuring on-time delivery [70].

The lockers have extensive tracking and notification systems that allow clients to receive real-time updates on their shipments as well as access the codes to retrieve them [71]. Maintenance and monitoring activities are also part of the supply chain for automated parcel lockers. Locker operators inspect and service the lockers on a regular basis, ensuring that they are in proper working order and fixing any technical difficulties as soon as possible to minimize inconveniences [72]. Finally, the supply chain includes the consumer experience. Customers can pick up their packages at their leisure, eliminating the need to wait for home deliveries or visit post offices. This streamlined and efficient method improves client satisfaction while shortening the supply chain's overall delivery time [73].

Building an effective supply chain for automated smart lockers presents several pros and cons [74]. On the positive side, it enhances operational efficiency by reducing delivery times and costs associated with last-mile logistics [75]. Smart lockers also improve customer convenience by offering secure and accessible pickup locations, reducing missed deliveries and enhancing overall satisfaction [76]. Additionally, optimizing the supply chain for smart lockers can lead to reduced carbon emissions and congestion in urban areas, contributing to environmental sustainability [48]. However, there are challenges to consider. Initial investment costs for installing and maintaining the locker infrastructure can be significant. Integration with existing logistics networks and coordination with multiple stakeholders may pose complexities. Moreover, ensuring adequate capacity and availability of lockers to meet fluctuating demand requires careful planning. Balancing these factors while maintaining service reliability and scalability is essential for successfully building an effective supply chain for automated smart lockers.

9. Urban Logistics Examples for Smart Cities

The movement of goods and their transportation in urban areas is known as urban logistics. Urban logistics refers to all movements within a city district, both in terms of supplying end customers and in terms of supplying retail, industry or trade.

The urban last mile presents a significant challenge for the freight industry, as congestion and emissions caused by second-lane parking are higher compared to the parcel segment on a per-vehicle basis. Although the public sector has initiated pilot projects and implemented various initiatives on a city level, there is a lack of systemic change and unified regulatory frameworks.

Different examples of urban logistics for smart cities include urban freight shipping, which promotes social and environmental justice; zero-emission cars, involving downstream and life-cycle sustainability evaluations; infrastructure and logistics complexity with the evolving urban freight fleet; non-motorized and micro shipments, including solutions with walking and cycling; community-driven and participatory urban freight planning and elicitation integrated planning for people and goods; the impact of "Complete Streets" and "15-min city" on freight transit; city shipping and the perspective of zero-crash avoidance targets; cyber innovation, governance of data, open data and data sharing; curb procedures and assignment of modes; low/zero pollution limits; home connectivity and availability of products; political economy of emerging urban freight trends (e.g., warehouse and port automation and digitization, gig economy) and workforce implications; green tech innovations and applications; and crowd logistics, coopetition and liability.

According to a calculation made by the World Economic Forum, around thirty percent of e-commerce decline of private retail volume could mitigate related delivery flow. They assessed the impact of growing B2B and B2C urban deliveries across several dimensions, and these were the results:

> *"First, the number of delivery vehicles on the road will increase by 36% between 2019 and 2030 (top 100 cities globally). Second, these vehicles will emit an additional 6 million tonnes of CO_2, putting additional pressure on cities' and automotive OEMs' decarbonization targets. Third, cities will be burdened with even more congestion. Our research has shown that the average commute time could increase by 21% (purely last-mile delivery induced), equalling an additional 11 min of commute time for each passenger*

every day by 2030. This modelling outcome is very much aligned with what we have seen in real life in recent years, with an increase of commute times of between 20% and 35% since 2010 in cities". [49]

10. Last-Mile Delivery Electricity Risk

Electricity usage has a significant impact on last-mile delivery strategies employing automated smart parcel lockers, capillary distribution and crowdshipping. While these innovations aim to streamline delivery processes and reduce carbon emissions by optimizing routes and leveraging shared resources, they heavily rely on electricity to operate [77].

Automated smart parcel lockers need electricity to power their systems for secure storage and retrieval of parcels. Capillary distribution systems, which involve setting up smaller distribution centers closer to customers, require energy for sorting, packaging and transportation. Crowdshipping platforms, reliant on mobile apps and communication technologies, consume electricity for their operations [78].

Increased electricity usage raises concerns about environmental sustainability and carbon footprints. The energy sources powering these operations, if not renewable, can contribute to greenhouse gas emissions and environmental degradation.

Moreover, reliance on electricity poses a risk of service disruption during power outages or shortages [79], potentially leading to delays and inefficiencies in last-mile delivery. Businesses need to consider implementing backup power solutions or investing in renewable energy sources to mitigate these risks and minimize their environmental impact. Balancing the benefits of these innovative delivery methods with their energy requirements is crucial for creating sustainable and resilient last-mile logistics systems.

11. Literature Review

This section provides an in-depth assessment of the literature on automated smart lockers systems (ASLS) for parcels and other delivery products, including their use, popularity, and consumer behavior. There are numerous studies that highlight the contributions to sustainable mobility made by self-collection delivery systems. Furthermore, studies based on facility location problem (FLP) optimization [80], agent-based modeling [81], and system dynamics simulations [82] are reviewed, all of which are applied to the field of last-mile logistics with a connection to vehicle routing problem (VRP) for delivery schedules for automated smart lockers facilities [83].

The amount of literature on parcel lockers has increased recently, and it is abundantly evident that there are numerous benefits to using one. The usage of automated smart lockers for parcels and other delivery items instead of traditional home delivery decreases vehicle miles traveled while being effective [84]. By streamlining the pick-up of returned goods, automated smart parcel lockers can also help the supply chain. Additionally, the self-service feature of lockers, according to data from focus groups, not only lowers costs but may also boost value for the clients [85].

Regarding location preferences, in Poland, customers strongly preferred locations close to their homes or on their commutes, while those near retail malls and transit hubs were the least desirable [86]. However, in some countries like Brazil and Sweden, the most desired places were supermarkets and malls [87]. This shows how economy, culture and many other factors take part in determining the location of the lockers, but these are not the most relevant aspects that are considered. Six criteria that affect locker location have been identified by a recent review of the literature: potential 24 h service accessibility, security, environmental effects, installation costs, and governmental restrictions. Household income and internet usage are significant factors that influence online purchases, according to e-commerce literature [88]; higher-income households with greater access to computers and the internet are more likely to do so [89].

An automated smart parcel locker is suggested by experts to enhance urban logistics operations. But choosing where to put these automated smart lockers is not an easy matter [90]. In recent studies, researchers have used a simulation–optimization approach that integrates a system engineering simulation model with a multi-period capacitated facility location problem based on the city of Dortmund, Germany [46,47]. To first illustrate the fundamental elements and interdependencies of the automated locker system, they constructed causal-loop and stock-flow diagrams. The ideal number of automated lockers to be installed in each period was then determined using a multi-period model. The cost and dependability level for many situations with arbitrary needs were finally estimated using a Monte Carlo simulation. According to their results, only one solution reached 100% reliability. To improve this, they suggest increasing the detail in some parameters used in the simulation and remodeling the code to enhance accuracy. Models have become the main tool to solve the facility location problem, and they tend to be unique for every case study. It is important to manage significant amounts of information about the place where automated smart lockers will be located; this will not only help the model to be more reliable, but it will also help the researchers to improve the model.

One of the most important parameters to pay attention to is demand. The assessment of the prospective demand for an automated parcel locker system that is being implemented is presented in this study [46]. For determining the potential demand for automated lockers, a two-stage methodology was devised. Based on random utility modelling, they present the current demand for attended and unattended deliveries in the first step. Further in the study, they found out that their proposed option for the automated locker location is more suitable for cities with a well-developed network of minimarkets. This is one of the reasons that the facility location problem is sometimes so challenging, as it may only satisfy certain conditions, while for others, a totally different approach is needed.

12. Graph Representations of Automated Smart Locker System Optimization Problems

After the facility location problem is optimized owing to the demand of delivery items, the set of available lockers (first vertex presentation) and the set of client locations (second vertex presentation) are connected by axes. The movement of clients picking up goods from lockers is represented by axes. The optimization model is optimized using the GUROBI 9.5.1 solver. Author is using the GUROBI 9.5.1 solver for optimization, as well as various graphical tools to design a network with client position points (vertex) and chosen (after optimization) location points (vertex) of the automated smart lockers. We know all the prospective customer locations as of the input date, but we do not know which locker locations will be optimum. The set of all feasible locker sites in the city is also known; however, as a solution, we always received a vertex from the set of lockers. To answer the question of what kind of graph represents the two networks, we believe it is a directed graph because this graph is, more accurately, the new optimal network (graph) after every optimization round is a graph made up of vertices connected by directed edges (arcs). The link is between the customer's location (vertex) and the nearest automated smart locker location (vertex). The arc on the directed edge represents the number of parcels retrieved weekly by the customer from the locker. Considering the information below, we feel the graph describing our network customer locker is directed and acyclic.

In the urban area, we gave a satellite view of the installed automated smart lockers in the network at the start of the period t = 0. We displayed a satellite view of the network's installed automated lockers at the end of the period t = 151 in the urban area. We opted not to include the directed edges—arcs between all client locations (vertex) directed to the nearest automated parcel locker site (vertex)—in both figures. Our network customer-locker graph is directed and acyclic; however, adding directed edges (arcs) between the customer and locker will render both images illegible.

On the other hand, automated smart lockers suffer the same problem as most of the delivery and transport industries, the FLP (facility location problem). The FLP is a classic optimization problem that determines the best location for a factory or warehouse to be placed based on geographical demands, facility costs, and transportation distances. The significance of the best location is determined by the nature of the problem in terms of the constraints and site optimality criteria [91]. Hospitals, fire stations, bus stops, train stations, petrol stations, blood bank centers, retail businesses, neighborhoods, libraries, parks, post offices, airports and landfills may all be located using FLPs. The FLP can be thought of as a more generalized version of the vehicle routing problem with fixed expenditures for facility installation [92], providing an in-depth analysis and explanation of the FLPs.

In Figure 3, we can see that the demand points are represented on the customer nodes with the corresponding distances between the distribution facility and the customers. Suppose we are interested in covering only customers located within a maximum distance of 'x' km of all the customers represented in the plane (left side of), where the right side shows that the distribution facility can serve only three customers. In this example, calculations were made considering only the distance from the distribution facility to the customer; however, the value may be measured using other quantities like time, cost and demand satisfaction.

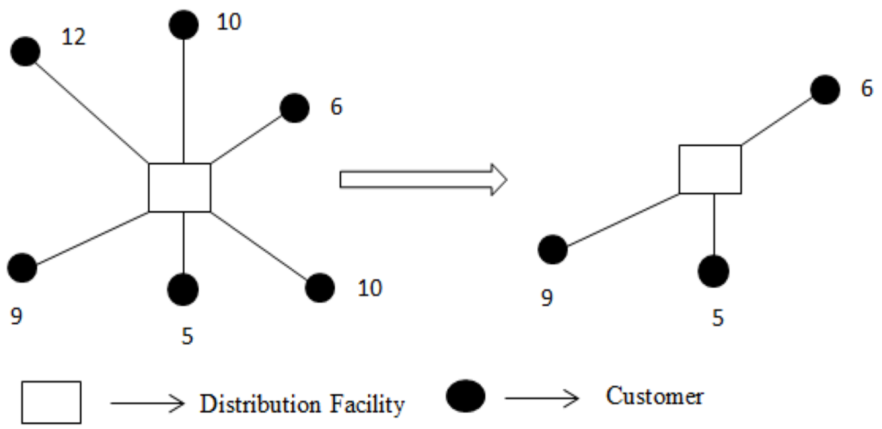

Figure 3. Example of the automated smart locker location of the facility location problem, taking only into account the distance from the distribution facility to the customer.

