Smart Delivery Mobile Lockers

Smart Delivery Mobile Lockers: Design, Models and Analytics

By
SI LIU,
M.Sc. (Mechanical Engineering)

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AUTHOR:
Si Liu,
M.Sc. (Mechanical Engineering)

SUPERVISOR:
Dr. Elkafi Hassini
Professor, Operations Management, DeGroote School of Business
McMaster University, ON, Canada

SUPERVISORY COMMITTEE MEMBERS:
Dr. Manish Verma
Professor, Operations Management, DeGroote School of Business
McMaster University, ON, Canada

Dr. Kai Huang
Professor, Operations Management, DeGroote School of Business
McMaster University

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Lay Abstract

This doctoral thesis represents pioneering research in integrating Smart Mobile Lockers with City Buses (SML-CBs) for e-commerce last-mile delivery. It explores the innovative use of underutilized urban bus capacities for parcel transportation while incorporating smart parcel lockers to facilitate self-pick-up by customers. Comprising six chapters, the thesis delineates its background, motivations, contributions, and organization in Chapter 1. Chapter 2 presents a comprehensive review of the recent literature on last-mile freight deliveries. In Chapter 3, we study Canadian consumers' attitudes towards adopting SML-CBs, focusing on deterrents such as excessive walking distances to pick-up locations and incentives led by environmental concerns. To address the concerns over walking distances identified in Chapter 3, Chapter 4 presents models and algorithms for operating SML-CBs. Chapter 5 presents an assessment of the sustainability of SML-CBs. The dissertation is concluded in Chapter 6, summarizing the principal contributions and suggesting avenues for future research.

Abstract

This doctoral thesis represents pioneering research in integrating Smart Mobile Lockers with City Buses (SML-CBs) for e-commerce last-mile delivery, a novel concept rooted in the sharing economy. It explores the innovative use of underutilized urban bus capacities for parcel transportation while incorporating smart parcel lockers to facilitate self-pick-up by customers. Comprising six chapters, the thesis delineates its background, motivations, contributions, and organization in Chapter 1. Chapter 2 presents a comprehensive review of the recent literature on last-mile freight deliveries, including a bibliometric analysis, identifying gaps and opportunities for SML-CBs intervention. In Chapter 3, using survey data, we conduct empirical analytics to study Canadian consumers' attitudes towards adopting SML-CBs, focusing on deterrents such as excessive walking distances to pick-up locations and incentives led by environmental concerns. This chapter also pinpoints demographic segments likely to be early adopters of this innovative delivery system. To address the concerns over walking distances identified in Chapter 3, Chapter 4 presents a prescriptive model and algorithms aimed at minimizing customer walking distance to self-pick-up points, considering the assignment of SML-CBs and customers. The case study results endorse the convenience of SML-CBs in terms of short walking distances. To systematically assess the sustainability benefits, a key motivator identified in Chapter 3, Chapter 5 includes analytical models for pricing and accessibility of SML-CBs. It also employs a hybrid life cycle assessment (LCA) methodology to analyze the sustainability performance of SML-CBs. It establishes system boundaries, develops pertinent LCA parameters, and illustrates substantial greenhouse gas (GHG) savings in both operational and life cycle phases when SML-CBs are utilized instead of traditional delivery trucks. The dissertation is concluded in Chapter 6, summarizing the principal contributions and suggesting avenues for future research. This comprehensive study not only provides empirical and analytical evidence supporting the feasibility and advantages of SML-CBs but also contributes to the literature on sustainable logistics and urban freight deliveries.

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Contents

List of Figures

List of Tables

Declaration of Academic Achievement

This thesis, titled **Smart Delivery Mobile Lockers: Design, Models and Analytics**, was prepared in accordance with the guidelines set by the School of Graduate Studies at McMaster University for a sandwich thesis. I, Si Liu, declare that this thesis and works presented in it are my own, with the guidance and supervision of Prof. Elkafi Hassini. The main chapters (Chapters 2 through 5) contain scholarly work either published or submitted for publication.

As this thesis contains materials published, submitted, or accepted for publication in journals, all steps have been taken to ensure that the necessary copyright limitations and rights have been respected.

Chapter 1

Introduction

1.1 Thesis Background and Motivation

With the widespread accessibility of the internet, e-commerce sales have experienced significant growth globally. According to Statista, global e-commerce sales reached 4.2 trillion U.S. dollars in 2020, marking a 27.6% increase from the previous year, with over two billion individuals purchasing services or goods online. This surge was further catalyzed by the COVID-19 pandemic, exemplified by a 42.85% increase in online grocery sales as a proportion of total grocery sales in 2020. Specifically, in Canada, the share of online retail sales was more than doubled during the pandemic, as reported by the Mastercard Economics Institute. While the continuous expansion of the e-commerce market provides convenience and safety to customers, as well as opportunities for businesses during the pandemic, it also introduces significant challenges. A primary concern for businesses is managing the delivery of an unprecedented volume of parcels using the existing supply chain infrastructure [5]. Under normal business conditions, incorporating flexibility up to 25% in the supply chain network is advisable to accommodate disruptions [1]. However, the recent e-commerce volume spikes, sometimes as high as 75% as reported by Canada Post for June 2020 compared to June 2019 [3], far exceed conventional flexible network capacities and necessitate the adoption of innovative strategies to mitigate these pressures. This thesis aims to explore one such strategy: utilizing alternative last-mile e-commerce delivery methods that leverage the sharing economy concept to alleviate the strain on the current supply chain network.

The final stage in an e-commerce supply chain, known as last-mile delivery, is pivotal yet notably the most costly component, accounting for 28% [11] to 50% [6] of total delivery costs. Moreover, it is acknowledged as the least efficient and most environmentally detrimental phase within the supply chain [10]. Recognizing its significance, extensive research has been directed towards enhancing last-mile delivery operations, aiming to reduce costs, increase efficiency, and mitigate environmental impacts. Merely expanding network capacity, such as through the addition of delivery vehicles to manage increased e-commerce volumes, introduces a spectrum of additional challenges [15]. Firstly, the augmented movement of delivery vehicles exacerbates traffic flow and congestion, particularly during peak periods or within congested urban centers, while simultaneously escalating the environmental footprint. Secondly, urban infrastructures are generally not designed to support the increased influx of delivery vehicles, leading to heightened occurrences of illegal and unsafe parking and associated costs. For instance, in 2018, the giant delivery players UPS and FedEx incurred fines totaling \$33.8 million and \$14.9 million, respectively, in a single U.S. city due to such infractions [2]. Consequently, various studies have shifted focus towards exploring innovative and non-traditional delivery alternatives that circumvent these escalating logistical and environmental challenges.

Various innovative delivery alternatives have been explored in the literature, encompassing automated parcel lockers (APLs), drones, and autonomous vehicles. APLs, in particular, are preferred for their economies of scale [9]. Defined as "a group of lockers situated in strategic locations such as apartment blocks, workplaces, and railway stations, equipped with electronic locks and variable opening codes to facilitate multiple users at their convenience," APLs have seen a surge in popularity, being implemented in over 20 countries by 2018 [4]. However, their stationary nature introduces drawbacks. Firstly, the cost associated with land occupancy can be substantial, exacerbated by zoning regulations that restrict APL placement [7]. Secondly, their fixed locations limit adaptability to fluctuating consumer demands [14]. Thirdly, inefficient parcel turnover can slow system replenishment, leading to logistical delays [13]. In response to these limitations, a novel concept known as 'mobile parcel lockers' (MPLs) has emerged. MPLs are characterized as lockers capable of relocating throughout the day, either autonomously or via human operation, thereby enhancing accessibility and reducing the need for numerous stationary units [12]. Despite these advantages, MPLs are not without their own constraints [8]. The construction of autonomous MPLs entails significant investment, while manual operation incurs additional running costs. Moreover, their movement contributes to traffic congestion and necessitates designated parking spaces, which may be expensive or scarce. These multifaceted challenges and opportunities underscore the need to comprehensively evaluate MPLs as a viable last-mile delivery solution.

To address these challenges, this thesis introduces a pioneering e-commerce delivery alternative: self-monitoring, analysis, and reporting technology (SMART) mobile lockers

(SMLs) utilized in conjunction with city buses, referred to as SML-CBs in the sequel. Embracing the sharing economy ethos, this approach seeks to integrate with existing urban transit systems to mitigate the complexities associated with last-mile e-commerce deliveries. Each SML, affixed to a city bus, leverages the bus's routes and stops to distribute parcels efficiently to customers. These lockers are enhanced with artificial intelligence (AI) and internet of things (IoT) technologies, enabling them to function intelligently, adaptively, and safely within the urban delivery ecosystem. This system not only aims to utilize the pervasiveness and regularity of city buses but also intends to significantly reduce the congestion and environmental impact typically associated with traditional delivery methods.

1.2 Thesis Contributions and Organization

Being a pioneer by alternating the last mile delivery by coupling the sharing economy and smart parcel lockers, this thesis aims to explore numerous research opportunities for utilizing SML-CBs and building foundations for future extensions.

In Chapter 2, we review the literature on freight last-mile delivery from 2010 to the end of 2021 to identify research gaps and position the contributions of the thesis in the literature. This chapter defines the concepts of last-mile logistics, distribution, and delivery. In addition, a bibliometric analysis is carried out and classifies the literature into three clusters: humanitarian relief, commercial logistics, and emerging technologies. We identify research gaps within each cluster and suggest future research directions.

The primary objective of Chapter 3 is to elucidate consumer perceptions regarding adopting emergent SML-CB technology. We focus on two critical research questions: (1) What are the dominant attitudes of Canadian e-commerce consumers towards embracing SML-CBs? and (2) What demographic cohorts are predisposed to be early adopters of SML-CBs? Our findings indicate that the system's environmental sustainability and cost-efficiency are the two main drivers of adoption. Notably, approximately 50% of participants expressed a willingness to collect parcels from bus stops within a 100-meter proximity of their locations, and about 44% of them were amenable to waiting at these stops for up to five minutes. Furthermore, a 50% reduction in delivery fees, relative to conventional service charges, was perceived as a compelling incentive by 73% of respondents. Employing a rating methodology, we have delineated the specific participant groups and clusters that exhibit a pronounced propensity towards adopting SML-CBs compared to their counterparts. This nuanced understanding paves the way for targeted strategies and interventions to accelerate the adoption of this innovative last-mile delivery solution. This knowledge will be employed in the rest of the thesis to inform our data-driven approach to developing models and algorithms for operating SML-CBs.

After revealing the importance of the impact of the walking distance between customers and parcels, Chapter 4 is devoted to developing models and solution approaches for assigning customers to bus stops and lockers to buses while minimizing customers' total walking distances. This results in a quadratic assignment problem with quadratic constraints (QAPQC). We propose a hybrid construction-greedy (HCG) heuristic to solve the QAPQC. Our numerical results show that HCG is efficient regarding solution quality and execution time in small and large data instances and performs well with various customer characteristics. Finally, we implement a case study in Mississauga City, Canada, to demonstrate the applicability of our models and solutions in real-world data.

Having identified that potential customers are motivated to use SML-CBs due to their environment-friendly benefits, we conduct sustainability analysis in Chapter 5. We make use of the sharing economy context and systematically quantify the sustainability performance of SML-CBs in terms of greenhouse gas emissions. In addition, we assess the economic and social impacts of SML-CBs. We find that delivery costs can be reduced by around 55% using SML-CBs compared to trucks, and the accessibility, in terms of ridership, can be increased by more than 100% when using SML-CBs on bus routes over fixed parcel lockers at transit facilities. Then, we present a hybrid life cycle assessment (LCA) methodology for environmental assessment. After defining the system boundaries for analysis, we provide the SML-CBs LCA parameters in the manufacturing and operational phases. We find three important results (1) The SML-CBs have the lowest fuel economy value and emissions per parcel when operating within cities and are 2.91% of the delivery trucks with the same power source; (2) by optimizing the SML-CBs parameters, including power source, capacity, and operation frequency, the GHG emissions of SML-CBs per parcel can be reduced by 53.92% from the highest emissions of the given SML-CBs; and (3) the life cycle GHG emissions per parcel of the optimized SML-CBs is 9.80% of the delivery trucks with the lowest emissions in the literature. Our studies prove that SML-CBs have significant advantages in fuel and GHG life cycle emission savings compared to delivery trucks, reflecting them as a promising sustainable delivery technology. Chapter 6 summarizes the contributions of this thesis and discusses possible extensions for future research.