In this paper, we seek to improve and optimize the usage of last-mile delivery by studying the case of a company in selected urban areas. Wroclaw is the second-largest city in Poland, which is one of the most developed countries regarding the automated parcel lockers business. Additionally, Wroclaw itself has significant relevance in the e-commerce industry, as the DHL, FedEx and UPS centers are based there. We consider a real company that has around 400 lockers installed over the whole region that are unevenly spread in the 78 districts. Those with a greater and denser population contain more lockers than those that are more depopulated, and distance and population are key factors in determining the location of the lockers.

To achieve the target of optimizing the automated smart locker distribution and usage, we apply two mathematical optimization models that will be implemented in AMPL language so they can be executed with the help of GUROBI 9.5.1 solver. One is focused on an agent-based modeling criterion and solves the data for important parameters such as population, e-shoppers, automated smart locker users and demand. The other one is the FLP model; hence, it gives us the distribution of lockers by district and the costs for executing that solution. It is important to remark that the modeling is set for the next three years, while the current status of a company in a selected city is heavily influenced by a 5-year investment that increases the number of automated smart lockers in comparison with the model. The model shows that automated smart locker installation is very sensitive to demand, and it depicts the evolution of this industry. Based on the results, it can be stated that anticipation with a good approximation of future events in the e-commerce industry may lead to a better optimized automated smart locker system.

Because of the constraints that were in place to tackle the pandemic, both local and worldwide supply chains encountered performance problems, while e-commerce demand increased. Regardless, despite the tremendous COVID-19 shock [93], much of the spike in online shares has been revealed to be a temporary phenomenon. These disruptions have worsened the difficulty of alternative last-mile options in urban logistics, resulting in novel package delivery systems that mix physical and digital solutions such as self-collection delivery systems. Self-collection delivery systems benefit both courier companies and clients by providing time-window flexibility while lowering overall mileage, delivery time, and, as a result, gas emissions [94,95].

This research focuses on common-carrier automated smart lockers for parcels and other delivery items, which contain automated multi-compartment storage systems that allow couriers to appropriately dispose of things and temporarily and securely store online purchases until they are picked up by clients [96]. These storage systems are commonly found in residential structures, stores, petrol stations and community centers, where they serve groups of people [97,98]. Correos has had automated smart lockers called "Citypaq" since 2015, with over 4200 automated smart lockers in Spain.

Unlike previous research that used hybrid modeling to create automated parcel locker networks, this study combines a system engineering optimization model to assess e-commerce demand in a dense urban area and investigates the model's scalability for additional locations [99,100]. The multiple criteria location of the facility technique was used to present and solve problems [101,102] by combining the objective functions of profit maximization, cost minimization, demand coverage maximization and locker number minimizing in a set. Demand forecasting was utilized, and the optimization technique made use of the GUROBI 9.5.1 solver.

An API for Bing Maps calculates the actual driving distances between customer nodes and automated smart locker service nodes, calculating the maximum distance a client is willing to go to pick up their parcel. This is defined as a parameter in the model, and it constrains the resulting automated smart locker network solution to reduce the customer's trip distance. The success of automated smart lockers is primarily due to the flexibility they provide to all players in the last mile supply chain, as implementing parcel lockers reduces parcel delivery time and courier vehicle dwell time, lowering the negative environmental impact of last-mile logistics in cities.

This paper examines the input data using a case study of Wrocław, a city in Southwest Poland where automatic smart parcel lockers have been in operation for several years. An optimization technique is given based on the case study to construct a hybrid model that is capable of addressing a configuration of automatic smart parcel lockers for the proposed demand scenarios and vehicle fleet optimization. The goal for creating these models is to have a tool that can be utilized as an aid in the decision-making processes of entities and businesses when planning projects for the installation of automated lockers in cities. The fundamental contribution of this research is to investigate the feasibility of combining optimization techniques to address difficult real-world challenges, specifically in the context of developing delivery networks for last-mile distribution. It highlights the benefits of combining system engineering optimization into the simulation of real-life features, especially when dealing with interconnected demands from various clients. This study demonstrates the efficiency of a multi-criteria approach in handling complex optimization challenges in urban logistics.

13. Methodology

In this section, we present the mathematical models used for solving the demand evolution of automated smart lockers for packages and other delivery items with the use of the vehicle routing problem for delivery to ASL systems and the facility location problem for the optimal allocation of lockers in the urban area. The models are then translated into AMPL language and implemented into the optimization software with the help of the GUROBI 9.5.1 solver.

13.1. Simulation Procedure

At the end of every month, the FLP solver process is run using the simulated data at that time. Later, the FLP solution provides feedback to the simulation model by deciding the optimal location and number of automated smart lockers.

The above methodology has also been implemented by the author in previous papers [79,80]. The author has also used a similar approach for estimating eShoppers, automated smart lockers users and parcel demand growth in a paper [81] about a case of automated smart locker usage.

The main contribution of this study lies in exploring the potential of integrating optimization and simulation techniques to address complex real-world problems, specifically in the context of creating an automated smart locker network for last-mile distribution.

Finally, this paper highlights the effectiveness of a hybrid model in effectively tackling complex optimization problems within urban logistics. Additionally, it demonstrates the advantages of incorporating system dynamics into the simulation of real-life features, particularly when dealing with interrelated demands from diverse customers.

All the advances in operations research are favorable for the improvement of models that are similar to the one presented, which could be applicable to problems involving autonomous vehicles, assisted delivery by robots [103] or unmanned aerial vehicles (drones), among other innovative solutions for last-mile delivery.

Future work should overcome the main limitation of this research, which is the parameter tuning. It is crucial to move forward by acquiring data from primary sources, which could involve conducting in-field surveys [104] to gather more accurate and reliable data so that a more comprehensive understanding of the behavior of the parcel demand system is provided and the accuracy of their findings is improved.

13.2. Agent-Based Model

The simulation models [31,47,80–82] were implemented in Anylogic using an agent-based modeling approach over city district nodes $i \in I = \{1, 2, 3, \ldots, I\}$, customer nodes $j \in J = \{1, 2, 3, \ldots, J\}$ and time $t \in T = \{0, 1, 2, \ldots, T\}$.

The simulation starts with given initial values at $t = 0$ related to the population, eShoppers, automated smart locker users, and parcel demands. The simulation is built using the districts as the basic agents. Therefore, the previous magnitudes are referred to in each district as $i \in I$. Afterwards, these data are updated on a weekly basis for the population, eShoppers, automated smart locker users and parcel demands, where α_{it} is a random variable for the historical population growth in the city, and β_{it}, γ_{it} and δit are the growth factors for eShoppers, automated smart locker users and purchases per user, respectively, from $t - 1$ to t such that $\beta_{it} = \beta_{i,t-1\varepsilon}$, $\gamma_{it} = \gamma_{i,t-1}\varepsilon$ and $\delta_{it} = \delta_{i,t-1}\ \varepsilon\ \forall i \in I$, $\forall t \in T$: $t > 0$. The βit variables need to be adjusted at $t = 0$ by dividing the real eShoppers' yearly growth rate over the eShoppers' share of the initial value. Moreover, ε is a uniform random variable in the interval [a,b] ($\varepsilon \sim U[a,b]$) that represents the random effects. Additionally, φ it stands for the effect of automated smart locker availability (the number and location of automated smart lockers in district i at time t).

This effect is formulated in our simulation model as follows: ω is the sensitivity of increasing the number of automated smart locker users, and y_i the number of automated smart lockers available in district $i \in I$. Furthermore, the purchases per automated smart locker user (ppu_{it}) are obtained by combining the average purchases per year and automated smart locker user (ppy) with the demand distribution (ddt) on a yearly basis. Finally, every month, the FLP solver procedure is launched, considering the simulated data at that point and feed-backing the simulation model by determining the optimal number and location of the automated smart lockers.

14. Multi-Criteria Automated Smart Locker System Optimization Models with Vehicle Routing Constraints

The multi-objective mathematical programming conceptual models are designed to support the planning, organization and optimization of automated smart lockers system, taking into consideration vehicle routing networks of delivery between depots and automated smart lockers as well as supply chain efficiency. Possible optimization criteria can consider the following aspects:

- Minimization of assignment cost in all districts, for all customers, to all automated smart lockers.
- Minimization of delivery distance for all trucks/vans to all automated smart lockers.
- Minimization of delivery time for all trucks/vans to all automated smart lockers.
- Minimization of delivery costs for all trucks/vans to all automated smart lockers.
- Maximization of the efficiency of usage of the automated smart locker network.
- Maximization of the utilization of usage of the automated smart locker network.
- Maximization of the sustainability of the supply chain.
- Maximization of the level of delivery accomplishment.
- Maximization of a set of resilient suppliers.
- Minimization of disruptions in the supply chain network of depots vs. automated smart lockers.
- Minimization of the number of automated smart lockers vs. maximization of revenue from the usage of the automated smart locker network.
- Minimization of automated smart locker network costs vs. maximization of the utilization of the automated smart locker network.
- Minimization of the number of automated smart lockers vs. maximization of the utilization of the automated smart lockers.

Before going through the results, it is important to distinguish between the total revenue to which the network could aspire and the real profit that is obtained from the assigned parcels to the automated smart lockers. The total revenue corresponds to the case where all the demand of the system would be attended by the installed automated smart lockers, while the real revenue corresponds to that obtained from the actual attended demand. This, combined with the objective of minimizing the number of automated smart lockers, leads to the solution with the least number of automated smart lockers in the network.

In this case, the objectives that are pursued are minimizing costs and maximizing the utilization of lockers, aiming to cover the maximum demand of parcels with the minimum amount of expenses. This optimization model is defined over the same set of nodes $i \in I$ and $j \in J$, representing the districts and customers, respectively. This automated smart locker model seeks the optimal location of automated smart lockers and the assignment of customers to districts hosting automated smart lockers in such a way that total costs are minimized, subject to a number of constraints.

This automated smart locker optimization model is defined over the same set of nodes $i \in I$ and $j \in J$ representing, the customers and districts respectively. Thus, the optimization model searches for the optimal assignment of customers to districts and the automated smart locker optimal location with the objective of minimizing the total costs. Details about the model decision variable, model parameters and model criteria are shown in Tables 1–5.

The presented set of criteria to be considered in the multi-objective conceptual optimization model has been chosen based on decision maker preferences. These criteria should be included in the multi-objective function of the optimization model.

Table 1. Model I—decision variables.

Decision Variable	Description
x_{ijkl}	1 if delivery with the use of truck/van $k \in K$ to automated smart locker $l \in L$ for assigned customer $j \in J$ to district $i \in I$, 0 otherwise
y_{il}	1 if automated smart locker $l \in L$ is located in district $i \in I$, 0 otherwise
z_{klo}	1 if delivery with use of truck/van $k \in K$ to automated smart locker $l \in L$ from depot $o \in O$, 0 otherwise
u_{kl}	Number of truck/van $k \in K$ used for delivery to automated smart locker $l \in L$
w_{il}	Number of automated smart locker $l \in L$ located in district $i \in I$

Table 2. Model I—parameters.

Parameter	Description
c_{ijl}	Assignment cost in district $i \in I$ for customer $j \in J$ to an automated smart locker $l \in L$
d_j	Delivery demand for customer $j \in J$
e_{il}	Operating cost for an automated smart locker $l \in L$ located at district $i \in I$
f_{iklo}	Cost of delivery by truck/van $k \in K$ to an automated smart locker $l \in L$ located at district $i \in L$, from depot $o \in O$
g_i	Cost for an automated smart locker located at district $i \in I$
M	Minimum percentage of automated smart locker capacity utilization
a_{il}	Capacity at district $i \in I$ of automated smart locker $l \in L$
d_{lo}	Distance between automated smart locker $l \in L$ and depot $o \in O$

Table 3. Criteria included in Model I—the multi-objective function.

Criterion	Description
$\sum\limits_{i \in I} \sum\limits_{j \in J} \sum\limits_{l \in L} c_{ijl} w_{il}$	Assignment cost for all districts, and for all customers, to all automated smart lockers
$\sum\limits_{k \in K} \sum\limits_{l \in L} d_{lo} u_{kl}$	Delivery distance for all trucks/vans to all automated smart lockers

Table 4. Model II—decision variables.

Decision Variable	Description
X_{ij}	Takes the value 1 if customer $j \in J$ is assigned to district $i \in I$, 0 therwise
Y_i	APLs that are located at district $i \in I$

Table 5. Model II—parameters.

Parameter	Description
c_{ij}	Assignment cost for customer $j \in J$ to an APL located at district $i \in I$
d_j	Customer $j \in J$ demand
sc_i	Setting up cost for an APL located at district $i \in I$
dc_i	Removing cost for an APL located at district $i \in I$
uc_i	Upkeep cost for an APL located at district $i \in I$
M	APL capacity utilization minimum percentage
a_i	APL capacity at district $i \in I$
$b_{i,t-1}$	Previously existing APL located at district $i \in I$

The set of objectives in Model I are subject to both symmetric and asymmetric traveling salesman and vehicle routing problem [105] constraints with Miller–Tucker–Zemlin MTZ [106] subtour elimination constraints.

The set of criteria chosen by the decision maker in the objective function of Model II is subject to the following set of constraints:

$$\sum_{i \in I} x_{ij} = 1, \forall j \in J \tag{1}$$

$$M x_{ij} \geq y_i, \forall i \in I, \forall j \in J : i = j \tag{2}$$

$$\sum_{j \in J} d_j \geq m \sum_{i \in I} a_i y_i \tag{3}$$

$$\sum_{j \epsilon J} d_j x_{ij} \leq a_i y_i, \forall i \in I \tag{4}$$

$$x_{ij} \in \{0, 1\}, \forall i \in I, \forall j \in J \tag{5}$$

$$y_i \in \mathbb{Z}^+, \forall i \in I \tag{6}$$

The multicriteria in Model II is defined by the criteria presented in Equations (2) and (3), with Equation (6) defining the constraints:

1. Equation (2) assigns each customer $j \in J$ to a district $i \in I$ only if an APL is there.
2. Equation (3) ensures that if an APL is located in a district, the customers in that district are assigned to it. Here, M indicates a sufficiently large number.
3. Equation (4) guarantees a minimum APL use for a given demand.
4. Equation (5) ensures that the APL's capacities are not violated.
5. Equations (6) describes the variable ranges.

The objective, depending on the decision maker's preferences, can consist of two objectives: minimizing the number of lockers and maximizing the utilization of lockers to ensure that the system covers the maximum demand of parcels. The items listed below start with the service costs of assigning customers to districts where an APL is accessible. These service prices are determined by distance and demand. The second term indicates the costs of establishing the APL, whereas the third term represents the costs of decommissioning an existing APL.

15. Case Study

In order to compile and run the models in Anylogic, the author use excel tables with the input data needed to obtain the results. For the first model, the author needs the population of each district obtained from reference [107]. Figure 4 depicts the density distribution across Wroclaw and shows the more populated areas in a darker red. The number of lockers from the company in each district were given by the company.

Then, with the help of Google Maps, the author obtained the approximated coordinates for each district so the agent-based model could be solved. Additionally, Company A provided the data for the assignment costs of each district. Furthermore, the size of the locker, price for setting up a locker, decommissioning costs and maintenance costs were also given. They are depicted in Table 6.

Although the model varies internally, for variables such as e-shoppers or population growth there must be some initial values that approximate the current situation in Wroclaw. Growth rates of population, e-shoppers, automated smart locker users and purchases are shown in Table 7.

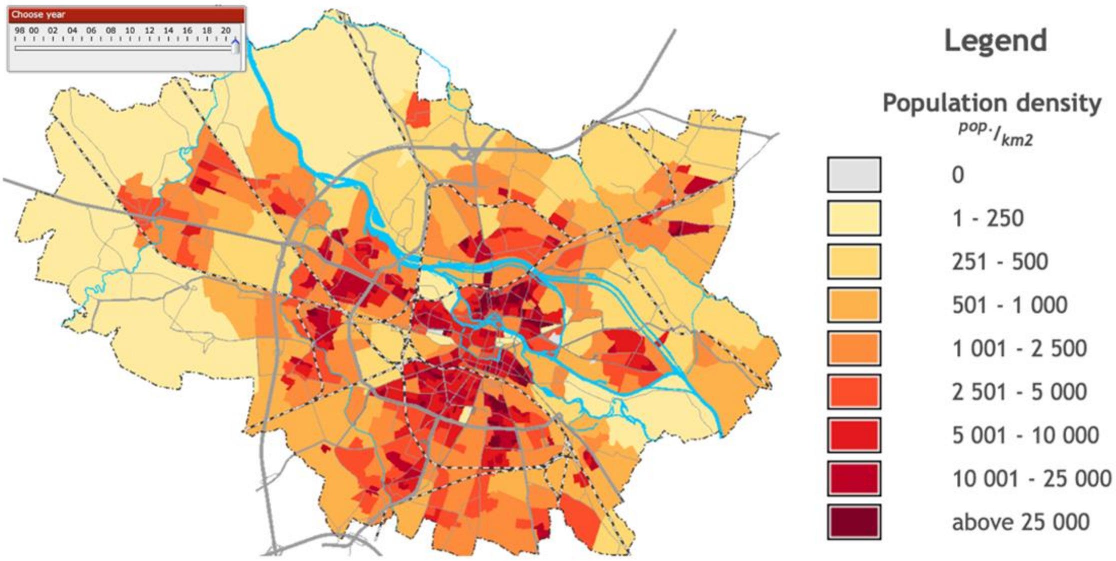

Figure 4. Demography density of the city of Wroclaw, Poland.

Table 6. Costs and capacity of an automated smart locker.

lockerCapacity (cm^3)	setUpLockerCost (EUR)	decommissioningCost (EUR)	upKeepCost (EUR/Week)
320	2450	80	155

Table 7. Growth rates of population, e-shoppers, automated smart locker users and purchases.

populationGrowthRate	eShoppersGrowthRate	Automated Smart Locker usersGrowthRate	AvPurchaseGrowthRate
0.009	0.1	0.15	0.2

Finally, crucial information with a significant impact on the results is the expected demand. Each week, the demand changes and the model adapts accordingly to optimize its performance to the fullest extent possible. In Poland, Christmas has a huge impact, with orders increasing in the months of November and December, whereas in January and February, sales fall by almost half. Figure 5 shows a graphical representation.

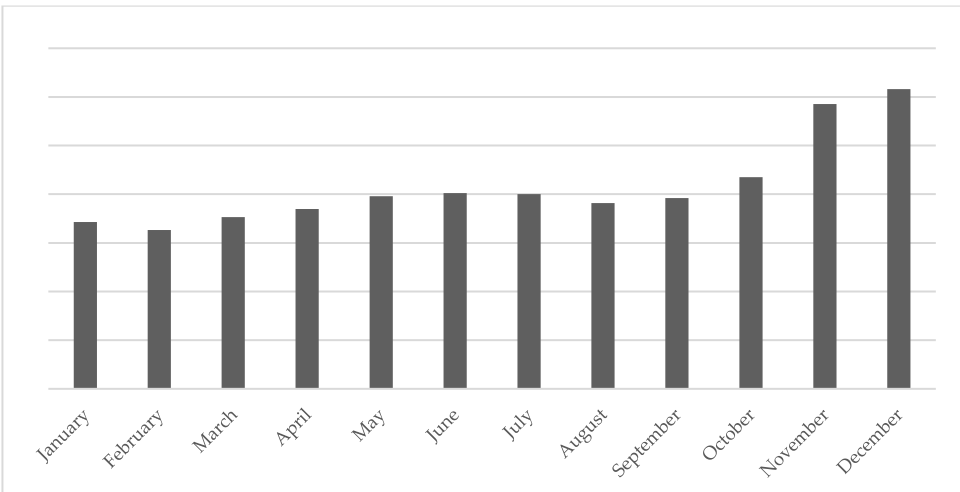

Figure 5. Monthly expected demand representation.

16. Results

16.1. E-Shoppers and Automated Smart Locker Users

Wroclaw's population is on the rise. Throughout the years, this will affect in the automated smart locker industry. Thus, the author have considered an initial growth of 0.9% yearly, but this will vary slightly according to the agent-based model. Every year, the population will grow, and consequently, more e-shoppers will appear. However, this is not the only factor that affects e-shoppers, as the model introduces a variable that produces random effects.

Figure 6 shows the random effects introduced by the model, varying e-shopper growth. E-shopper evolution is very dependent on population growth, as it follows a similar tendency. This increment in e-shoppers has a positive impact in the number of automated smart locker users, which by the end of the 3rd year is nearly double the number of users at the beginning.

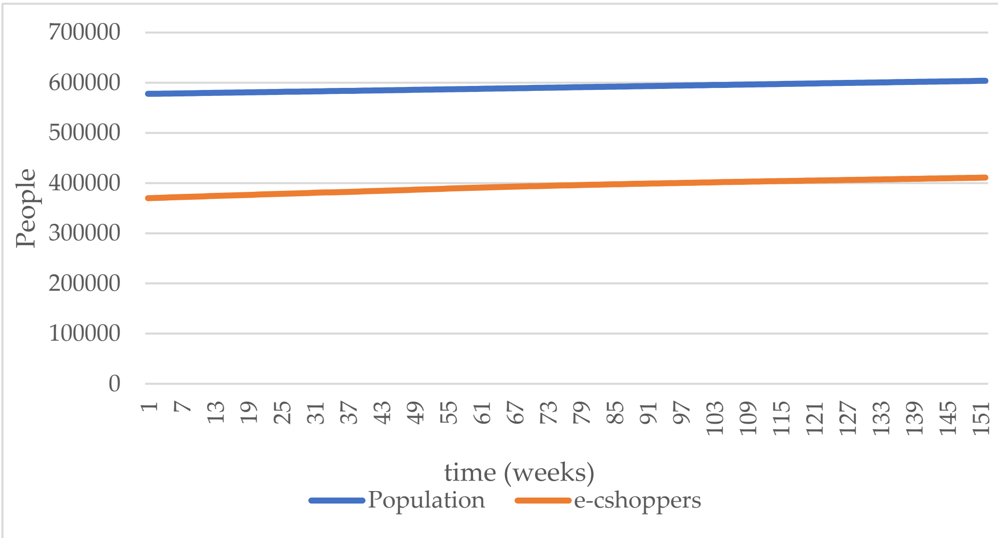

Figure 6. Population and e-shopper growth.