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Chapter 2

A Review of Last-mile Freight Deliveries - Challenges and Opportunities

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Freight last mile delivery: a literature review

Si Liu
DeGroote School of Business
McMaster University, Hamilton, ON, Canada
Email: lius278@mcmaste.ca

Elkafi Hassini
DeGroote School of Business
McMaster University, Hamilton, ON, Canada
Email: hassini@mcmaster.ca

Abstract

The authors review the literature on last-mile delivery logistics within commercial and humanitarian supply chains from 2010 to the end of 2021. The scope of the last mile, including last-mile logistics, last-mile distribution, and last-mile mile delivery, is covered. A unifying terminology of the major concepts in this field and a bibliometric analysis are provided. Based on the analysis, the authors further classify and discuss the literature into three clusters: humanitarian relief, commercial logistics, and emerging technologies. Within each generated cluster, research gaps and current trends are identified. Future research directions are suggested based on this literature review.

Keywords: *Last mile delivery, Logistics, E-commerce, Humanitarian logistics*

2.1 Introduction

It has been widely recognized that transportation in the last mile is critical for the whole supply chain since it can account for as much as 75% of the total transportation cost [61]. Besides increasing supply chain costs, the transportation-related activities in last-mile deliveries have other indirect costs such as congestion [133], air pollution [153], and greenhouse gas emissions [50, 186]. Thus, last-mile transportation is considered the supply chain's most expensive and complex part [62]. As a result, there is a growing interest in studying last-mile delivery operations from both academia and industry to identify the underlying challenges and possible solutions, as reflected by an exponential increase in the number of publications related to last-mile deliveries [142]. While there is a growing body of literature addressing the last mile delivery operations, the authors found a lack of coherency when it comes to identifying challenges as well as the role of emerging technologies. This can be explained by the fact that this is a nascent field of research, and there is a lack of a conceptual framework to guide the research progress.

The existing last-mile delivery solutions are insufficient to handle the exponential increase in e-commerce deliveries, which has been boosted by the covid pandemic and the restrictions of brick-and-mortar shopping. Therefore, retailers are considering alternative delivery solutions, resulting in additional logistics challenges [44]. The interest in last-mile logistics has also been driven by two other major factors. The role of emerging technologies, such as the Internet of Things and digitalization, in the last mile deliveries and the importance of studying this area has been highlighted in many recent transportation studies, e.g., [96, 195]. In addition, the increase in occurrence and cost of humanitarian relief operations, e.g., [113] has triggered interest in studying humanitarian logistics, with a specific call for additional research in humanitarian last mile distribution networks, e.g., [139]. This literature review aims to comprehensively analyze the state-of-the-art of related literature and fill the identified research gaps. The authors propose a framework for classifying the last mile operations literature and conduct a systematic literature review for both commercial and humanitarian operations. Additionally, this review contributes to the current literature in several ways:

- Introduce the concept of the last mile network and cover the scope of the last mile, including last-mile logistics, last-mile distribution, and last-mile delivery.
- Offer a unifying definition for 'last mile delivery' and related operations.
- Conduct a bibliometric study to categorize and discuss the relevant literature. Three main research clusters are identified:
  - Humanitarian last mile delivery: This contrasts this review with other reviews primarily focused on last mile deliveries for commercial purposes.
  - Commercial last mile delivery: This area focuses on freight transportation using classical transportation technologies for business-to-consumer (B2C)

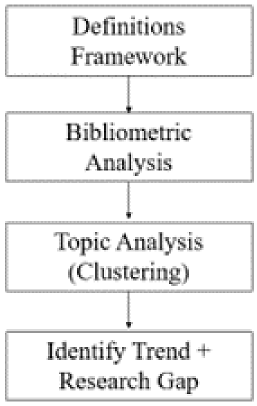

FIGURE 2.1: Structure of the Literature Review.

operations. The models and algorithms that were applied in this area are discussed.

- Technology-driven last mile deliveries: This includes literature focusing on the impact of emerging transportation technologies for commercial purposes.

- Discuss the research streams and identify research gaps based on classified literature.

- Generate the underlying research trends.

The structure of the rest of the paper is organized as follows and illustrated in Figure 2.1: In Section 2.2, the authors discuss relevant definitions, differentiate them from other closely related terms as well as their inter-relationships, and propose a clear unifying definition in the context. In Section 2.3, the authors consider existing literature review studies on last-mile operations and discuss why a more comprehensive systematic review is required. In Section 2.4, the authors present the methodology for the literature review, including the literature selection methodology and the bibliometric analysis. Based on the bibliometric literature classification, the authors provide in Section 2.5 a detailed review of three research clusters: applications for humanitarian relief, commercial last mile operations, and application of emerging technologies and concepts. The limitations of the existing literature identified gaps and research trends are discussed in Section 2.6. In Section 2.7, the authors finally propose avenues for future research directions and a summary of major conclusions.

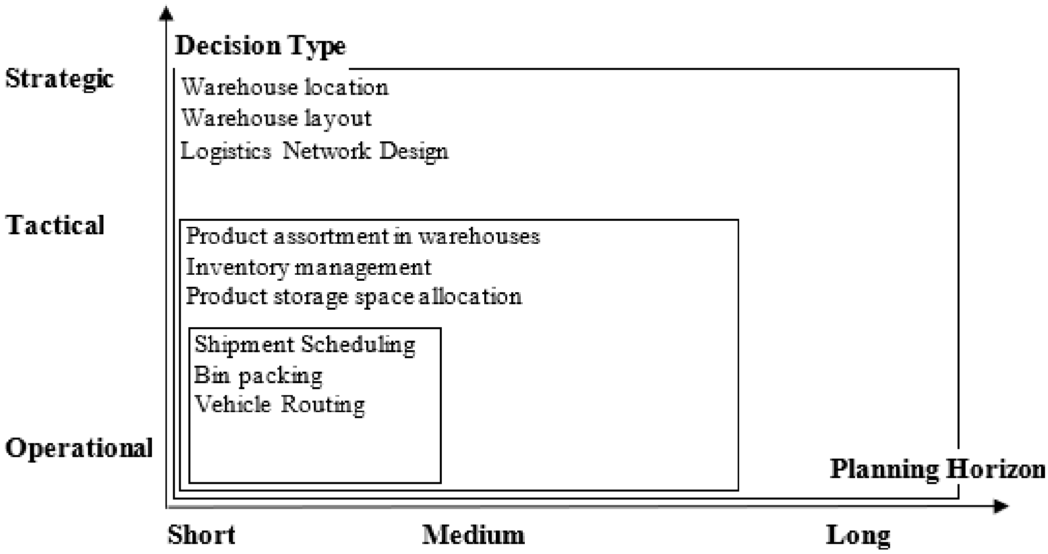

FIGURE 2.2: A framework for last mile operations.

2.2 Literature Framework and Definitions

2.2.1 Last Mile Literature Framework

The authors propose a last mile literature framework to classify the last mile operations, which serves as a foundation to unify definitions. Classification of decisions aids firms in prioritizing decisions, allocating resources, and developing capabilities [169]. Management scholars agree that conflating the types of decisions can have devastating impacts on the business [169]. Defining a planning horizon is important for a business's competitive strategy [173]. Therefore, classifying the last mile operations literature based on the type of decisions and planning horizon will help aid businesses in optimizing their resource allocations and supporting their competitive strategy.

In Figure 2.2, three examples are listed of last mile distribution under each type of decision. Since strategic decisions impact medium decisions that, in turn, impact operational decisions, the operational decision horizon is a subset of medium planning-horizon decisions, and the latter is a subset of the strategic decisions.

2.2.2 Definitions

The last stretch of the supply chain has been described using several terms, including last-mile logistics, last-mile distribution, and last-mile deliveries [108, 142]. These terms have been loosely defined and sometimes used interchangeably, leading to a lack of coherence and consensus. As a result, it is common to find that one term may correspond to various definitions in different literature. As an example of inconsistency, we found that Lim and Srai [109] defined last-mile logistics as 'the last segment of a delivery process' while Lindner [111] used the same phrase to define last-mile delivery. Though the authors acknowledge the contributions of the definitions that were proposed by Olsson et al. [142] to clarify some of these terms, this review differs from them in several ways: (1) introduce the term "last mile network," which is believed to become an important part of e-commerce logistics, (2) synthesize the definitions from the literature and contrast them to each other and propose a comprehensive definition, and (3) use the decision-making framework as well as the new definition of "last mile network" to propose a unified set of definitions.

In this review paper, the authors propose a framework in Figure 2.2 and related definitions from the studied literature to define related last mile terms. The proposed definitions are made as general as possible. Using the framework in Figure 2.2, the authors incorporate the type of decision and planning horizon in the definition to better reflect the inter-relationships between the terms of last-mile operations.

Given the increase in last-mile deliveries, largely due to increased online shopping volumes, the last-mile operations have increased in complexity. For example, some online retailers have introduced fulfillment and delivery centers as well as mobile depots. These different facilities are forming an infrastructure network for last-mile operations. Therefore, the authors introduce the notion of the last mile network in Definition 1.

Definition 1. *A last-mile network is a system of interconnected parties and processes that could range from distribution centers to the final customers.*

Figure 2.3 illustrates a typical modern e-commerce last-mile network incorporating different stakeholders. Such stakeholders could include the e-retailer that owns the distribution centers (DCs) and possibly fulfillment centers (FCs), the third-party logistics providers (3PLs) that operate the Delivery Centers, and possibly some FCs, as well as the cities and end customers. The processes in the network of different stakeholders' perspectives can involve warehousing, sorting, inventory replenishment, transportation, and facility location.

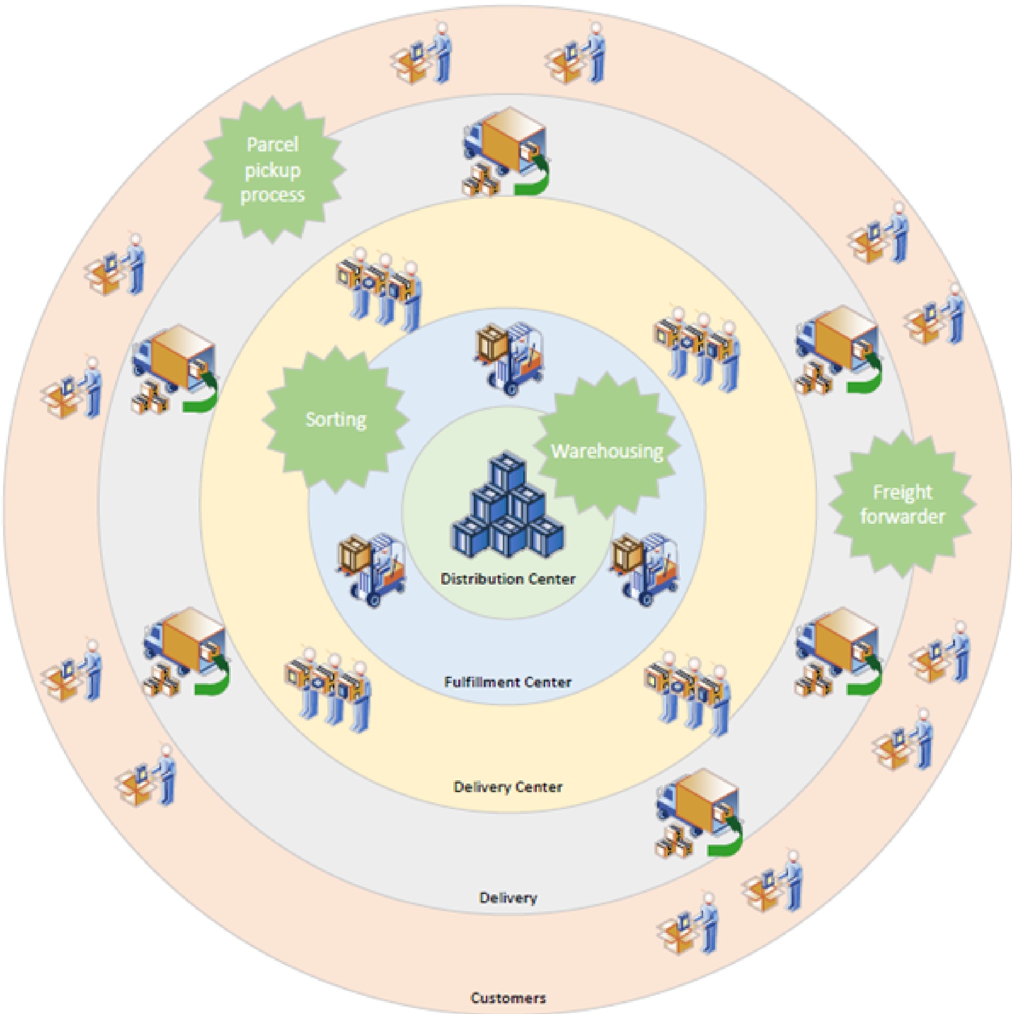

FIGURE 2.3: A typical modern e-commerce last mile network.