Number of automated smart locker users are presented in Figure 7.

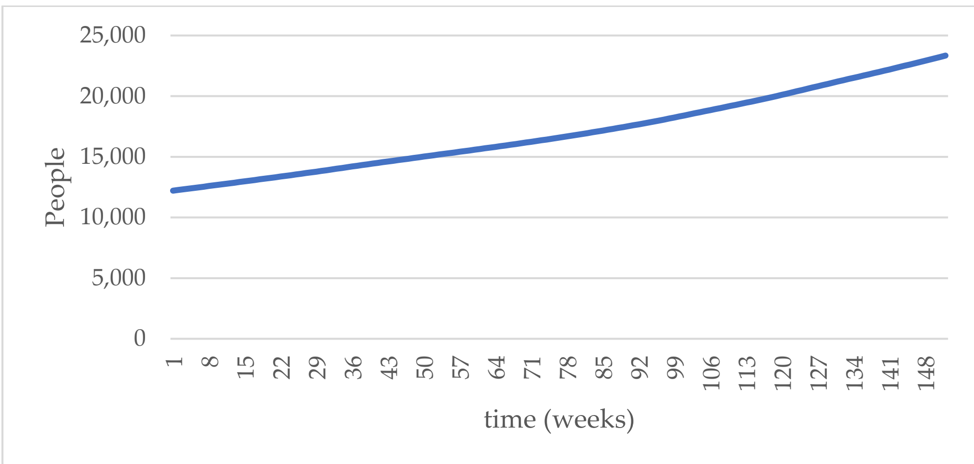

Figure 7. Number of automated smart locker users.

16.2. Parcel Demand

Parcel demand is directly correlated with the number of automated smart locker users. The more users, the more parcel deliveries will be made to an automated smart locker. In the agent-based model, it is defined that the purchases per automated smart locker user (ppu_{it}) are obtained by combining the average purchases per year and automated smart locker user (ppy) with the demand distribution (dd_t) on a yearly basis, so $ppu_{it} = ppy \cdot dd_t$.

Essentially, this shows how dependent parcel demand is from the expected demand at the time. Once the purchases per automated smart locker user are obtained, it is as simple as multiplying the two factors, automated smart locker user$\cdot ppu_{it}$, to define the parcel demand. Parcel demand evolution is given in Figure 8. The simulation gives the following solution:

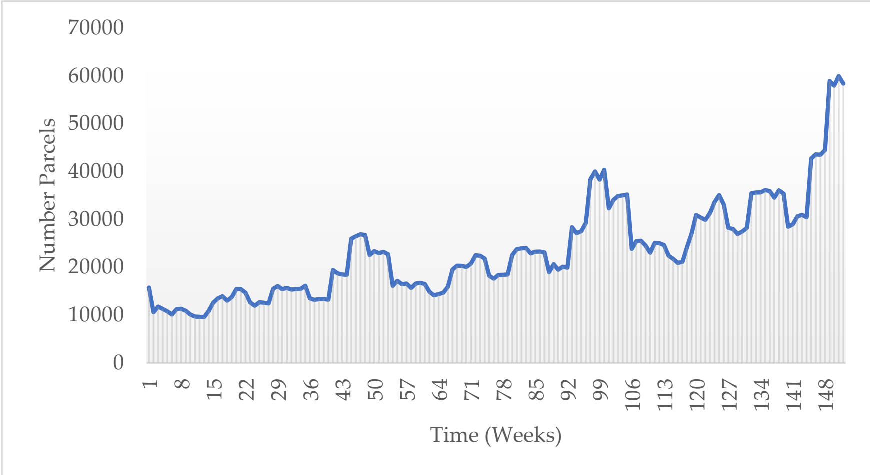

Figure 8. Parcel demand evolution.

The demand distribution throughout the year is the same every year. As was shown the data section, the expected demand has its own distribution depending on the month. Additionally, as the number of automated smart locker users increases yearly, so does the demand, and in the 152nd week, there were almost 60,000 parcels.

16.3. Number of Lockers

At the beginning of the simulation, there were no lockers previously installed; hence, for the first week, the model locates many lockers in different districts. Then, once the model checks the demand for the first months, it removes a substantial number of lockers. From that point on, the number of lockers follows a similar behavior to the demand, which emphasizes its reliance. Evolution of the number of lockers is shown in Figure 9.

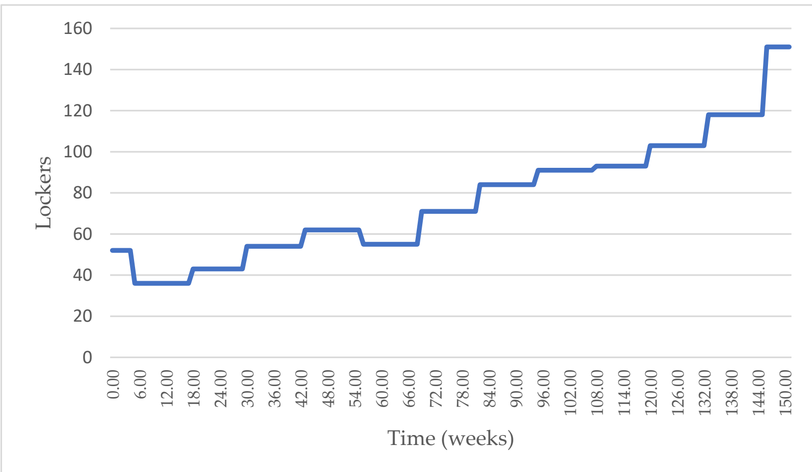

Figure 9. Evolution of the number of lockers.

At the end of the 152nd week of the simulation, there are 151 lockers installed, which falls short compared to the nearly 400 set up by Company A in Wroclaw. However, as has been stated before, Company A implemented a 5-year project, and our simulation considers the upcoming three.

Table 8 shows how for some districts, the number of lockers is reasonably reduced due what has been explained, but in others, it is augmented, which contrasts with what it should be.

Table 8. Number of lockers by district from Company A and the simulated model.

District	Actual Lockers	Model Lockers
Pilczyce	10	6
Popowice	14	6
Gaj	16	6
Oporów	6	12

16.4. Set of Costs

16.4.1. Opening and Closing Costs

The opening cost is the cost of installing a locker. For Company A, the price for setting up a locker is 2450 EUR. This includes every expense in the process until setting up the locker, and it is the same in every district. Hence, the opening costs will be the cost of implementing a locker (2450 EUR) times the number of lockers installed.

One of the factors that must be considered when opening a new automated parcel locker is the current demand. Depending on how many purchases are being made by automated smart locker users, the simulation will promote a certain number of lockers. The higher the demand, the more lockers are installed. Thus, in the weeks after months with a high demand (November and December), more lockers will be set up as the model calculates with the data previously collected.

On the other hand, the closing costs are the cost of decommissioning an automated smart locker in a district. This price has been fixed at 80 EUR, and it is the same for all the cases. Hence, the closing cost will be 80 EUR times the number of lockers removed. Opening cost evolution is presented in Figure 10.

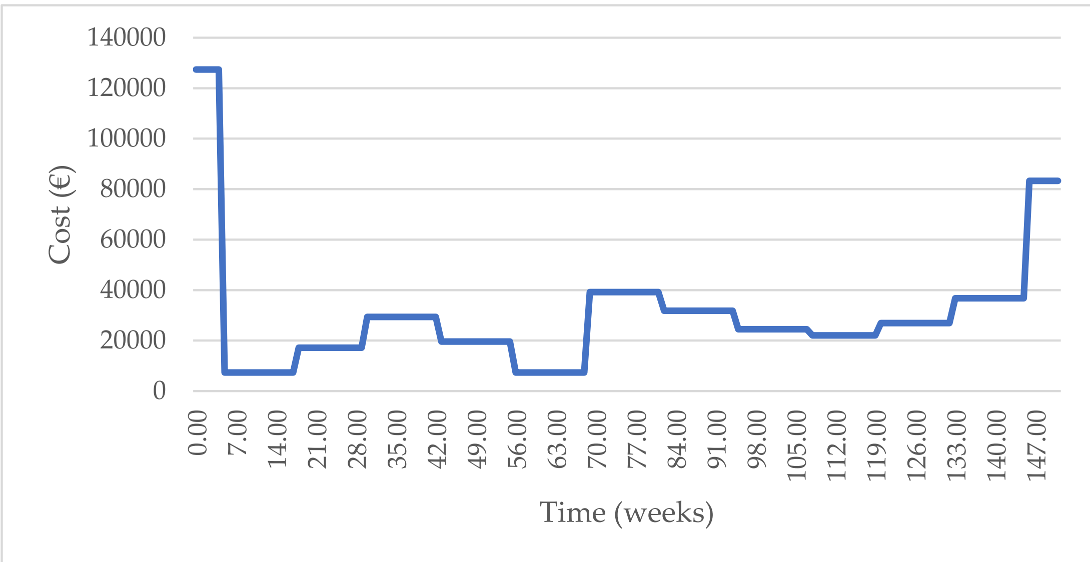

Figure 10. Opening cost evolution.

Every month, the model calculates the new distribution of parcel lockers. At the beginning, as has been noted before, the model starts from scratch and builds 56 lockers.

Then, many of them are removed the next month, as seen in Figure 11. The reason why there are both removed and installed lockers in some months is because they are no longer needed in certain districts while being required in others. The model tends to reduce decommissioning costs every year due to convergence and installs more automated smart locker as user demand increases.

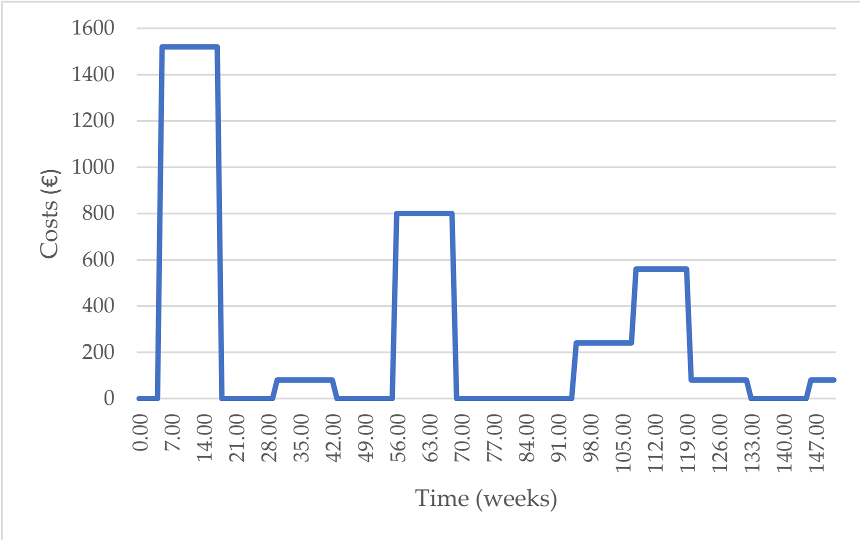

Figure 11. Closing cost evolution.

16.4.2. Maintenance Costs

Regular maintenance can help keep costs down by ensuring that the equipment is serviced on a timely basis. Neglecting assets and deferring maintenance until the last minute may result in increased maintenance expenditures. For that reason, Company A spends 155 EUR weekly per locker, and this figure represents the upkeep costs.