A distribution center (DC) is a large regional warehouse facility that is used to fulfill the needs of long-term inventory of all the fulfillment centers that it serves. DC is usually owned by an e-commerce retailer. A fulfillment center (FC) is used to fulfill customer orders. It contains material handling equipment, such as robotics, scanning machines, and computer systems. It houses inventory that is already scheduled to be shipped or inventory that is likely to be ordered, such as fast-moving items. An FC can be owned by the e-retailer, such as in the case of Amazon, which operates more than 175 FCs worldwide, or outsourced by a third-party logistics provider. Finally, a delivery center is the closest point to customers, and it often houses limited inventory already confirmed to be shipped to final destinations. A delivery center is often operated by third-party logistics partners such as post offices or other major carrier services. It is sometimes called the sortation center, where several shipments from an FC get sorted out to be shipped to specific customer zones. Delivery centers are the smallest in size, allowing them to be located within dense population areas to allow for same- and next-day e-commerce deliveries. Some e-retailers use mobile delivery centers where a trailer, or set of trailers, may be located in certain locations in a city, such as in parking lots, and e-bikes or walkers deliver to the customers. Depending on availability and lead times, direct shipments may occur between a DC and a delivery center, as well as a fulfillment center and a final customer. It is worth noting that the last mile network in Figure 3 is only an example; there are other variations, such as when an e-tailer owns a brick-and-mortar store network that may also be used for serving online customers. Figure 2.3 can also be adapted to humanitarian last-mile delivery networks where often a DC, FC, and delivery centers are referred to as primary hub (or port of entry), secondary hub (or central warehouse), and tertiary hub (or local distribution) [13].

Having defined and explained the last mile network, the authors now turn to other last mile terms used in the literature: 'last mile logistics,' 'last mile distribution,' and 'last mile delivery.' To clarify the relationship between the three last mile terms, the authors propose to define them based on two dimensions: planning horizon and type of decision-making, as illustrated in Figure 2.2.

From a perspective of the planning horizon, last mile logistics, distribution, and delivery are often concerned with long, medium, and short-term planning, respectively. From the perspective of the type of decision-making, the last mile delivery, distribution, and logistics deal with operational, tactical, and strategic decisions, respectively. As examples from Figure 2.2, logistics activities such as inventory replenishment and FC locations are strategic long-term decisions, where to store products are medium-term tactical decisions, and shipment scheduling and routing are of short-term operational scope.

The definitions of 'last mile logistics,' 'last mile distribution,' and 'last mile delivery' are listed in Tables 1 to 3. In each table, the authors list representative definitions from the literature and highlight the main features as well as whether they address the two dimensions of last-mile operations in the framework in Figure 2.2. No existing definition is found to cover all factors related to last-mile operations. Thus, the authors propose unifying definitions that cover all common characteristics of last-mile operations and that are consistent with the framework presented in Figure 2.2.

The definitions of 'last mile logistics,' 'last mile distribution,' and 'last mile delivery' are listed in Tables 2.1 to 2.3. In each table, the authors list representative definitions from the literature and highlight the main features as well as whether they address the two dimensions of last-mile operations in the framework in Figure 2. No existing definition is found to cover all factors related to last-mile operations. Thus, the authors propose unifying definitions that cover all common characteristics of last mile operations and that are consistent with the framework presented in Figure 2.2.

The authors note that some definitions are constrained to B2C or e-commerce, and the nodes in logistics are limited to home or collections points. Besides, some definitions are silent about which parties or processes are involved. While Aized et al. [4] provided the most comprehensive definition of those reviewed, they refer to the "delivery process," which does not include strategic decisions such as deciding about where to locate fulfillment and delivery centers. We believe that it is important for the definition of last-mile logistics to be inclusive of such decisions, given the increase in e-commerce delivery volumes and the need to add delivery facilities closer to urban areas.

It is observed that the scope of the last mile distribution varies in different literature, ranging from a large scope as part of the chain to just movement between nodes like distribution centers and homes. Compared with last-mile logistics, the last-mile distribution should be more specific and focused on the tactical supply chain level.

The authors observe that the scope of the definitions differs from those focusing on the strategic level, such as 'city logistics' [131], to only delivery as an element of the order fulfillment process [111]. The last-mile delivery should only refer to activities related to the delivery process at an operational level.

	Paper				
	[61]	[4]	[23]	[109]	This chapter
Definition	"The final leg in a business-to-consumer delivery service whereby the consignment is delivered to the recipient, either at the recipient's home or at a collection point."	"The last part of the physical goods delivery process which involves a set of activities that are necessary for the delivery process from the last transit point to the final drop point of the delivery chain."	"The last stage of the supply chain."	"The last segment of a delivery process."	The final part of any supply chain. It encompasses logistical operations at the strategic decision and long-term planning horizon levels, ranging from the distribution center to the final destination.
Planning horizon					x
Decision type					x
Origin	x	x	x	x	x
Destination	x	x			x
Activities		x			x
Scope	x	x	x	x	x

TABLE 2.1: Definitions of 'Last Mile Logistics.'

In Figure 2.4, the authors illustrate the proposed definitions in Tables 2.1-2.3 from the last mile network perspective (see Definition 1 and Figure 2.2). The last mile delivery operations include the delivery centers, delivery process, and customers. The last-mile distribution adds fulfillment centers to the components under the last-mile delivery. Finally, last-mile logistics adds the distribution center to the last-mile distribution network components.

2.3 Related literature reviews

By entering the keywords 'the last mile' and 'review' in the Web of Science database and deleting the literature that is not in the scope of this review, for example, the concept

	Paper				
	[13]	[185]	[68]	[142]	This Chapter
Definition	"The final stage of a humanitarian relief chain."	"It involves warehouse selection and customer delivery at the city and state scale."	"It involves the linear movement of merchandise from the source of the merchandise to customer homes."	"It is associated with the handling, movement, and storage of goods to the point of consumption through various channels."	Last mile decisions, at the Tactical and mid-planning horizon, for freight storage, handling, and order fulfillment at the last fulfillment center, as well as the movement of freight from the fulfillment center to its final destination through all channels.
Planning horizon					x
Decision type					x
Channel				x	x
Scale		x			x
Application	x				x
Origin	x		x		x
Destination			x	x	x
Activities		x			x
Scope	x	x	x		x

Table 2.2: Definitions of 'Last mile Distribution.'

of the last mile in conflict management [189], we found literature reviews that study last mile related issues in the area of supply chain management from 2010 to 2021. The main features of the selected review papers and how this review differs from them are illustrated in Table 2.4.

Ranieri et al. [153] focused their paper on how the recent innovative strategies would reduce external costs, such as external air pollution, marginal climate change, and congestion cost, in last-mile logistics. Lim et al. [108] reviewed the distribution structures and their associated contingency variables in e-commerce last-mile logistics. Olsson et al. [142] found that the current literature on last-mile logistics is diversified and fragmented. They proposed a framework where they integrated five last-mile components (logistics,

	Paper				
	[21]	[111]	[131]	[142]	This Chapter
Definition	"It implies delivery to the physical address of the end customer from the location (depot) where the purchased item is maintained and is acknowledged as a key element of the order fulfillment process."	"It is defined as the last segment of a delivery process, which "involves a series of activities and processes that are necessary for the delivery process from the last transit point to the final drop point of the delivery chain."	"It is usually referred to as "city logistics," understood as the last link of complex supply chains involving numerous stakeholders (carriers, shopkeepers, customers, inhabitants, city government and public administration, etc.)."	"It refers to the activities necessary for physical delivery to the final destination chosen by the receiver."	The shipping decisions, at the operational and short planning horizon levels, of freight between the delivery center and the final destination through various delivery methods among all stakeholders.
Planning horizon					x
Decision type					x
Stakeholders			x		x
Origin	x	x	x		x
Destination	x	x		x	x
Activities	x	x			x
Scope	x	x	x	x	x

Table 2.3: Definitions of 'Last mile Delivery.'

distribution, fulfillment, transport, and delivery). Mangiaracina et al. [116] focused on last-mile delivery cost components, factors, and viable innovative solutions that aim to increase efficiency in B2C e-commerce. Archetti and Bertazzi [10] addressed up-to-date challenges in routing and inventory routing for e-commerce last-mile delivery.

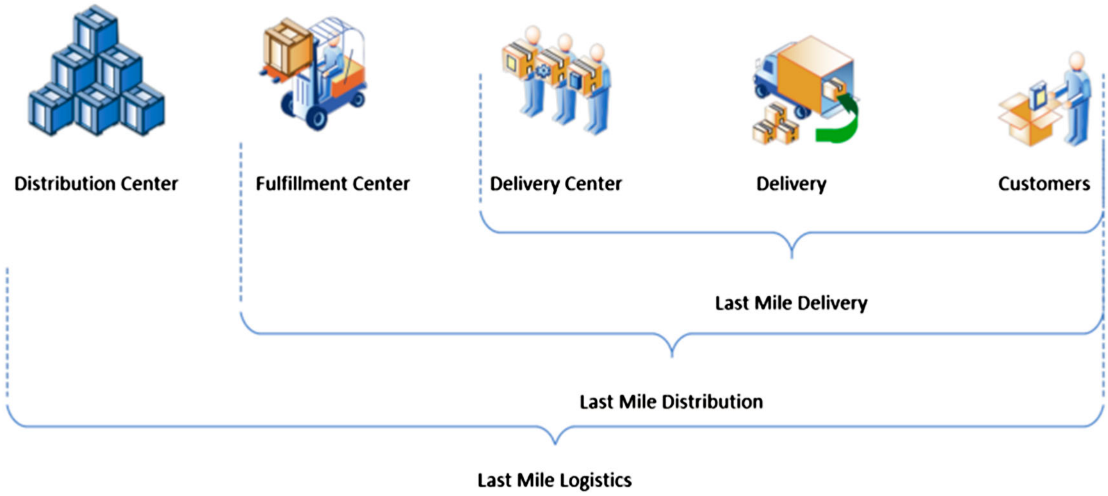

FIGURE 2.4: Components of the last mile logistics, distribution, and delivery.

From Table 2.4, the authors see that this work is the only review paper where previous definitions of last-mile operations have been analyzed and more comprehensive definitions are proposed. In addition, this paper is the first to offer a bibliometric study where we conduct topic analysis to classify the reviewed literature. Furthermore, this review is more comprehensive in that it also includes humanitarian last-mile operations. Finally, the reviewed literature in this paper is significantly different from that reviewed in the other papers. The highest overlap in cited references is 17.7% with Olsson et al. [142], while the overlap with the other five papers is below 8%. Therefore, a review of last-mile operations that unifies the literature and generates new insights is needed.