Essentially, the cost of maintenance is just the cost of keeping up a locker (155EUR/week) times the number of lockers that week. The progression is directly proportional to the number of lockers and accounts for 3% of the total costs. Cost of locker maintenance is given in Figure 12.

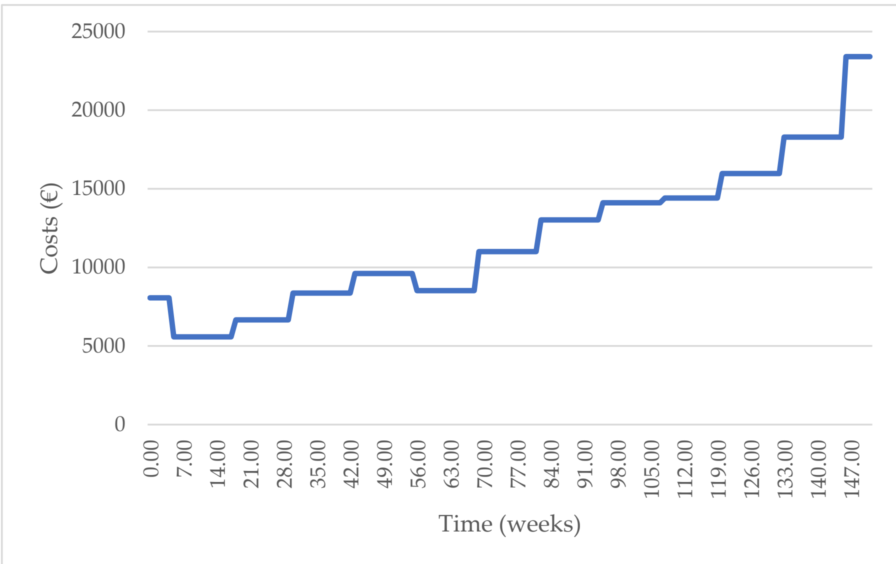

Figure 12. Cost of locker maintenance.

16.4.3. Service Costs

Service costs represent the cost of assigning a customer to districts where automated smart lockers are available. Service cost evolution is displayed in Figure 13. This service is strongly dependent on the distance and the demand, as assigning a customer to a locker in a district far away from his own is much more expensive than doing so for a nearby district. Furthermore, when demand is stronger, more clients will have to be assigned, and the service cost increases. Hence, every year, the service cost augments:

- Year 1: 11,383,981.88 EUR
- Year 2: 1,683,058.45 EUR
- Year 3: 23,160,894.49 EUR

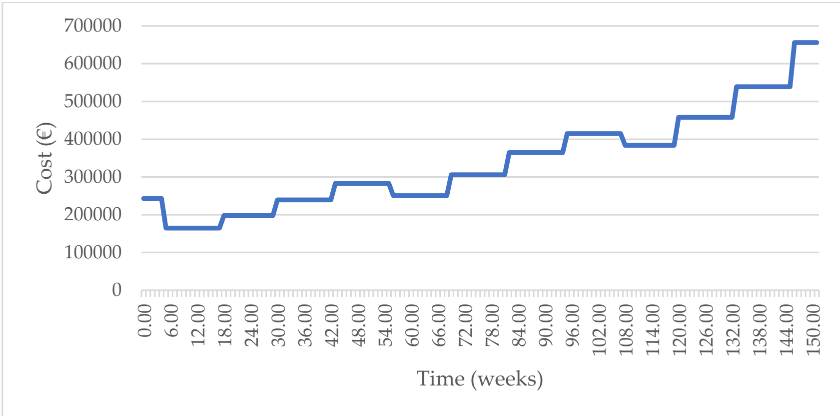

Figure 13. Service cost evolution.

16.5. Total Costs

The total cost is mathematically defined in the facility location problem model in Function (1). This function could be divided into four different types of costs that added together constitute the total cost for the facility location problem. Previously, they were defined in the results section as follows:

- Service costs: cost of assigning a customer to a locker in a district.
- Opening costs: cost of setting up a locker.
- Closing costs: cost of decommissioning a locker.
- Up-keep costs: cost of the maintenance of a locker.

Figure 14 shown the distribution of the total costs, the weight that service costs have in the overall context. Each year, service costs account for 95% of the total costs, whereas the closing costs account for less than 0.1%.

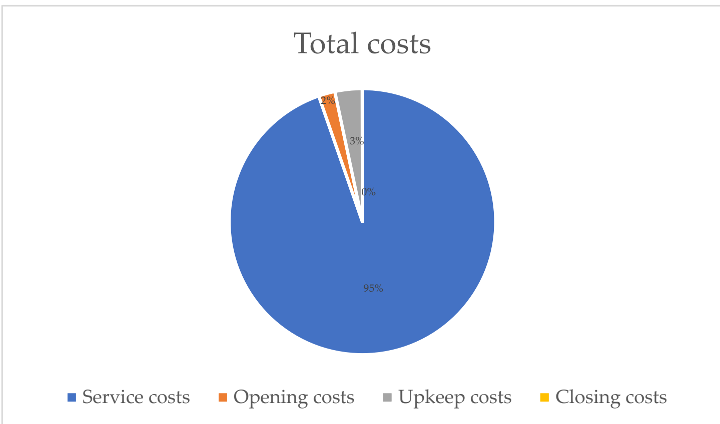

Figure 14. Distribution of the total costs.

If Company A decides to apply this model in real life, they will have to spend 54,263,184.82 EUR. The total expenses for the 152 weeks are divided as follows:

- Service costs: 51,380,934.82 EUR
- Opening costs: 1,080,450 EUR
- Upkeep costs: 1,791,800 EUR
- Closing costs: 10,000 EUR

Although there is a significant investment at the start of the simulation, the expenses in years two and three are larger due to the reasons previously stated. The most significant cost is service, which is directly proportional to the number of lockers. As time goes by, more e-shoppers arrive, resulting in more automated smart locker users, a larger demand for parcels, and the installation of more lockers in Wroclaw. Finally, more clients must be assigned to a locker, resulting in increased service expenses. Total cost evolution are presented in Figure 15.

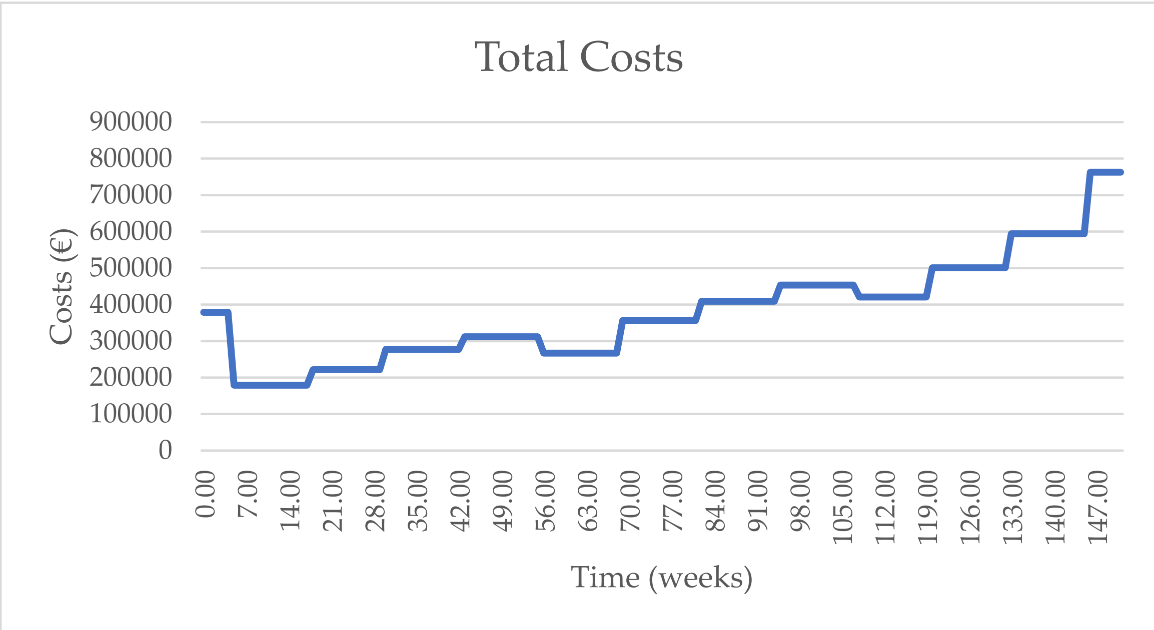

Figure 15. Total cost evolution.

17. Conclusions

This study provides a thorough analysis of several cutting-edge concepts and technologies in the realms of last-mile delivery and supply chain management. The author provide an in-depth examination of the potential of automated parcel lockers, capillary distribution, and crowdshipping as developing solutions to the issues associated with the final leg of product delivery. This research introduces a multiple criteria optimization model to aid decision-making and improve supply chain operations. This model considers a variety of criteria, such as cost, delivery time, customer satisfaction and environmental impact. Decision-makers can effectively select the most efficient and effective delivery options while improving their complete supply chain by combining these diverse criteria. A detailed case study is included in this paper to demonstrate the practical application of the suggested paradigm. This case study demonstrates how one company effectively integrated automated parcel lockers, capillary distribution, and crowdshipping into their supply chain processes. This deployment resulted in significant improvements in delivery performance and customer satisfaction. Overall, this article gives significant insights into the possibilities of these innovative delivery systems, as well as a practical framework for decision-making and optimization in the domains of last-mile delivery and the supply chain. Businesses that embrace these developments can improve their delivery operations, streamline their supply chain, and ultimately provide a better client experience.

We saw in this study that when e-commerce grows, new challenges emerge for which we must find solutions. One of the main reasons for the progression of this business has been the COVID-19 pandemic and its effects around the world. The pandemic forced many families to rely on e-shopping as their only way of purchasing goods.

These reasons led major delivery companies to invest in the already existing but underdeveloped industry of automated smart lockers. Smart lockers have become the solution and seem to be the most successful one to the last-mile-delivery problem in many countries. However, as for every delivery industry, it presents a facility location problem that may be optimized to engage more consumers and become profitable. One way to do so is by modeling the facility location problem for a specific situation (this project does this in Wroclaw) and run it using real data from a company. This is what has been done in this study.

According to the results, Company A should build 151 lockers in Wroclaw for the next 3 years. This figure seems reasonable, considering this company already has around 400 lockers installed for a 5-year project and the exponential development and reception of automated smart lockers. However, some results regarding the number of lockers in some districts seem off, since many of them do not have a single locker, and most automated smart lockers are concentrated in a few districts. This may happen due to the lack of information on the specific case of study.

Population growth will directly affect e-shopper numbers—ergo, automated smart locker users—and finally the demand for parcel lockers. As has been shown, demand is a key factor in the model. This means that a good estimation of the demand will help improve the optimization of automated smart locker usage.

Among the set of costs, the one that stands out most is the service cost, which is the cost of assigning a customer from one district to the automated smart locker of another. It is impressive how much money is invested in this matter, and it shows the importance of a good location for the lockers. Improving and polishing the agent-based model could lead to better optimization of the automated smart lockers.

One of the most important parameters is demand; with a good forecasting of demand, more optimized results can be obtained. It is important to remark that this study has been carried out with little information compared to what Company A manages. There are many relevant aspects that automated smart locker companies consider for the location of their lockers, such as population fluctuation, customers preferences, etc.