2.4 Methodology

Inspired by Colicchia and Strozzi [34], the authors combined the Systematic Literature Review (SLR) and the Citation Network Analysis (CNA), which is defined as a Systematic Literature Network Analysis (SLNA) review methodology. Such a combination would identify research topics and select keywords to perform the most relevant contributions in the field based on SLR and recognize a mainstream in a citation network that helps to understand how the body of knowledge has been created, transferred, and developed based on CNA. As a result, the review methodology has two stages: a systematic literature review, followed by a bibliometric analysis to advance the understanding by evaluating relevant existing literature and future research issues from a dynamic perspective.

	Paper					
	[153]	[108]	[142]	[116]	[10]	This Chapter
Logistics	x	x	x			x
Distribution			x			x
Delivery			x	x	x	x
Unifying definition						x
Bibliometric study						x
Literature framework			x			x
Humanitarian deliveries						x
Database	Scopus, IEEExplore, ScienceDirect, Researchgate, Transport Research	Web of Science, Science Direct, Scopus, ABI/Inform Global	Scopus, EBSCOhost, Web of Science	Scopus, Web of Science	N/A	Web of Science
# of Reviewed papers	106	47	155	75	107	158
# and (%) of common references	2 (1.3%)	2 (1.3%)	28 (17.7%)	9 (5.7%)	11(7.0%)	

Table 2.4: Comparison of recent literature reviews with this paper.

2.4.1 Literature selection

The authors have chosen the Web of Science (WoS) as the search database to guarantee the quality of the journal papers and conference proceedings to be reviewed. To make sure that all potentially related literature is included, the keywords "last mile delivery," "last mile logistic," or "last mile distribution" were used as the ‘topic’ filter. The search period was set from 2010 to 2021, which leads to 620 works. Upon examination of the studies, we noticed that those published from May 2020 to December 2022 have a significant number of papers that address COVID-19-related issues. Therefore, we decided to split the data into two sets to analyze the impact of COVID-19 on the studies in this review. We chose the date of May 2020, as that is the date when most of the world implemented COVID-19 measures and the earliest COVID-related studies started to appear, e.g., [119, 137]. This resulted in 302 studies in the pre-COVID period (2010 to May 2020) and 318 in the COVID period (June 2020 to December 2021). This primary search is further refined by selecting the results that fall under the top five WoS categories: 'transportation,' 'transportation science technology,' 'operations research,' 'computer science interdisciplinary applications,' and 'engineering industrial.' This resulted in 158 and 155 studies in the two periods, respectively. A final refinement that manually checked the titles and abstracts to make sure that the selected literature was related to our chosen topic, which led to a final number of 158 and 155 studies for the two periods, respectively.

2.4.2 Bibliometric Analysis

Facilitated by the fast development of the internet and computers, bibliometric analysis has become an increasingly popular technique and fundamental methodology among researchers [121, 132]. The bibliometric approach has been used in management research to improve the understanding of theoretical structures in various fields [17]. The bibliometric analysis in this review is conducted using the bibliometrix R-package developed by Aria and Cuccurullo [11] by analyzing the plain text citation file generated by WoS. The growing number of publications by year in Figure 2.5 shows an increasing interest in studying last-mile delivery.

2.4.2.1 Topic clustering

Topic clustering is one means of classifying knowledge in the growing body of literature. Mann et al. [117] revealed that such clustering provides a clearer view of the research areas and their interactions. The authors used the same bibliometric R package to conduct a co-citation analysis for papers both in the pre-COVID period and after-COVID period.

Pre-COVID period (2010 to May 2020) It is found that the studied topics can be classified into three main clusters based on their research scopes, as shown in Figure 2.6. The bigger size of circles represents more co-citations, and the core literature is selected based on the largest circle size within each cluster. The authors focused on the core literature within each cluster and found that these three clusters are relatively

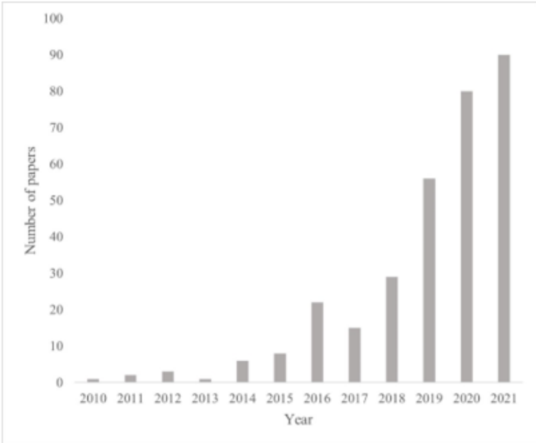

FIGURE 2.5: Distribution of reviewed papers by year.

FIGURE 2.6: Co-citation network (January 2010 to May 2020).

independent and focus on different topics. Table 2.5 shows the main studies, based on co-citations, that contributed to each cluster. Cluster 1 represents the early literature focusing on humanitarian relief last-mile operations, including disaster response and relief systems. For example, Balcik et al. [13] developed performance metrics for the humanitarian relief chain. Cluster 2 groups the literature covering a wider range of topics in commercial last-mile logistics. For example, Morganti et al. [126] compared the alternatives to home delivery that are developed by French and German parcel delivery operators that own pick-up points in stores and automated lockers' networks. Cluster 3 is formed by literature focusing on last-mile technologies. For example, Murray and Chu [130] addressed drone technology and proposed a model for optimal routing and scheduling of drones and delivery trucks for last-mile delivery.

	Clusters		
Topics	Humanitarian last mile operations	Commercial last mile operations	Last mile technology
Key Papers	[9, 13, 14, 180]	[82, 126, 166, 196]	[1, 69, 130, 149]

TABLE 2.5: Co-citation cluster topics (January 2010 to May 2020).

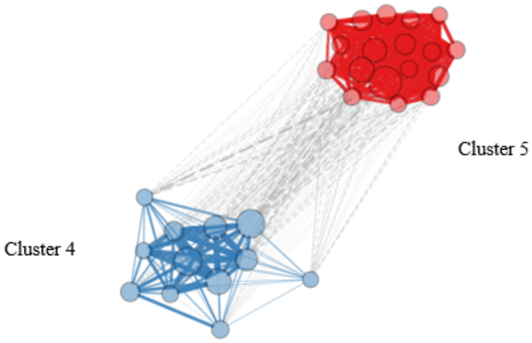

FIGURE 2.7: Co-citation network (June 2020 to December 2021).

During-COVID period (June 2020 to December 2021) From the network shown in Figure 2.7, it is found that the research is divided into two clusters and COVID-19 boosts the emergence of new research clusters [19, 87, 89, 92, 102, 124, 129, 175]. In Table 2.6, the authors summarize the topics of the clusters and the main studies that contributed to each cluster. Cluster 5 consists of literature studying last mile technologies, and the topics of most cited papers within the cluster are similar to Cluster 3 in Table 2.5. For example, Simoni et al. [171] explored implementing an integrated truck-robot system for last-mile delivery. In addition to cluster 5, the papers in cluster 4 focus more on crowd-based technologies, including crowdsourcing, crowd shipping, and crowd tasking. For example, Mousavi et al. [128] studied stochastic last-mile delivery using crowd-shipping and mobile depots. This suggests that researchers are becoming more interested in utilizing methods rooted in the sharing economy that rely on current traffic infrastructure.

2.5 Main Research Topics

Based on the topic analysis in the bibliometric study, the authors thoroughly explore the three identified research topics in the pre-covid period and offer further subcategorization of the literature in this section. The papers in the after-covid period are not analyzed

	Clusters	
Topics	Humanitarian last mile operations	Commercial last mile operations
Key Papers	[9, 13, 14, 180]	[82, 126, 166, 196]

TABLE 2.6: Co-citation cluster topics (June 2020 to December 2021).

due to the possible effects of COVID-19. Table 2.7 summarizes the distribution of the reviewed papers by topic cluster and their related sub-categories, the latter of which are generated by carefully reading the full papers and conventional content analysis [192]. The literature on humanitarian last mile is classified based on whether the literature focuses on designing a humanitarian relief network or employing innovative models and technologies for humanitarian operations. The cluster of commercial last mile operation literature is classified based on a more subdivided research focus that is identified, considering its larger proportion in all literature. The four subcategories include conceptual frameworks and business models, analytical models, algorithms, and case studies. Finally, the last mile technology cluster is classified based on vehicle, computational, and delivery technologies. The delivery technology is further categorized based on the delivery solutions. Note that the total number of papers is 146, as the authors do not account for review papers and papers that do not fit in the main clusters. More details about each subcategory are provided in the next subsections, and the authors summarize topics with more than ten papers in Tables 2.8 to 2.16 to keep the length of this section reasonable.

2.5.1 Cluster 1: Humanitarian last mile operations

2.5.1.1 Network design

The literature on network design for humanitarian relief is reviewed, and these networks could be multi-stage, multi-period, or multi-level. Cook and Lodree [36] identified vehicle dispatching policies to minimize unsatisfied demand. They investigated a two-stage relief network, consisting of a single staging area where donations arrive over uncertain time intervals and are periodically distributed to random numbers of disaster survivors at the distribution point. Elci and Noyan [53] designed a multi-stage stochastic relief network for resource reallocation. They introduced a new accessibility metric and developed a two-stage stochastic programming model for a more accessible and equitable distribution of relief supplies. The proposed model is tested by real-world data from

Topic Cluster	Areas of research focus	Number of papers	Total
Humanitarian last mile operations	Network design	5	20 (13.7%)
	Models and technologies	15	
Commercial last mile operations	Conceptual frameworks and business models	31	72 (49.3%)
	Analytical models	20	
	Algorithms	5	
	Case studies	16	
Last mile technology	Vehicle technology	26	54 (37.0%)
	Computational technology	7	
	Delivery tech - Freight tricycles	4	
	Delivery tech - Parcel lockers	4	
	Delivery tech - Fixed locations	7	
	Delivery tech - Non-road solutions	6	

Table 2.7: Distribution of reviewed papers by topic cluster and related subcategories.

an earthquake in Turkey. A multi-period relief network with a time window and split delivery is discussed by Huang and Rafiei [76]. They illustrated the impact of equity by comparing delivery quantities, arrival times, and deprivation times in different locations. Zhang et al. [203] introduced a three-level humanitarian relief network design problem where the network is considered under an uncertain post-disaster environment. Their network could determine the positions of candidate local distribution centers for reallocating relief supplies. In addition to the abovementioned topics, Rancourt et al. [152] focused on food security and designed a last-mile food aid distribution network under frequent and regular shocks. Their location model considers the welfare of all involved stakeholders to determine a set of distribution centers for the region of Garissa in Kenya.

2.5.1.2 Models and technologies

The most common type of used model for humanitarian relief is the vehicle routing problem. Some studies considered more comprehensive models that incorporate other factors, such as inventory and distribution issues. The remaining papers in this category used computer-based techniques, including simulation tools and advanced algorithms. The studies are classified in Table 2.8.

	Model Type		
	Vehicle Routing	Simulation and Decision Support Systems	Comprehensive Models
Papers	[3, 65, 93, 158]	[51, 58, 77, 123, 156]	[56, 80, 115, 188]

TABLE 2.8: Distribution of model types

2.5.1.3 Uncertainties

In addition to the two topics discussed above, it is also important to identify whether the models in the papers are static models or models considering uncertainties. For humanitarian last-mile deliveries, uncertainty often holds on the location and magnitude of the disaster itself. In Table 2.9, the authors summarize the papers that do not consider uncertainties in their research and those that consider the uncertainties while classifying the type and the solution of the uncertainties.

No uncertainties	**Considering uncertainties**		
Papers	**Papers**	**Uncertain Variables**	**Solution Methods**
[51, 56, 76, 77, 93, 123, 145, 152, 156, 188, 199]	[158]	Vehicles available for transportation, state of the infrastructure, and demand of the potential beneficiaries	Stochastic programming
	[3]	Travel time	Stochastic programming
	[58]	Demand	Optimization and simulation
	[36]	Donations, Disaster survivors	Stochastic programming
	[80]	Travel costs	Deterministic approximation using Monte Carlo simulation
	[115]	Demand	Stochastic programming
	[53]	Post-disaster demands, transportation network conditions	Stochastic programming
	[203]	Transportation time	Robust optimization

TABLE 2.9: Classification of uncertainties

2.5.2 Cluster 2: Commercial last mile operations

2.5.2.1 Conceptual Frameworks and Emerging Models

The authors classify the papers within this subsection into two streams: The first stream introduces new variants of existing problems, and the second stream refers to emerging managerial problems (EMP) that existing concepts or frameworks cannot solve. For the first stream, an important type of literature answers performance-related research questions (PRRP), while other studies investigated how behaviors (BE), or strategies (ST) can be integrated into or influence the last mile delivery. The papers in terms of authors, year, topic, objective, and innovation are summarized in Table 2.10.

Papers	Topic	Objective	Innovation
[135]	EMP	To assess the performance of the last mile distribution of urban freight terminals.	The evaluation is multi-stakeholder and multi-criteria.
[66]	EMP	To support collecting and classifying information on the features of urban freight transport (UFT).	Prove the usability and effectiveness of the framework in engaging stakeholders and supporting shared UFT solutions.
[148]	EMP	To optimize city logistics for building instances and assess operational settings through simulation.	Investigate the impact of instance parameters on realistic scenarios.
[101]	EMP	To extend tactical and operational planning for e-fulfillment.	Combine concepts from both revenue management and vehicle routing.
[85]	EMP	To integrate collection-delivery points (CDPs) in a distribution network.	The network is a multi-echelon distribution network.
[84]	EMP	To characterize urban last mile e-commerce distribution strategies in mature and emerging markets.	Highlight variables that impact the network design decisions.

[179]	PRRP	To compare the efficiencies, sustainability, and trends of five last-mile delivery methods.	The methods considered include reception box, collection point, post office, attended home delivery, and unattended home delivery.
[59]	PRRP	To evaluate a logistics system's overall efficiency and to explore the influence of demand on the distribution channel.	The channel is for material flows in consumer-driven last mile deliveries.
[73]	BE	To introduce behaviors into a competitive queuing system and solve the problem.	The behaviors are bounded rational behaviors.
[20]	BE	To value people's positive behaviors, rewarding choices, etc., to raise people's awareness.	They engaged the tool in a collaborative environment to meet targets in the domain of energy and mobility for urban logistics.
[45]	ST	To study and review how strategies can be designed to reduce externalities.	Externalities can be reduced if the proposed innovations are applied increasingly, and all stakeholders are committed.
[106]	ST	To embed the concept of warehouse postponement into a cloud-based e-order fulfillment pre-processing system	The fulfillment process incorporates genetic algorithm and a rule-based inference engine.
[57]	ST	To develop a decision support system to investigate food losses in e-grocery deliveries.	Incorporate agent-based simulation and dynamic routing procedures.
[174]	BE	To identify situational crime prevention practices that can interrupt porch piracy.	Examine unattended package theft through crime script analysis driven by video data.

Table 2.10: Summary of literature on conceptual frameworks and emerging models.

For the second scream, business models are efficient in solving emerging managerial problems. One such emerging business model is centered around the sharing economy and turning into an important aspect of collaborative freight [32]. They are based on the premise of making better use of existing resources. There has been much attention in the literature about the sharing economy, and the authors devote Table 2.11 to summarize the major findings. The literature is classified into crowdsourcing, crowd-shipping, and others.

Papers	**Topic**	**Objective**	**Innovation**
[71]	Others (sharing double auction)	To maximize the total cost savings of all carriers with privacy preservation.	Discussed carrier collaboration via order sharing double auction.
[193]	crowd-tasking	To support real-time delivery optimization.	Proposed a large-scale mobile crowd-tasking model with a pool of citizen workers.
[29]	crowdsourcing	To compare the performance of the service level and asset utilization.	Proposed an agent-based simulation model.
[44]	crowdsourcing	To reduce delivery costs and total emissions meanwhile ensuring delivery performances.	Explored the social networks of retail store customers for delivering online orders.
[5]	crowdsourcing	To estimate the number of neighbors needed, the number of parcels, and the reward for drivers.	Proposed a collaborative crowd-based solution that uses circle packing.

[150]	Others (shared mobility)	To address economic objectives and environmental concerns.	Characterized open-loop car routes, car drivers' wage-response behavior, and interplay with the ride-share market.
[49]	crowdsourcing	To compare the performance of three types of crowdsourced delivery: bicycles, cars, and both.	Simulated conditions with an urban setting.
[75]	crowdsourcing	To compare the last mile delivery with different crowdsourcing integration strategies.	Developed a solution method with the construction and improvement heuristics.
[104]	crowd-shipping	To explore the drivers' willingness to work as crowd-shippers and their tolerance for travel time.	Proposed a binary logic model and an ordinary least-square regression model that is integrated with a selectivity-bias term.
[30]	crowdsourcing	To achieve equilibrium decision-making.	Formulated a game between stakeholders, including the platform, sponsors, and participants on a crowdsourcing platform.
[15]	crowd-shipping	To maximize the platform's profit and the number of fulfilled requests.	Integrated crowd-shipping and item-sharing to facilitate collaborative consumption.
[16]	crowd-shipping	To solve a crowd-shipping problem and a capacitated item-sharing problem.	Proposed sets of packing formulations.

[103]	crowd-shipping	To improve behavioral and societal impacts of the dynamic and sustainable crowd-shipping system.	Reviewed the components of crowd-shipping services.
[18]	Others (shared routes)	To integrate first-mile pickup and last mile delivery in urban e-commerce distributions	Considered a set of adjustment factors that influence the operations.

TABLE 2.11: Summary of literature on the sharing economy.

In addition to crowd-based business models, Van Duin et al. [183] recognized that the main obstacle to the urban consolidation center (UCC) is a lack of a sustainable business model, and they developed a model to organize a UCC for social and logistical value propositions of multi-beneficial relations between the involved stakeholders.

2.5.2.2 Analytical Models

Concerning the topic discussed within the analytical models, most researchers focus on the application or extension of the VRP (E-VRP), especially the problem with multi-depot, multi-day, multi-compartment, or multi-trip specifications. The rich VRP (R-VRP) and other extensions of VRP (O-VRP) are also commonly studied. Another stream of research that relied on extending classical distribution models is that which combines location and distribution optimization (LDO), while several other studies have used other miscellaneous models (MM). Five main features of the papers are summarized in Table 2.12.

Papers	Topic	Objective	Innovation
[205]	E-VRP	To model a multi-depot two-echelon VRP with various delivery options.	Involve two levels of route design: the first level for a vehicle fleet at depots and the second level for the fleet from the satellites to all customers.

[207]	E-VRP	To study robust, consistent space-time delivery paths for a multi-day VRP.	Optimize delivery paths by providing daily schedules with limited variations from the master schedule.
[27]	E-VRP	To model a multi-compartment VRP with time windows.	Develop a hybrid particle swarm optimization (PSO) with simulated annealing that outperforms a conventional PSO.
[107]	E-VRP	To study a multi-trip VRP with order release time.	Propose an adaptive large neighborhood search algorithm combined with a labeling procedure for large-sized instance
[147]	E-VRP	To study four different multi-trip VRP.	Develop an exact solution framework using column generation, column enumeration, and cutting plane.
[204]	E-VRP	To minimize the traveling time of a multi-depot-multi-trip VRP with time windows and release dates.	Propose a solution that consists of a hybrid particle swarm optimization algorithm and a hybrid genetic algorithm.
[39]	R-VRP	To extend the rich VRP with private fleet and common carrier.	Consider more realistic cost structures and time windows in the problem.
[6]	R-VRP	To study a rich VRP considering long-haul transport, incompatibility among goods, driver hours regulation, and multiple depots and pickup locations.	Develop new heuristics and evaluate performance with other metaheuristics.

[52]	O-VRP	To study a time dependent VRP.	Integrate the VRP with time-dependent travel times for attended home delivery in city logistics.
[131]	O-VRP	To find transportation costs and service levels in capacitated VRP.	Incorporate collaborative and non-collaborative scenarios in the capacitated VRP.
[33]	O-VRP	To model a VRP with a lunch break.	Introduce new mathematical formulations and solutions for the model.
[125]	LDO	To propose a location model for palletized goods for the optimal hub location.	Apply the model for palletized building material in Belgium.
[105]	LDO	To find the optimal number and location of loading bays (LBs).	Use a multi-parametric approach to statistically assess the most relevant number and location of LBs.
[172]	LDO	To discuss the value of physical distribution flexibility in serving uncertain urban markets.	Propose a large-scale stochastic MILP model to incorporate three commonly deployed measures of physical distribution flexibility.
[176]	MM	To develop an ICT-based reference model for e-grocery in smart cities.	Discuss whether a new local food supply chain model for e-grocery is useful.
[78]	MM	To find the environmental implications of e-commerce in rural areas.	Explore how sellers and buyers are conscious of e-commerce sustainability in rural areas and what environmental consequences are associated with various types of delivering innovations.

[198]	MM	To plan an efficient delivery route.	Analyze the succession of drivers' behavior, including searching for a parking place, parking, taking out baggage, and visiting customers at entrances.
[28]	MM	To show that a congestion surcharge mechanism can influence the behavior of both home delivery.	Propose an effective pricing model to alleviate e-commerce congestion.
[86]	MM	To find a minimum cost tour over given customers and shared delivery facilities for a TSP with time windows.	Develop a general variable neighborhood search heuristic.
[120]	MM	To predict urban route distances in more realistic settings.	Incorporate the structure of the underlying road network into the approximation method.

TABLE 2.12: Summary of literature on the analytical models.

2.5.2.3 Algorithms

The main research efforts focused on developing algorithms for routing problems, including vehicle and location routing problems. Reyes et al. [159] developed improved heuristics for vehicle routing with roaming delivery locations. They employed two strategies: optimizing the delivery locations for a fixed customer delivery sequence and switching a predecessor's or successor's delivery location during the insertion/deletion of a customer in a route. Ahmadi-Javid et al. [2] presented a profit-maximization location-routing problem with price-sensitive demands and proposed an algorithm that can be used to solve more basic problems such as location-routing with profit and price-inelastic demands or vehicle routing with profit and price-sensitive demands. Zhou et al. [206] developed an algorithm for bilevel multi-sized terminal location-routing problems in the last mile delivery with simultaneous home delivery and customer pickup services, which combines a genetic algorithm and simulated annealing.

Other studies focused on extensions of the neighborhood search algorithm. Santos et al. [165] developed a variable neighborhood search algorithm for bin packing with compatible categories that determines the best assignment of deliveries for distinct products to a homogeneous fleet of capacitated vehicles to minimize the number of required vehicles. Urru et al. [182] presented a heuristic algorithm based on utility analysis with a modular approach that accounts for stakeholders' requirements and available technologies.

2.5.2.4 Case studies

The authors review papers of case studies where existing models and algorithms are applied for last mile deliveries in different countries or cities. 12 case studies were done in Europe, while the rest of the case studies cover locations worldwide. A summary of the research in case studies is shown in Table 2.13.

Papers	Locations	Objective
[26]	Shanghai, China	Explored people's willingness to use self-pickup points from the metro
[114]	Zilina Region, Slovakia	Compared to the delivery centers in the regional postal transportation networks
[136]	Barcelona and Valencia in Spain	Explored the impact of factors including economic, operational, environmental, and social combining electric tricycles and transshipment terminals
[135]	Thessaloniki and Kuehne Nagel in Greece	Compared two urban intermodal freight transport terminals based on (KPI) assessment framework
[183]	London, Bristol, and Bath in the U. K.	Provided solutions to organize urban consolidation centers
[47]	France	Utilized surveys and interviews to analyze the change drivers across supply chains of fishery ad aquaculture

[37]	Pilot cities in Bulgaria, Italy, Poland, United Kingdom, Germany, and Malta	Integrated a framework for energy-efficient demand management and planning
[140]	Brussels-Capital Region in Belgium	Analyzed the last mile distribution model for drug deliveries
[63]	Thessaloniki, Greece	Assessed the performance of intermodal city logistics terminals
[118]	Rio de Janeiro in Braizl	Utilized motorized cargo tricycles alongside conventional trucks in a mobile-depot-based procedure
[8]	Central London, UK	Investigated the parcel delivery operations
[7]	London, UK	Summarized the challenges of last mile parcel delivery by pavement porters.
[54]	Melbourne, Australia	Developed plausible future scenarios and identified stakeholders in an urban setting.
[138]	London, UK	Solved a parcel distribution model that combines walking and driving for a single driver.
[38]	Brazil	Analyzed consumers' willingness to use pick-up sites.
[114]	Slovakia	Evaluated delivery options of e-shops from the customer's perspective.