The model launches the number of automated smart lockers removed and installed every 4 weeks, and having a model that does this every week will also optimize the results. As the data show, demand changes quickly at times, and waiting 4 or 5 weeks to make changes will cost more than doing so at the proper time.

Lastly, is important to mention how far-reaching models can be for the FLP and many other optimization problems. The creation of these models will help not only the automated smart locker industry but also many others to develop and overcome the last-mile-delivery problem in a more efficient way.

In this paper, we have explored the intricacies of last-mile delivery and supply chain optimization through the integration of multiple innovative strategies including automated smart lockers, capillary distribution, and crowdshipping. The aim was to develop a comprehensive understanding of the challenges faced in this domain and propose a novel optimization model to address them. Through a thorough review of the existing literature, we have highlighted the significance of last-mile delivery in the overall supply chain, emphasizing its impact on customer satisfaction, cost efficiency and environmental sustainability. Traditional approaches to last-mile delivery have proven insufficient in coping with the growing demands of e-commerce and urbanization, necessitating the adoption of innovative solutions. Author proposed optimization model integrates automated lockers, capillary distribution networks and crowdshipping to streamline the last-mile delivery process. By leveraging the advantages of each strategy and utilizing multiple criteria facility location and vehicle routing techniques, the model aims to minimize delivery costs, reduce delivery times and enhance service quality. Through practical examples and case studies, the author has demonstrated the feasibility and effectiveness of the author proposed model in real-world scenarios. From the implementation of automated lockers in urban centers to the utilization of crowdshipping for on-demand deliveries, author's model offers a versatile framework that is adaptable to diverse operational contexts. Moreover, the author has highlighted the potential synergies and trade-offs between different optimization strategies, emphasizing the importance of considering holistic approaches in last-mile delivery planning. By incorporating factors such as customer preferences, traffic conditions, and environmental impact, our model provides decision-makers with valuable insights to optimize their supply chain operations. While our research presents a significant step towards addressing the challenges of last-mile delivery, it also identifies several avenues for future exploration. Further research could focus on refining the optimization algorithms, integrating real-time data analytics and exploring emerging technologies such as drones and autonomous vehicles. The optimization of last-mile delivery and supply chain operations is essential for enhancing customer satisfaction, reducing costs and mitigating environmental impacts. By embracing innovative strategies and leveraging advanced optimization techniques, businesses can stay competitive in an increasingly dynamic and demanding market landscape. Our proposed model serves as a valuable tool for guiding decision-making and fostering sustainable growth [108] in the evolving realm of last-mile logistics [109].

18. Future Research

Future research in hybrid models, incorporating simulation–optimization with a multi-objective approach for last-mile delivery, is poised to revolutionize logistics efficiency. By integrating the bootstrapping method [110] for simulation and multi-criteria for optimization, this approach promises to optimize last-mile delivery process significantly. The utilization of a network of automated smart lockers, capillary distribution and crowdshipping further enhances the system's adaptability and efficacy. The simulation–optimization multi-objective approach allows researchers to fine-tune various parameters to achieve optimal results. Through simulation bootstrapping, researchers can obtain more reliable and accurate results, thereby enhancing the overall effectiveness of the model. By considering multiple criteria for optimization [111] such as delivery time, cost and environmental impact, the model ensures a well-rounded approach to last-mile delivery. Moreover, the integration of automated smart lockers provides a secure and efficient way to handle packages, reducing the need for human intervention and minimizing delivery times. Capillary distribution facilitates the decentralization of delivery centers, allowing for quicker and more convenient access to packages. Additionally, crowdshipping enables the utilization of existing resources, such as commuters or local residents, to deliver packages, further optimizing the delivery process. Future research in this area will focus on refining and fine-tuning these hybrid models to achieve even greater efficiency and sustainability in last-mile delivery, thereby revolutionizing the logistics industry.

Funding: This research was partially supported by the AGH University of Kraków, Kraków, Poland (16.16.200.396) and the financial aid of the Polish Ministry of Science and Higher Education (MNISW) grants (N N519 405934; 6459/B/T02/2011/40) and the Polish National Science Centre (NCN) research grant (DEC-2013/11/B/ST8/04458). Moreover, I appreciate the support of the Spanish Ministry of Science, Innovation, and Universities (RED2018-102642-T; RED2022-134703-T; PID2019-111100RB-C22/AEI/10.13039/501100011033). Additionally, I acknowledge support from the Public University of Navarra, Pamplona, Spain and University of California at Berkeley, USA. The research was also partially supported by the European Union Horizon 2020 research and innovation program under Marie-Skłodowska Curie, No: 101034285.

Data Availability Statement: The data are available from the author upon request.

Acknowledgments: The author is grateful to three anonymous reviewers for reading the manuscript carefully and providing constructive comments which helped to improve this paper.

Conflicts of Interest: The author declares no conflicts of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

References

1. Deutsch, Y.; Golany, B. A parcel locker network as a solution to the logistics last mile problem. *Int. J. Prod. Res.* **2018**, *56*, 251–261. [CrossRef]
2. Krawczyk, J.B. Delivering Left-Skewed Portfolio Payoff Distributions in the Presence of Transaction Costs. *Risks* **2015**, *3*, 318–337. [CrossRef]
3. Juan, A.A.; Mendez, C.A.; Faulin, J.; De Armas, J.; Grasman, S.E. Electric Vehicles in Logistics and Transportation: A Survey on Emerging Environmental, Strategic, and Operational Challenges. *Energies* **2016**, *9*, 86. [CrossRef]
4. Sawik, B.; Faulin, J.; Pérez-Bernabeu, E. Multi-Criteria Optimization for Fleet Size with Environmental Aspects. *Transp. Res. Procedia* **2017**, *27*, 61–68. [CrossRef]
5. Zhou, L.; Li, C.; Hu, C.; Du, J. Parcel locker location problem with selectable volume sizes and heterogeneous customers in the last mile delivery. *Transp. Lett.* **2023**, 1–15. [CrossRef]
6. Sawik, B.; Faulin, J.; Pérez-Bernabeu, E. A Multicriteria Analysis for the Green VRP: A Case Discussion for the Distribution Problem of a Spanish Retailer. *Transp. Res. Procedia* **2017**, *22*, 305–313. [CrossRef]
7. Bieda, B.; Książek, R.; Gdowska, K.; Korcyl, A. Strategic Decision-Making for Multi-Period Fleet Transition Towards Zero-Emission: Preliminary Study. *Sustainability* **2023**, *15*, 16690. [CrossRef]
8. Martins, L.d.C.; Tordecilla, R.D.; Castaneda, J.; Juan, A.A.; Faulin, J. Electric Vehicle Routing, Arc Routing, and Team Orienteering Problems in Sustainable Transportation. *Energies* **2021**, *14*, 5131. [CrossRef]
9. Giosa, I.D.; Tansini, I.L.; Viera, I.O. New assignment algorithms for the multi-depot vehicle routing problem. *J. Oper. Res. Soc.* **2002**, *53*, 977–984. [CrossRef]
10. Pan, S.; Zhang, L.; Thompson, R.G.; Ghaderi, H. A parcel network flow approach for joint delivery networks using parcel lockers. *Int. J. Prod. Res.* **2021**, *59*, 2090–2115. [CrossRef]
11. Yazdi, A.K.; Mehdiabadi, A.; Wanke, P.F.; Monajemzadeh, N.; Correa, H.L.; Tan, Y. Developing supply chain resilience: A robust multi-criteria decision analysis method for transportation service provider selection under uncertainty. *Int. J. Manag. Sci. Eng. Manag.* **2023**, *18*, 51–64. [CrossRef]
12. Ding, M.; Song, Y.; Hu, Y. Supply–Demand Matching of Smart Parcel Lockers in a Residential Area: Insights from Tianjin. *Buildings* **2023**, *13*, 2088. [CrossRef]
13. Leung, E.K.H.; Ouyang, Z.; Huang, G.Q. Community logistics: A dynamic strategy for facilitating immediate parcel delivery to smart lockers. *Int. J. Prod. Res.* **2023**, *61*, 2937–2962. [CrossRef]
14. Available online: https://www.meridiankiosks.com/solutions/automated-smart-locker-system/ (accessed on 15 March 2024).
15. Golinska-Dawson, P.; Sethanan, K. Sustainable Urban Freight for Energy-Efficient Smart Cities—Systematic Literature Review. *Energies* **2023**, *16*, 2617. [CrossRef]
16. INPOST. Quick Send. Send Parcels Quickly and Conveniently with InPost. Send Parcels Quickly and Conveniently. Available online: https://inpost.pl/SzybkieNadania/ (accessed on 31 December 2023).
17. Sawik, B. The Modification of Markowitz Portfolios Made for Stocks from the Warsaw Stock Exchange. *J. Min. Inst.* **2006**, *167*, 306–308. Available online: https://pmi.spmi.ru/pmi/article/view/8033 (accessed on 25 March 2024).
18. Che, Z.-H.; Chiang, T.-A.; Luo, Y.-J. Multiobjective Optimization for Planning the Service Areas of Smart Parcel Locker Facilities in Logistics Last Mile Delivery. *Mathematics* **2022**, *10*, 422. [CrossRef]
19. Ericsson, E.; Larsson, H.; Brundell-Freij, K. Choice for Lowest Fuel Consumption—Potential Effects of a New Driver Support Tool. *Transp. Res. Part C* **2006**, *14*, 369–383. [CrossRef]
20. Esper, T.L.; Jensen, T.D.; Turnipseed, F.L.; Burton, S. The Last Mile: An Examination of Effects of Online Retail Delivery Strategies on Consumers. *J. Bus. Logist.* **2003**, *24*, 177–203. [CrossRef]
21. Corlu, C.G.; de la Torre, R.; Serrano-Hernandez, A.; Juan, A.A.; Faulin, J. Optimizing Energy Consumption in Transportation: Literature Review, Insights, and Research Opportunities. *Energies* **2020**, *13*, 1115. [CrossRef]
22. Schachenhofer, L.; Kummer, Y.; Hirsch, P. An Analysis of Underused Urban Infrastructures: Usage Opportunities and Implementation Barriers for Sustainable Logistics. *Appl. Sci.* **2023**, *13*, 7557. [CrossRef]
23. Shahmohammadi, S.; Steinmann, Z.J.N.; Tambjerg, L.; van Loon, P.; King, J.M.H.; Huijbregts, M.A.J. Comparative Greenhouse Gas Footprinting of Online versus Traditional Shopping for Fast-Moving Consumer Goods: A Stochastic Approach. *Environ. Sci. Technol.* **2020**, *54*, 3499–3509. [CrossRef] [PubMed]
24. Akeb, H.; Moncef, B.; Durand, B. Building a collaborative solution in dense urban city settings to enhance parcel delivery: An effective crowd model in Paris. *Transp. Res. Part E Logist. Transp. Rev.* **2018**, *119*, 223–233. [CrossRef]
25. Karlı, H.; Tanyaş, M. Innovative Delivery Methods in the Last-Mile: Unveiling Consumer Preference. *Future Transp.* **2024**, *4*, 152–173. [CrossRef]