TABLE 2.13: Summary of Case Studies.

2.5.3 Cluster 3: Last mile Technologies

2.5.3.1 Vehicle technology

The authors classify the novel vehicles covered in this paper as ground novel vehicles and aerial autonomous vehicles (AAVs). The papers on ground novel vehicles are further classified as electric vehicles (EVs) and autonomous vehicles (AVs), which are summarized in Table 2.14.

Papers	Vehicle-Type	Objective	Innovation
[43]	EV	To discuss a disruption management model for an EVs fleet.	Investigate a reassignment problem for the EV fleet that determines a backup plan as soon as disruptions happen.
[160]	EV	To minimize the cost of activities including acquisition, travel, and recharging vehicles for an EVs fleet.	Provide a variable neighborhood search algorithm to solve the model.
[154]	EV	To calculate the fleet composition and energy consumption in EV route planning.	Study the effect of the EV's ambient temperature on operations.
[100]	EV	To investigate the critical process requirements of EVs in operations encountered by supply chain providers and retailers.	Consider both supply chain providers and retailers.
[177]	EV	To provide a model for operating the delivery EVs	Consider 10 weight classes and 4 charging strategies in a hypothetical grocery outlet replenishment case.
[194]	EV	To propose a model for improving the fuel economy of an extended-range EV.	Solve the model through a reinforcement learning method and a rule-based method.
[170]	AV	To model and simulate an AV that can make travel decisions to some extent.	The model can be used for further advanced control systems and strategies.

[72]	AV	To identify new challenges and opportunities in a fully autonomous driving scenario.	Introduce authors' research platform for driverless shuttles.
[88]	AV	To investigate the users' acceptance of autonomous delivery vehicles for last-mile deliveries in Germany.	Utilize an extended Unified Theory of Acceptance and Use of Technology and structural equation modeling.

TABLE 2.14: Summary of literature on ground novel vehicles.

Aerial AVs, such as drones, are emerging in different last-mile applications, and the majority of drone-related literature focuses on providing efficient solutions to classic problems of operations utilizing drones in last-mile deliveries, including Traveling Salesperson Problems with drones (TSP-D), Vehicle Routing Problems with drones (VRP-D), assignment-scheduling problems, and location optimization problems. Besides, there is also an increasing interest in combining trucks and drones to serve the last mile deliveries, and the majority of the literature on this topic involves the routing problem. Another research stream in truck-drone deliveries focuses on the variants or extensions of TSP and the Traveling Repairperson Problem with drones (TRP-D). Papers that concentrate on AAVs are summarized in Table 2.15.

Papers	**Innovations**	**Delivery**	**Research methods**	**Drone#**	**Drone capacity**	**Routes#/ drone**
[130]	New TSP-D heuristic	Truck and drone	MILP	Multiple	One	One
[1]	New TSP-D heuristic	Drone	MILP	One	One	One
[69]	New TSP-D heuristic	Drone	Extension of the MIP	Single	Multi-parcels	Multi-routes
[201]	Innovative delivery concept	Drone	Design Science Research	Single	Single	Single

[12]	Modeling framework	Drone	Use of economic viability criterion	Multiple	One	One
[99]	New TSP-D heuristic	Drone	MILP	One-Multiple	One-Multiple	One-Multiple
[162]	New VRP-D heuristic	Drone and truck	MIP	Multiple	One	One
[167]	New VRP-D heuristic	Drone	MILP	Multiple	One	One
[191]	New Algorithm for bi-objective TSP	Truck and drone	MILP	One	One	One
[40]	A hybrid heuristic	Truck and drone	MIP	One	One	One
[98]	A routing model	Truck and drone	MILP	Multiple	One	One
[97]	Energy consumption model of drone	Drone	Comparative study	Multiple	Multiple	Multiple
[127]	New TRP-D heuristic	Truck and drone	MILP	Multiple	One	One
[151]	New heuristic	Drone	MILP	Multiple	One	One
[67]	New heuristic	Truck and drone	MIP	One	Multiple	Multiple
[161]	A network routing problem	Truck and drone	MIP	One	One	One

Table 2.15: Summary of literature on AAVs.

2.5.3.2 Computational technology

Computer-based techniques have also been a popular technology to boost research in last-mile deliveries, and simulation appears to be the most common tool. Herrel [74] introduced a visual simulation application into an animated user interface to improve the outbound logistical efficiency in time-sensitive attended home deliveries. The simulation can incorporate factors including profitability, the friction of transportation distance, and varying customer populations per region. Karakikes and Nathanail [91] used simulation techniques to evaluate various smart logistics solutions for sustainable urban distribution. Karakikes et al. [90] utilized a microscopic traffic simulation tool to evaluate three smart urban freight transport measures, including increased heavy goods vehicles load factor, alternative fuel vehicles, and enforcement and intelligent transport systems. The simulation is applied to a European urban interchange-commercial port to decide the most effective measure in terms of environmental and transport aspects.

Besides, advanced computer algorithms like deep machine learning have been used. Habault et al. [70] investigated the possibility of enhancing food deliveries using machine learning. Hughes et al. [79] tested and evaluated various machine learning methodologies on vehicle GPS data to predict the stop delivery time and to determine whether the total stop delivery time will exceed a predefined time. James et al. [83] proposed a neural combinatorial optimization strategy, which is based on deep reinforcement learning, to transform the online routing problem into a vehicle tour generation problem. They also developed a structural graph embedded pointer network to generate the tours iteratively. Ducret and Gonzalez-Feliu [48] utilized spatial modeling and clustering techniques to build a decision-making tool for delivery within cities.

2.5.3.3 Delivery technology

Delivery technologies include parcel lockers, freight tricycles, fixed location delivery, and non-road mobile delivery (NRMD) alternatives. For the fixed location, the authors further classify them into urban consolidation centers (UCC), pick-up points (PUP), and self-collection services (SC). The NRMD alternatives include waterways, railways, multimodal, light goods vehicles, and cargo bikes. In addition to features including publication, year, technology, objective, and results of the publications, the authors also cluster the literature into different topics, as shown in Table 2.16.

Papers	**Tech**	**Topic**	**Objective**	**Results**
[82]	Parcel Locker	Performance Evaluation	To assess the usability of the parcel lockers from customers.	Introduce the results of the pilot survey realized in Szczecin, Poland.
[55]	Parcel Locker	Optimization problem	To discuss various optimization-based design methods for smart lockers.	Propose optimization models for both fixed-configuration locker banks and modular tower-based locker banks.
[168]	Parcel Locker	Optimization problem	To propose a mobile parcel locker that can change its locations during the day	The mobile lockers largely reduce the locker fleet size.
[178]	Freight Tricycles	Performance Comparison	To compare the competitiveness of tricycles with small delivery vehicles and diesel vans in urban areas.	The competitiveness of each delivery method relies on urban policies, design variables, and drivers' costs.
[163]	Freight Tricycles	Performance Comparison	To compare the carbon footprint of a tricycle logistics service with a traditional logistics company.	The greenhouse gas emissions (GHG) can be reduced by up to 72% using tricycles.
[35]	Freight Tricycles	Performance Comparison	To estimate and compare the performance of human-powered cargo cycles to motorized delivery vehicles	The cargo cycles can be competitive in a congested area with comparative environmental benefits.

[187]	Fixed Location Delivery (UCC)	Performance evaluation	To study the effects, including air quality, residents' inconvenience, and noise nuisance of a Dutch UCC.	The effects are limited.
[110]	Fixed Location Delivery (UCC)	Performance evaluation	To examine the effectiveness of the UCC.	Potential logistics and environmental benefits are proved under certain conditions.
[64]	Fixed Location Delivery (UCC)	Performance evaluation and optimization problem	To evaluate the performance indicators of UCC using a two-level methodology.	The performance indicators of UCC are evaluated, and the facility location problem is solved.
[146]	Fixed Location Delivery (UCC)	Survey	To survey stakeholders in terms of differences in timeliness, reliability, and safety.	Retailers in Bristol, the U.K., is satisfied, while potential users in Cagliari, Italy, are not with UCC.
[184]	Fixed Location Delivery (UCC)	Optimization problem	To model the time-windows delivery dispatching problem for UCC as a variant of the delivery dispatching problem with a Markov decision model.	Solve it by an approximate dynamic programming algorithm that outperforms the benchmark policies.
[24]	Fixed Location Delivery (PP and SC)	Framework	To develop a framework for urban logistics that considers geographical and functional elements.	Define terms for urban logistics and classify the PP and SC into the last mile logistics.

[202]	Fixed Location Delivery (SC)	Survey	To survey the customers' intention to use self-collection for last mile deliveries in Singapore.	The customers' intention to access SC is influenced positively by relative advantage, compatibility, and trialability.
[144]	Fixed Location Delivery (SC)	Optimization problem	To develop a logistics model for delivering small parcels to SCs.	The parcel recipients may have no strong preference among the SCs so that the delivery tasks can be performed at a lower cost and shorter amount of time.
[125]	NRMD (Inland waterway)	Method innovation	To organize the last mile distribution via a limited number of local water-bound warehouses.	Transportation flows can be shifted to the inland waterways at a profitable cost, and the associated truck transport distances can be reduced.
[60]	NRMD (Wagonload transport)	Performance Evaluation	To provide a series of practical solutions for a sustainable wagonload transport method.	The effectiveness of these solutions has been verified in field tests and pilot operations.
[41]	NRMD (Multimodal)	Method innovation	To deliver goods to Bentobox instead of the customers' location for customer pickup.	Test the combination of a freight bus that loads generic parcels at the depot and a lighter delivery van for inner-city logistics.

[118]	NRMD (Multi-modal)	Method innovation	To integrate multi-modal methods of a mobile depot (a bus or truck) and cargo bikes or light electric vehicles.	A significant reduction in GHG and local air quality pollutants and slight cost advantages over the traditional setups is proved.
[197]	NRMD (light goods vehicles)	Optimization problem	To construct an agent-based model for the light goods vehicles serving last mile deliveries in London, U.K.	Expanded model to incorporate parking behaviors.
[141]	NRMD (cargo bikes)	Field research	To prove whether using cargo bikes to serve the last mile deliveries can meet the needs of the local administration in Stargard, Poland.	It can meet the delivery demands.

TABLE 2.16: Summary of literature using delivery technologies.

2.6 Discussion

2.6.1 Humanitarian last mile operations

Within network design, there is a need for more research on multi-objective optimization, both on decision-makers [36] and multiple decision-makers [152], to guarantee efficient and equitable last mile humanitarian operations. Secondly, it is worth exploring the collaboration between many agents with the same goal [36] to calculate the benefits of integrated decision-making. A third topic is overcoming current literature's limitations where they treat dispatch vehicles or critical supplies equally. To address this shortcoming, it is suggested that we incorporate non-identical vehicles while differentiating or prioritizing critical supplies [76].

Within the literature on operational models, the assumptions that are taken while modeling the last mile humanitarian relief deliveries are critical to the results. For example, when facing uncertain post-disaster relief demand, current literature usually assumes that the demand at different depots is stochastic or that they are assigned different priorities. However, it may not be practical in real cases where demand can be highly time-dependent, location-dependent, or fluctuating irregularly. Nevertheless, we must solve the associated ethical and legal questions [58]. Another example is that the authors study humanitarian fleet management while they develop hypotheses based on interviews for commercial operations, which could limit their research [51]. The second area of potential improvement concerns data collection, sharing, and testing to improve the availability and reliability of the data. Since each disaster has its unique unfolding and post-disaster characteristics, accurate, up-to-date, and detailed data must be provided to support the design and development of meaningful and reliable models and algorithms. The reliability of the results can be weakened if data is from a single source like one humanitarian organization [51], and data from actual crises may not be available to validate the proposed model [188]. Another possible improvement in dealing with the data comes from applying big data technologies [190]. While optimization based on big data has been widely used in supply chain management with numerous results proving that they can vastly boost the solution efficiency, limited related studies were found in this area [122], though the benefits are apparent like the model training, prediction, and decision making under the highly uncertain environment of disasters that are driven by big data techniques can significantly reduce humanitarian relief response time. One possible reason for this gap is that humanitarian organizations have limited resources to access data scientists.