26. Kämäräinen, V.; Saranen, J.; Holmström, J. The reception box impact on home delivery efficiency in the e-grocery business. *Int. J. Phys. Distrib. Logist. Manag.* **2001**, *31*, 414–426. [CrossRef]
27. Risher, J.J.; Harrison, D.E.; LeMay, S.A. Last mile non-delivery: Consumer investment in last mile infrastructure. *J. Mark. Theory Pract.* **2020**, *28*, 484–496. [CrossRef]
28. Reyes-Rubiano, L.; Serrano-Hernandez, A.; Montoya-Torres, J.R.; Faulin, J. The Sustainability Dimensions in Intelligent Urban Transportation: A Paradigm for Smart Cities. *Sustainability* **2021**, *13*, 10653. [CrossRef]
29. Sawik, T.; Sawik, B. Risk-Averse Decision-Making to Maintain Supply Chain Viability under Propagated Disruptions. *Int. J. Prod. Res.* **2024**, *62*, 2853–2867. [CrossRef]
30. Krawczyk, J.B.; Petkov, V.P. A Qualitative Game of Interest Rate Adjustments with a Nuisance Agent. *Games* **2022**, *13*, 58. [CrossRef]
31. Sawik, B. Selected Multiple Criteria Supply Chain Optimization Problems. In *Applications of Management Science*; Lawrence, K.D., Pai, D.R., Eds.; Emerald Publishing Limited: Bingley, UK, 2020; Volume 20, pp. 31–58. [CrossRef]
32. Schiefer, D.; van der Noll, J. The Essentials of Social Cohesion: A Literature Review. *Soc. Indic. Res.* **2017**, *132*, 579–603. [CrossRef]
33. Puka, R.; Łebkowski, P.; Duda, J. One Row Keyboard: The Concept of Designing a Common Layout for Physical and Virtual Keyboards. *Electronics* **2021**, *10*, 663. [CrossRef]
34. Richert, M.; Dudek, M. Selected Problems of the Automotive Industry—Material and Economic Risk. *J. Risk Financ. Manag.* **2023**, *16*, 368. [CrossRef]
35. Zhao, J.; Wang, W.; Zhao, S. Smart Cities and Global Value Chain Upgrading: Evidence from China. *Sustainability* **2024**, *16*, 2394. [CrossRef]
36. Soriano-Gonzalez, R.; Perez-Bernabeu, E.; Ahsini, Y.; Carracedo, P.; Camacho, A.; Juan, A.A. Analyzing Key Performance Indicators for Mobility Logistics in Smart and Sustainable Cities: A Case Study Centered on Barcelona. *Logistics* **2023**, *7*, 75. [CrossRef]
37. Peppel, M.; Spinler, S.; Winkenbach, M. Integrating mobile parcel lockers into last-mile delivery networks: An operational design for home delivery, stationary, and mobile parcel lockers. *Int. J. Phys. Distrib. Logist. Manag.* 2024; *early access*. [CrossRef]
38. Yi, Q.; Jashim, K.; Yuyang, S.; Jiao, T.; Shuo, Z. Impulse buying tendency in live-stream commerce: The role of viewing frequency and anticipated emotions influencing scarcity-induced purchase decision. *J. Retail. Consum. Serv.* **2023**, *75*, 103534. [CrossRef]
39. Mohammad, W.A.; Nazih Diab, Y.; Elomri, A.; Triki, C. Innovative solutions in last mile delivery: Concepts, practices, challenges, and future directions. *Supply Chain. Forum Int. J.* **2023**, *24*, 151–169. [CrossRef]
40. United-Nations. The 17 Goals—Sustainable Development Goals. 2015. Available online: https://sdgs.un.org/goals (accessed on 29 December 2023).
41. Reyes-Rubiano, L.; Voegl, J.; Hirsch, P. An Online Algorithm for Routing an Unmanned Aerial Vehicle for Road Network Exploration Operations after Disasters under Different Refueling Strategies. *Algorithms* **2022**, *15*, 217. [CrossRef]
42. Herrel, K. A visual interactive simulation application for minimizing risk and improving outbound logistical efficiency in time-sensitive attended home deliveries and services. *Simul. Trans. Soc. Model. Simul. Int.* **2014**, *90*, 377–404. [CrossRef]
43. Rabie, W.B.; Khalil, T.A.; Badra, N.; Ahmed, H.M.; Mirzazadeh, M.; Hashemi, M.S. Soliton Solutions and Other Solutions to the (4+1)-Dimensional Davey-Stewartson-Kadomtsev-Petviashvili Equation using Modified Extended Mapping Method. *Qual. Theory Dyn. Syst.* **2024**, *23*, 2. [CrossRef]
44. Lin, Y.H.; Wang, Y.; Lee, L.H.; Chew, E.P. Profit-maximizing parcel locker location problem under threshold Luce model. *Transp. Res. Part E Logist. Transp. Rev.* **2022**, *157*, 102541. [CrossRef]
45. Lu, Y.T.; Xu, S.; Liu, S.X.; Wu, J.Y. An approach to urban landscape character assessment: Linking urban big data and machine learning. *Sustain. Cities Soc.* **2022**, *83*, 103983. [CrossRef]
46. Rabe, M.; Gonzalez-Feliu, J.; Chicaiza-Vaca, J.; Tordecilla, R.D. Simulation-Optimization Approach for Multi-Period Facility Location Problems with Forecasted and Random Demands in a Last-Mile Logistics Application. *Algorithms* **2021**, *14*, 41. [CrossRef]
47. Serrano-Hernandez, A.; Martinez-Abad, S.; Ballano, A.; Faulin, J.; Rabe, M.; Chicaiza-Vaca, J. A Hybrid Modeling Approach for Automated Parcel Lockers as a Last-Mile Delivery Scheme: A Case Study in Pamplona (Spain). In Proceedings of the 2021 Winter Simulation Conference (WSC) 2021, Phoenix, AZ, USA, 13–17 December 2021; Kim, S., Feng, B., Smith, K., Masoud, S., Zheng, Z., Szabo, C., Loper, M., Eds.; Institute of Electrical and Electronics Engineers, Inc.: Piscataway, NJ, USA, 2021; pp. 1–12. [CrossRef]
48. Leyerer, M.; Sonneberg, M.-O.; Heumann, M.; Breitner, M.H. Shortening the Last Mile in Urban Areas: Optimizing a Smart Logistics Concept for E-Grocery Operations. *Smart Cities* **2020**, *3*, 585–603. [CrossRef]
49. Available online: https://www.weforum.org/?src=DAG_2&gclid=Cj0KCQjw8qmhBhClARIsANAtbodAcDm_oNIrORgVEHJPxY_-u9qtJERCL2IZznMFGYBWvaDgYxRMXAMaAiMXEALw_wcB (accessed on 30 December 2023).
50. Ghaderi, H.; Zhang, L.; Tsai, P.-W.; Woo, J. Crowdsourced last-mile delivery with parcel lockers. *Int. J. Prod. Econ.* **2022**, *251*, 108549. [CrossRef]
51. Tadić, S.; Krstić, M.; Dabić-Miletić, S.; Božić, M. Smart Material Handling Solutions for City Logistics Systems. *Sustainability* **2023**, *15*, 6693. [CrossRef]
52. Sawik, B. Multiobjective Newsvendor Models with CVaR for Flower Industry. *Appl. Manag. Sci.* **2020**, *20*, 3–30. [CrossRef]
53. Krstić, M.; Tadić, S.; Elia, V.; Massari, S.; Farooq, M.U. Intermodal Terminal Subsystem Technology Selection Using Integrated Fuzzy MCDM Model. *Sustainability* **2023**, *15*, 3427. [CrossRef]

54. Roszak, M.; Sawik, B.; Stańdo, J.; Baum, E. E-Learning as a Factor Optimizing the Amount of Work Time Devoted to Preparing an Exam for Medical Program Students during the COVID-19 Epidemic Situation. *Healthcare* **2021**, *9*, 1147. [CrossRef] [PubMed]
55. Wojtyla, K. The Task of Christian Philosophy Today. *Proc. Am. Cathol. Philos. Assoc.* **1979**, *53*, 3–4. [CrossRef]
56. Lv, X.; Wang, Z.; Zhou, W. SO_2 Emissions Reduction Effect of China's Pollution Levy Standard Adjustment: A Short-Term and Long-Term Analysis. *Sustainability* **2024**, *16*, 2916. [CrossRef]
57. Magiera, M. A multi-level method of support for management of product flow through supply chains. Bulletin of the Polish Academy of Sciences. *Tech. Sci.* **2015**, *63*, 933–946. [CrossRef]
58. Muñoz-Villamizar, A.; Solano-Charris, E.L.; Reyes-Rubiano, L.; Faulin, J. Measuring Disruptions in Last-Mile Delivery Operations. *Logistics* **2021**, *5*, 17. [CrossRef]
59. Kizys, R.; Juan, A.A.; Sawik, B.; Calvet, L. A Biased-Randomized Iterated Local Search Algorithm for Rich Portfolio Optimization. *Appl. Sci.* **2019**, *9*, 3509. [CrossRef]
60. de la Torre, R.; Corlu, C.G.; Faulin, J.; Onggo, B.S.; Juan, A.A. Simulation, Optimization, and Machine Learning in Sustainable Transportation Systems: Models and Applications. *Sustainability* **2021**, *13*, 1551. [CrossRef]
61. Mrabti, N.; Hamani, N.; Delahoche, L. A Comprehensive Literature Review on Sustainable Horizontal Collaboration. *Sustainability* **2022**, *14*, 11644. [CrossRef]
62. Serrano-Hernandez, A.; de la Torre, R.; Cadarso, L.; Faulin, J. Urban e-Grocery Distribution Design in Pamplona (Spain) Applying an Agent-Based Simulation Model with Horizontal Cooperation Scenarios. *Algorithms* **2021**, *14*, 20. [CrossRef]
63. Binsfeld, T.; Gerlach, B. Quantifying the Benefits of Digital Supply Chain Twins—A Simulation Study in Organic Food Supply Chains. *Logistics* **2022**, *6*, 46. [CrossRef]
64. Serrano-Hernandez, A.; Hirsch, P.; Faulin, J.; Fikar, C. The role of horizontal cooperation to improve service quality in last-mile distribution. *Int. J. Simul. Process. Model.* **2018**, *13*, 299–309. [CrossRef]
65. Serrano-Hernández, A.; Juan, A.; Faulin, J.; Perez-Bernabeu, E. Horizontal collaboration in freight transport: Concepts, benefits, and environmental challenges. *Stat. Oper. Res. Trans.* **2017**, *41*, 393–414. [CrossRef]
66. Abbasi, S.; Vlachos, I.; Samadzadeh, A.; Etemadifar, S.; Afshar, M.; Amra, M. Modelling a Logistics and Financial Supply Chain Network during the COVID-19 Era. *Logistics* **2024**, *8*, 32. [CrossRef]
67. Sawik, B. Space Mission Risk, Sustainability and Supply Chain: Review, Multi-Objective Optimization Model and Practical Approach. *Sustainability* **2023**, *15*, 11002. [CrossRef]
68. Yamin, M.A.; Almuteri, S.D.; Bogari, K.J.; Ashi, A.K. The Influence of Strategic Human Resource Management and Artificial Intelligence in Determining Supply Chain Agility and Supply Chain Resilience. *Sustainability* **2024**, *16*, 2688. [CrossRef]
69. Bento, A.I.; Cruz, C.; Fernandes, G.; Ferreira, L.M.D.F. Social Network Analysis: Applications and New Metrics for Supply Chain Management—A Literature Review. *Logistics* **2024**, *8*, 15. [CrossRef]
70. Ivanov, D. Supply Chain Resilience: Conceptual and Formal Models Drawing from Immune System Analogy. *Omega* **2024**, *127*, 103081. [CrossRef]
71. Dolgui, A.; Ivanov, D. Metaverse supply chain and operations management. *Int. J. Prod. Res.* **2023**, *61*, 8179–8191. [CrossRef]
72. Sawik, B. A single and triple-objective mathematical programming models for assignment of services in a healthcare institution. *Int. J. Logist. Syst. Manag.* **2013**, *15*, 249–259. [CrossRef]
73. Tiwari, M.K.; Bidanda, B.; Geunes, J.; Fernandes, K.; Dolgui, A. Supply chain digitisation and management. *Int. J. Prod. Res.* **2024**, *62*, 2918–2926. [CrossRef]
74. Shakur, M.S.; Lubaba, M.; Debnath, B.; Bari, A.B.M.M.; Rahman, M.A. Exploring the Challenges of Industry 4.0 Adoption in the FMCG Sector: Implications for Resilient Supply Chain in Emerging Economy. *Logistics* **2024**, *8*, 27. [CrossRef]
75. Alves, R.; Pereira, C.A.; da Silva Lima, R. Operational cost analysis for e-commerce deliveries using agent-based modeling and simulation. *Res. Transp. Econ.* **2023**, *101*, 101348. [CrossRef]
76. Sawik, B. Bi-Criteria Portfolio Optimization Models with Percentile and Symmetric Risk Measures by Mathematical Programming. *Prz. Elektrotechniczny* **2012**, *88*, 176–180.
77. Canelas, E.; Pinto-Varela, T.; Sawik, B. Electricity Portfolio Optimization for Large Consumers: Iberian Electricity Market Case Study. *Energies* **2020**, *13*, 2249. [CrossRef]
78. Drabecki, M.; Toczyłowski, E. Multi-Objective Approach for Managing Uncertain Delivery from Renewable Energy Sources within a Peer-to-Peer Energy Balancing Architecture. *Energies* **2022**, *15*, 675. [CrossRef]
79. Richert, M.; Dudek, M. Risk Mapping: Ranking and Analysis of Selected, Key Risk in Supply Chains. *J. Risk Financ. Manag.* **2023**, *16*, 71. [CrossRef]
80. Sawik, B.; Serrano-Hernandez, A.; Muro, A.; Faulin, J. Multi-Criteria Simulation-Optimization Analysis of Usage of Automated Parcel Lockers: A Practical Approach. *Mathematics* **2022**, *10*, 4423. [CrossRef]
81. Sawik, B.; Serrano-Hernandez, A.; Ballano, A.; Faulin, J. A simulation-optimization model for automated parcel lockers network design in urban scenarios in Pamplona (Spain), Zakopane, and Krakow (Poland). In Proceedings of the 2022 Winter Simulation Conference (WSC) 2022, Singapore, 11–14 December 2022; Feng, B., Pedrielli, G., Peng, Y., Shashaani, S., Song, E., Corlu, C., Lee, L., Chew, E., Roeder, T., Lendermann, P., Eds.; Institute of Electrical and Electronics Engineers, Inc.: Piscataway, NJ, USA, 2022; pp. 1648–1659. [CrossRef]