The third topic lies in overcoming the model's limitations, and we found that while many studies looked at last mile deliveries in the context of humanitarian relief, they are case-based and focus on limited types of disasters such as earthquakes, floods, and famine. There is a need for developing general models for humanitarian last mile operations that are not disaster-specific and can be customized according to the nature of the humanitarian relief operation, like avoiding the unique nature of the emergency response to provide a platform for a substantial body of research [123], or extend the model for other types of disasters that are not easily predictable [188]. Another limitation comes from the constraint of a particular phase of disasters [188], which can be generalized. Increasing the complexity of the model is another practice. For example, considering uncertainties in modeling, including the additional stochastic elements, like stochastic budget or demands [158], and joint uncertainty in demand and travel times

[77]. Another example involves multiple stops, like encountering a road failure, in the VRP [80].

Regarding the adoption of delivery technologies in the last mile humanitarian relief deliveries, studies have been limited to helicopters [145, 199], despite the success of innovative transportation technologies, like drones, for commercial and retail operations. There is a need for comparative studies on the performance of traditional and novel technologies for different disaster scenarios to help societies decide on appropriate last mile innovative technologies in humanitarian relief areas.

2.6.2 Commercial last mile operations

By overviewing the papers on conceptual frameworks and emerging models, we found that there are two directions for possible research extensions. The first direction is to generalize the framework or the model, either to enrich the list of features, such as to include stakeholders like large retailers and supermarkets as well as to test the framework in additional cities [66], to consider the last mile delivery service provider as an additional decision-maker [73], or to involve a more elaborated implementation of the framework [134]. The second direction is to narrow down and explore the framework or the model that suits specific cases. For example, Janjevic and Winkenbach [84] suggest extending the scope by investigating distribution strategies specific to grocery deliveries and additional types of companies pursuing an omnichannel strategy.

As for the sharing economy, the first stream of discussion is to include extra factors for the mathematical model, like the multi-hop delivery [44], the multi-period delivery [15], multi-items for each crowd shipper [15], a much larger pool of crowd-workers [193], and the delivery time requirements of consumers [193]. These factors contribute to complexity but make the models closer to realistic cases. A second stream concerns the assumptions for the models. For example, Devari et al. [44] assume that the probabilities of delivering a product are the same for a person. Further research needs to determine the number of times a person would help assist per unit of time. In addition, another stream will be to consider further development of the business concepts and models for the sharing economy to increase the reliability of the crowdsourcing workers [76] to understand the delivery behavior of friends [44], and to develop a better pricing strategy and higher system reliability [193]. The last stream refers to a more comprehensive performance assessment of the last mile delivery that would consider multiple objectives and, sometimes, conflicting objectives. For example, delivery trucks are prone to park on the curbside to meet their delivery time and targets, which may introduce extra traffic congestion that would contradict the city transportation objectives. Qi et al. [150] aim to include other implications such as social trust-building, service agility, and unemployment rate, while Behrend et al. [16] suggest addressing the environmental impacts. Additionally, Behrend and Meisel [15] propose to evaluate a platform's performance in a dynamic setting.

It is observed that a major obstacle in solving emerging managerial problems is the lack of a proper business model. Another interesting observation within our reviewed literature on business models, particularly of the sharing economy, is that most literature on the topic of crowdsourcing appeared between 2016 and 2020, while all the literature on crowd-shipping appeared after 2019. This suggests that research on crowd-shipping is facilitated by the earlier efforts of the crowdsourcing literature. For crowdsourcing, one mainstream of the literature focuses on comparing performance with other delivery methods and different types of crowdsourcing deliveries. Another stream is to improve the performance of a certain crowdsourcing approach, including reducing cost, reaching equilibrium decision-making, and estimating optimization parameters. For crowd-shipping, while promoting the performances is a key research focus, including maximizing profits, improving societal impacts and sustainability is also of interest to researchers, as well as incorporating drivers' willingness and capacitated item-sharing.

Regarding the analytical models developed in the papers, we have observed that they focus mostly on city logistics but neglect rural areas. The last mile delivery infrastructure of the rural regions differs from that of urban areas, especially in developing countries. B2C retail in rural areas is still in its infancy stage but has much potential for further development. In addition, last mile delivery in remote areas, such as the Northern Territories in Canada, is another critical area of study that would contribute to sustainable economic growth in those communities.

In the area of algorithms, the current literature mainly focuses on extensions or the development of classical algorithms, like branch-price and neighborhood search algorithms. There is still potential to consider studies in the area of advanced computational technologies that are built on big data distributed computing platforms such as Hadoop and Spark.

The case studies covered in this review are classified based on their locations, and the majority of the literature focuses on mature markets, like Europe or the U.S. There is potential to study emerging markets of B2C, such as cities in China, India, Brazil, etc. The transportation infrastructure in such countries is not yet fully developed, and there is a need to develop technologies that are more suited to such environments and their related models and algorithms.

2.6.3 Last mile technologies

The reviewed literature shows that parcel lockers can be classified into two types based on their mobility: fixed and mobile. For fixed parcel lockers, current research focuses on improving the performance, including usability and design methods for optimization. Though the fixed lockers share the characteristics of having customers picked up at certain locations with other fixed location delivery methods like urban consolidation centers, pick-up points, and self-collection services, they distinguish themselves by using smart technologies to pick up the parcels. However, there is a lack of literature to benchmark fixed lockers' comparative benefits and local effects. As a result, the suppliers may be uncertain when to upgrade their fixed location delivery services to fixed lockers, and they lack the guidance to choose among all the fixed-location delivery choices.

For drones, we have found rich research on modeling efforts for both drones along and multimodal delivery systems involving drones. However, limited research is found on insights or analytics based on real data from practical operations. Regulations and policies are one crucial factor accounting for it. For example, it is required to 'fly your drone where you can see it at all times in Canada' according to the regulations of Transport Canada, which limits the remote control or autonomous flying of drones. The limited travel range and capacity also keep the drones from being applied in the last mile delivery at a large scale.

As for the applications of novel vehicles in the last mile delivery, there is a time lag between the emergence of technologies and the research exploring their operational issues for electric vehicles (EVs). While the adoption of EVs increased in the late 2000s, driven by government incentives, the earliest paper on EVs for last mile operations in our selected literature appeared in 2015 [43]. Though various application scenarios of EVs are explored and addressed, the opportunities and challenges brought by the electrification of operating EVs in the last mile deliveries are not fully addressed and are worth further exploration. Furthermore, autonomous driving technology has proven to reduce delivery labor costs and boost delivery efficiency significantly [181], which has been tested in real cases with satisfying speed while meeting safety requirements and road conditions only for small autonomous driving robots for small and mid-size parcels [25], we found limited research that investigates the application of AVs in the last mile deliveries. One reason behind that is that legislation lags behind technology. In Ontario, Canada, the testing of automated vehicles (AVs) is only allowed on roads under strict conditions, including requiring a driver for safety reasons [143]. Limited guidelines or roadmaps are found to support AVs being applied to the last mile deliveries. Another reason is the complexities of the cooperation within the fleet of AVs due to the potentially large number of AVs needed to fulfill the delivery demand.

As for other limitations of the emerging delivery technologies in B2C freight transportation, there is a need to construct more general models that can apply to a broader set of scenarios. For example, the restricted travel ranges due to battery capacities and constrained flying areas due to government policy would greatly limit the application of drones. While the emerging delivery technologies are recognized with both advantages and limitations, it will be worth studying how they can be used in a multi-modal transport context to strengthen their advantages and overcome their limitations. A good example comes from combining drones and electric trucks, which can reduce the environmental impact through truck electrification and extend the travel distances of drones through truck deliveries.

2.7 Conclusion and future research directions

In this paper, the authors reviewed the recent research progress in last mile deliveries of freight with a focus on emerging technologies. This review started by reviewing terminology and providing a unifying framework for last mile delivery operations. The authors propose the concept of last mile network that emphasizes the idea that last mile deliveries engage different stakeholders and processes. It was found that there is a lack of studies on the network aspect of last mile deliveries. It is hoped that this review will instigate further research in this area. It provided a bibliometric analysis of the reviewed literature from 2010 to 2021. In addition to providing some temporal analysis of the literature, the authors proposed a topical classification that allowed this paper to further focus on synthesizing the literature and withdrawing insights for future research. Based on the clusters, the literature is categorized into three topics: humanitarian logistics, novel technologies, and B2C freight transportation. The humanitarian relief literature is further classified into network design, models, novel technologies, and other miscellaneous issues. Then, the paper addressed the application of various novel technologies in last mile deliveries for commercial purposes, including sharing economy, lockers, innovative vehicles, drones, and other technologies. Lastly, the rest of the literature on B2C freight transportation is categorized based on the contributions to new conceptual frameworks, models, algorithms, and case studies. Finally, the authors discussed findings from the literature review and analysis to identify possible research gaps. Based on the systematic review, the authors generate more up-to-date avenues for future research listed in alphabetic order.

Artificial Intelligence (AI) for last mile delivery and as a technology enabler: AI is identified as one of the most significant emerging technologies in the field of information systems. Thus, it is worth studying its development, maturity, and adoption [46]. It is recommended to extend new research to investigate the feasibility and efficiency of AI to develop resilient last mile delivery solutions [124]. As a technological enabler, it can also offer potential avenues for innovative mobility, for example, tracking certification via AI for autonomous shuttles [22].

Blockchain for high computational performance and security: Primarily developed for creating trust for sharing data, the blockchain has much potential for the transportation sector since it is completely decentralized and can be powerful in securing immutability. At the same time, the freight flows involve numerous stakeholders [46]. The potential of blockchain to improve the overall optimization effectiveness to solve complex last mile operations, for example, the joint optimization of drone routing and battery wear [200].

Business models for crowd-based delivery: With the prevalence of more technologies in crowd-based delivery systems, more research is needed to examine the business models, especially in urban areas, and how they can benefit practical applications. For example, in a bike-truck crowd delivery system, trucks can perform long-distance travel and leave the parcels at cross-docking points while the bikes deliver parcels from those points to customers [10]. However, such business models for crowd shipping involving bikes are missing.

Data collection for testing purposes: To enhance modeling and computational developments, it is necessary to have accurate and reliable data sources on the post-disaster humanitarian relief environment. Technologies such as the Internet of Things and drones, coupled with citizens' data collection efforts and social media outlets, can be used to gather real-time data. The availability of data would provide a more realistic image of the complexity of the operations and can set the ground for the development of advanced big data-based artificial intelligence solutions [42].

Dynamic last mile humanitarian relief routing: Dynamic last mile humanitarian relief routing: With the use of autonomous vehicles that are equipped with sensing technology, it is possible to create dynamic routes that may change depending on the data being transmitted from the vehicle [94]. This can involve using big data technologies, such as geographical positioning data and images, combined with AI to maximize the impact of last mile operations. For example, a drone camera may feed aerial video of the humanitarian scene and based on some classification algorithm, would be targeted to aid the people who need it most.

Ethical and legislative considerations for humanitarian deliveries: While more innovative technologies have been observed to be applied in humanitarian deliveries, they raise ethical and regulatory concerns [164]. For example, justice is a primary ethical consideration when using drones in humanitarian logistics [192]. In addition, different countries have different legislations on drones that limit their use for deliveries. More research to understand the ethical and legal issues associated with such applications is needed to develop guidelines and standards.

Expanding the scope of humanitarian relief research: We call for more research within the last mile of humanitarian relief delivery to encompass more types of disasters. In particular, more effort is required in the areas of post-disaster modeling and planning for subsequent disasters that have global reach, such as the current pandemic COVID-19 [81], and those that have a local but high impact, such as the air crash, etc.