82. Izco, I.; Serrano-Hernandez, A.; Javier, F.; Bartosz Sawik, B. A dynamic forecast demand scenario analysis to design an automated parcel lockers network in Pamplona (Spain) using a simulation-optimization model. In Proceedings of the 2023 Winter Simulation Conference (WSC) 2023, San Antonio, TX, USA, 10–13 December 2023; Feng, B., Pedrielli, G., Peng, Y., Shashaani, S., Song, E., Corlu, C., Lee, L., Chew, E., Roeder, T., Lendermann, P., Eds.; Institute of Electrical and Electronics Engineers, Inc.: Piscataway, NJ, USA, 2023; pp. 1759–1770. [CrossRef]
83. Wang, S.-T.; Li, M.-H.; Lien, C.-C. Analysis of the Optimal Application of Blockchain-Based Smart Lockers in the Logistics Industry Based on FFD-SAGA and Grey Decision-Making. *Symmetry* **2021**, *13*, 329. [CrossRef]
84. Kedia, A.; Kusumastuti, D.; Nicholson, A. Establishing Collection and Delivery Points to Encourage the Use of Active Transport: A Case Study in New Zealand Using a Consumer-Centric Approach. *Sustainability* **2019**, *11*, 6255. [CrossRef]
85. Vakulenko, Y.; Hellstrom, D.; Hjort, K. What's in the parcel locker? Exploring customer value in e-commerce last mile delivery. *J. Bus. Res.* **2017**, *88*, 421–427. [CrossRef]
86. Iwan, S.; Kijewska, K.; Lemke, J. Analysis of parcel lockers' efficiency as the last mile delivery solution—The results of the research in Poland. *Transp. Res. Procedia* **2016**, *12*, 644–655. [CrossRef]
87. de Oliveira, L.K.; Morganti, E.; Dablanc, L.; de Oliveira, R.L.M. Analysis of the potential demand of automated delivery stations for e-commerce deliveries in Belo Horizonte, Brazil. *Res. Transp. Econ.* **2017**, *65*, 34–43. [CrossRef]
88. Lagorio, A.; Pinto, R. The Parcel Locker Location Issues: An Overview of Factors Affecting Their Location. In Proceedings of the 8th International Conference on Information Systems, Logistics and Supply Chain ILS Conference 2020, Austin, TX, USA, 22–24 April 2020; pp. 414–421. Available online: https://www.researchgate.net/publication/350726102_The_parcel_locker_location_issues_an_overview_of_factors_affecting_their_location (accessed on 20 April 2024).
89. Rossolov, A. A last-mile delivery channel choice by E-shoppers: Assessing the potential demand for automated parcel lockers. *Int. J. Logist. Res. Appl.* **2021**, *26*, 983–1005. [CrossRef]
90. Pascoe, S. On the Use of Data Envelopment Analysis for Multi-Criteria Decision Analysis. *Algorithms* **2024**, *17*, 89. [CrossRef]
91. Costa, Y.; Melo, T. Facility Location Modeling in Supply Chain Network Design: Current State and Emerging Trends. In *The Palgrave Handbook of Supply Chain Management*; Sarkis, J., Ed.; Palgrave Macmillan: Cham, Switzerland, 2024. [CrossRef]
92. Melo, M.T.; Nickel, S.; Saldanha-da-Gama, F. Facility Location and Supply Chain Management—A Review. *Eur. J. Oper. Res.* **2009**, *196*, 401–412. [CrossRef]
93. Sawik, B.; Płonka, J. Project and Prototype of Mobile Application for Monitoring the Global COVID-19 Epidemiological Situation. *Int. J. Environ. Res. Public Health* **2022**, *19*, 1416. [CrossRef] [PubMed]
94. Gaweł, B.; Paliński, A. Long-Term Natural Gas Consumption Forecasting Based on Analog Method and Fuzzy Decision Tree. *Energies* **2021**, *14*, 4905. [CrossRef]
95. Malynovska, Y.; Bashynska, I.; Cichoń, D.; Malynovskyy, Y.; Sala, D. Enhancing the Activity of Employees of the Communication Department of an Energy Sector Company. *Energies* **2022**, *15*, 4701. [CrossRef]
96. Ginda, G.; Iwaszczuk, N.; Dudek, M. Supporting Multi-Attribute, Non-Compensating Selection of the Right Heat Pump Device for a Residential Building, Considering the Limited Availability of the Necessary Resources. *Energies* **2022**, *15*, 5478. [CrossRef]
97. Puka, R.; Łamasz, B.; Skalna, I.; Basiura, B.; Duda, J. Knowledge Discovery to Support WTI Crude Oil Price Risk Management. *Energies* **2023**, *16*, 3486. [CrossRef]
98. Sala, D.; Pavlov, K.; Pavlova, O.; Demchuk, A.; Matiichuk, L.; Cichoń, D. Determining of the Bankrupt Contingency as the Level Estimation Method of Western Ukraine Gas Distribution Enterprises' Competence Capacity. *Energies* **2023**, *16*, 1642. [CrossRef]
99. Gaweł, B.; Paliński, A. Global and Local Approaches for Forecasting of Long-Term Natural Gas Consumption in Poland Based on Hierarchical Short Time Series. *Energies* **2024**, *17*, 347. [CrossRef]
100. Naumov, V.; Kubek, D.; Więcek, P.; Skalna, I.; Duda, J.; Goncerz, R.; Derlecki, T. Optimizing Energy Consumption in Internal Transportation Using Dynamic Transportation Vehicles Assignment Model: Case Study in Printing Company. *Energies* **2021**, *14*, 4557. [CrossRef]
101. Loger, B.; Dolgui, A.; Lehuédé, F.; Massonnet, G. Approximate Kernel Learning Uncertainty Set for Robust Combinatorial Optimization. *INFORMS J. Comput.* **2024**, 1091–9856. [CrossRef]
102. Sawik, B. A Three Stage Lexicographic Approach for Multi-Criteria Portfolio Optimization by Mixed Integer Programming. *Przegląd Elektrotechniczny* **2008**, *84*, 108–112.
103. Sawik, B.; Tobis, S.; Baum, E.; Suwalska, A.; Kropińska, S.; Stachnik, K.; Pérez-Bernabeu, E.; Cildoz, M.; Agustin, A.; Wieczorowska-Tobis, K. Robots for Elderly Care: Review, Multi-Criteria Optimization Model and Qualitative Case Study. *Healthcare* **2023**, *11*, 1286. [CrossRef]
104. Czernek-Marszałek, K.; McCabe, S. Sampling in qualitative interview research: Criteria, considerations and guidelines for success. *Ann. Tour. Res.* **2024**, *104*, 103711. [CrossRef]
105. Sawik, B. Weighted-Sum Approach for Bi-objective Optimization of Fleet Size with Environmental Aspects. *Appl. Manag. Sci.* **2018**, *19*, 101–116. [CrossRef]
106. Sawik, T. A note on the Miller-Tucker-Zemlin model for the asymmetric traveling salesman problem. Bulletin of the Polish Academy of Sciences. *Tech. Sci.* **2016**, *64*, 517–520. [CrossRef]
107. Wrocław Spatial Information System. (n.d.). Available online: https://www.geoportal.wroclaw.pl/en/resources/ (accessed on 30 December 2023).

108. Dudek, M.; Bashynska, I.; Filyppova, S.; Yermak, S.; Cichoń, D. Methodology for assessment of inclusive social responsibility of the energy industry enterprises. *J. Clean. Prod.* **2023**, *394*, 136317. [CrossRef]
109. Hosseini, S.; Ivanov, D.; Blackhurst, J. Conceptualization and Measurement of Supply Chain Resilience in an Open-System Context. *IEEE Trans. Eng. Manag.* **2022**, *69*, 3111–3126. [CrossRef]
110. Lach, Ł. Optimization based structural decomposition analysis as a tool for supporting environmental policymaking. *Energy Econ.* **2022**, *115*, 106332. [CrossRef]
111. Sawik, B. Survey of multi-objective portfolio optimization by linear and mixed integer programming. *Appl. Manag. Sci.* **2013**, *16*, 55–79. [CrossRef]