Impact on local communities: With the increase in online shopping, especially after the COVID-19 pandemic, there are concerns about the impacts of last mile delivery operations on local communities. The increase in the number of deliveries will contribute to traffic congestion, curbside parking, safety, and security, as well as environmental issues. Given that existing communities were not designed for such online delivery volumes, local governments will need to understand well the impact of e-commerce logistics on their infrastructure network [155].

Last mile delivery technology for humanitarian relief: There is a need to develop models and solution techniques for applying novel technologies in humanitarian logistics. These technologies, such as autonomous vehicles and drone-truck systems, have been studied for last mile delivery for commercial purposes and have shown that they can improve performance [157].

Last mile deliveries in rural areas: Most literature on last mile deliveries focuses on city logistics. There is a need for models focusing on last mile delivery solutions for rural areas where the population is less dense, and the infrastructure is less developed [112].

Multiple delivery systems: With the proliferation of last mile technologies, it is important to develop models that will aid in analyzing inventory and routing decisions in last mile operations that involve more than one technology, such as drones with smart lockers or a team of drones [31].

Last mile networks: Considering the complexity of last mile networks, more research could be done to understand the roles of interconnected parties and processes that are within the network to improve various performances of last mile operations. For example, more research to verify the customers' preferences and behaviors is needed to construct sustainable last mile deliveries and satisfy growing customers' expectations [95].

Multi-model deliveries: With the increase in the demand for deliveries in high-traffic areas, such as city centers, there is a tendency to use other means of delivery, such as walkers, e-bikes, and robots. These different modes of delivery may be supported by mini-distribution centers that may be mobile. There is a lack of studies that look at the analysis of the performance of such delivery modes in different delivery zones with varying infrastructure networks.

Post-Pandemic Impact: Another stream of potential research is to consider last mile delivery in a post-pandemic world. A line of possible research is the last mile delivery for COVID-19 vaccines and the challenges brought by those vaccines that require special refrigeration and limited shelf lifetime. Another important potential topic for research is to consider the impacts of last mile deliveries on neighborhoods, given the drastic changes in delivery traffic flow and illegal and unsafe parking by delivery trucks.

In conclusion, we see a bright future for conducting research in this area, given the increasing importance of last mile deliveries with the exponential growth in online volumes. While e-commerce has great potential for local economic development and consumer convenience, it is also bringing with it challenges to business operations as well as the quality of life in neighborhoods. Several innovative last mile delivery technologies have the potential to offer alternative delivery solutions that can mitigate the impact of the increase in delivery volumes, but they still suffer from a lag in government policy that finds the right tradeoff between public safety and economic development.

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Chapter 3

Are Online Shoppers Ready to Use Smart Mobile City Bus Lockers?

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Are Online Shoppers Ready to Use Smart Mobile City Bus Lockers?

Si Liu
DeGroote School of Business
McMaster University, Hamilton, ON, Canada
Email: lius278@mcmaste.ca

Elkafi Hassini
DeGroote School of Business
McMaster University, Hamilton, ON, Canada
Email: hassini@mcmaster.ca

Abstract

The authors introduce an innovative delivery paradigm termed Smart Mobile Lockers with City Buses (SML-CBs). This system exploits the underutilized capacity of city buses for parcel transportation while incorporating smart locker technologies to facilitate consumer-driven parcel retrieval. The aim of the present study is to survey consumer perceptions pertaining to the adoption of this nascent technology. Our study is particularly focused on answering two pivotal research questions: (1) What are the prevailing attitudes among Canadian e-commerce consumers towards the adoption of SMLCBs? and (2) Which demographic segments can be identified as possible early adopters of SML-CBs? Our key findings reveal that the principal allurements for survey participants are the system's environmental sustainability and cost-effectiveness. In addition, as many as around 50% of respondents expressed willingness to retrieve parcels from bus stops located within a 100-meter radius of their locations. A discount of 50% compared to existing delivery fees emerged as an attractive proposition for as many as 73% of the survey participants. Our results further differentiate the responses of participants in different groups and clusters. Through a comprehensive rating system, we finally identify the participant groups and clusters that are most likely to adopt SML-CBs.

Keywords: *E-commerce, Last mile delivery, Sharing economy, Parcel lockers, Customer adoption*

3.1 Introduction

Recent years have observed an escalation in the realm of e-commerce, evidenced by a surge in global revenue to $3.32 trillion in 2022—representing a 129% augmentation relative to the figures from 2017, according to Statista. This rise in online commercial transactions has precipitated a transformative shift in operational strategies, most notably among courier service providers grappling with a burgeoning demand for parcel delivery services. Based on the data from Statista, the global parcel shipping volume ascended to 185 billion units in 2023, reaching a 14.9% year-over-year growth. This heightened demand has exerted considerable pressure on the extant transportation capacities of courier services, thereby catalyzing initiatives to investigate alternative technological solutions for managing the overflow of parcel deliveries. One innovation in this domain is the advent of Smart Parcel Lockers (SPLs), which have garnered attention for their benefits, such as enhanced flexibility in parcel retrieval at customer-preferred times and locales [30]. Further bolstered by integrating Internet of Things (IoT) technology, SPLs are emerging as a secure and cost-effective delivery paradigm for diverse settings, including multi-family residential communities, commercial edifices, and academic campuses [5].

In the evolving landscape of parcel delivery technology, a novel variant—Mobile Parcel Lockers (MPLs)—has recently come to reality, featuring either autonomous or human-operated mobility to facilitate parking at varying locations for customer pick-ups [27]. In contrast to their fixed counterparts, MPLs offer the advantage of dynamic locker utilization by strategically relocating to align with fluctuating consumer demands, thereby minimizing the number of lockers required for optimal operation. Moreover, MPLs can elevate customer convenience by establishing rendezvous points closer to customer-preferred collection sites than fixed parcel locker locations. Despite these merits, implementing MPLs encounters several logistical and economic impediments. Both autonomous and human-mediated mobility introduce extra operational costs, and the identification of parking spots in vicinities amenable to customers presents additional challenges, often exacerbated by regulatory constraints. To ameliorate these obstacles and catalyze the broader adoption of MPLs, we propose the integration of the sharing economy, a burgeoning paradigm in last-mile delivery solutions. Conforming to the definition articulated by Benjaafar and Hu [1], the sharing economy encompasses various on-demand business models wherein single entities proffer products or services to many smaller-scale consumers.

Our research serves as an endeavor to systematically scrutinize the prospective of intelligent parcel locker systems with urban public transit frameworks to augment the efficiency of last-mile delivery in e-commerce. The Smart Mobile Lockers integrated with the City Buses (SML-CBs) that we have developed leverage the underutilized capacity of existing bus routes for parcel transportation while also capitalizing on bus stop dwell times for expedient customer pick-ups via state-of-the-art locker technology. Notwithstanding the innovative nature of SML-CBs, there exists a gap in the literature pertaining to potential customers' perceptions and inclinations toward this emergent delivery mechanism. By assimilating feedback from these potential users, we aspire to identify customer segments that exhibit a higher propensity for SML-CB adoption, thereby facilitating the cultivation of a more robust delivery ecosystem predicated upon SML-CBs. The objective of this investigation is to bridge this knowledge gap, centering on the ensuing research queries: (1) What are the prevailing attitudes and perspectives among Canadian e-commerce consumers regarding the acceptance of SML-CBs? (2) Which demographic groups constitute the optimal target customer base for SML-CBs?

3.2 Literature Review

In this section, we review two relevant research streams to understand the trends for parcel locker delivery and how to measure customers' adoption of novel last-mile delivery technology.

3.2.1 Trends for last-mile parcel lockers delivery services

Last-mile technology is recognized as one of the main research clusters in last-mile deliveries literature [17]. Parcel lockers are driven by smart technology, which is defined as the integration of computing and telecommunication technology into other technologies without such capabilities [31]. By using the internet of things (IoTs), Ooi and Tan [22] reduced the time that delivery persons and customers spend interacting with the system to deposit and withdraw parcels. Bin Mohd Rusli et al. [3] enhanced the security of parcel retrieval by IoT-supported locker boxes by providing a password to couriers once their messages are the same as the users' specified messages. Sangiampak et al. [24] proposed an IoT-based smart locker system to enable access sharing among trusted individuals to improve locker utilization and customer convenience, given limited storage resources. Other technologies, in addition to smart technology, have also gained popularity. Wang et al. [32] applied blockchain technology in smart lockers for logistics tracking without any extra charges. Schwerdfeger and Boysen [27] proposed a design of mobile parcel lockers based on the autonomous driving platform that moves closer to customers at rendezvous points. Another notable trend that drives the development of parcel locker deliveries is to enhance stakeholders' welfare. To complement the existing commercial parcel locker network set up by large delivery companies, Lyu and Teo [18] studied a network of public lockers in a residential community to improve the operational efficiency of couriers. Lin et al. [16] maximize the profit for locker operators under the competition of other delivery modes with the revenue estimated using the threshold Luce model for customers' service usage likelihood. Mohri et al. [21] model the benefits of on-premises parcel lockers besides residents, considering carriers and local governments as key beneficiaries. Through the literature review in this stream, we have found that the application of emerging technologies in parcel lockers creates safer and more convenient delivery services for customers. Besides, an increasing interest is identified in studying optimizing welfare for all parcel locker delivery stakeholders beyond customers, including delivery companies and governments.

3.2.2 Customers' acceptance of innovative last-mile delivery service techniques

It is important to understand what drives technology acceptance to increase the chance of success with tech-based services and how to measure the drivers [7]. Klein and Popp [12] studied the perceived sustainability and other drivers of consumers' acceptance of to-door delivery, parcel lockers, and click-and-collect. By integrating a conceptual framework and a structural model into 536 German online purchasers, the authors have found significant influences of perceived sustainability on accepting delivery alternatives. Kapser and Abdelrahman [11] investigated the users' acceptance of autonomous delivery vehicles (ADVs) in Germany through an extended unified theory of acceptance and use of technology. Their results revealed that price sensitivity predicts user acceptance most significantly. Tsai and Praewwanit [30] applied resource matching theory, innovation diffusion theory, theory of planned behavior, and partial least squares structural equation modeling into a dataset of 302 participants living in Thailand to clarify Thai consumers' intention to utilize smart lockers. Six factors, including convenience, have been identified by the authors to influence Thai consumers' intention to use smart lockers. Chen et al. [6] explored the consumers' choice between two kinds of parcel lockers: stationary and mobile. Based on a choice experiment that is context-dependent, the authors employed the multinomial logit model and the mixed logit model to illustrate the mechanisms behind customers' choices. Through the literature review in this stream, we have found that sustainability, pricing and cost, and convenience have been proven to exert influence on customers' attitudes toward accepting emerging delivery techniques.

The literature review of both research streams also enables us to identify research gaps. Within the trend of tech-driven parcel locker services, little research has been found to integrate parcel lockers with the sharing economy, an emerging economic model, as an alternative last-mile delivery method that benefits from both concepts. It also remains a nascent area of how customers would react to such an innovative integration.

3.3 Introducing the Concept of SML-CBs

To utilize the idle capacity of the transit systems, there has been literature studying the co-transportation of passengers and freight in urban settings [4]. However, the whole process of freight delivery via transit to final customers could be complex. For example, Ghilas et al. [9] proposed a long supply chain in the last mile for utilizing partial transit capacity, which starts from the depot via van, public transit, van, and delivery person to the final customers. Masson et al. [20] developed a last-mile delivery network that transports parcels from depots to micro hubs at bus stations in city centers, and parcels are further delivered to customers through bikes from these micro hubs. The coordination of such a long and complex chain may be time-consuming and costly. We are among the first to introduce the integration of smart parcel lockers with transit systems as mobile parcel lockers, which enables customers to pick up their parcels from nearby bus stops. Rooted in the sharing economy, SML-CBs is an innovative system that shares the bus terminals as micro depots, the bus routes for transportation, and bus dwell time at stops for parcel pick-ups. Compared to the existing people-freight co-transportation systems, the SML-CBs largely reduce the number of transferring processes to lower the system's complexity. Compared to home truck deliveries, the SML-CBs require minimal trucks and drivers in urban areas, which provides a supplementary delivery alternative with cheaper delivery costs and is more environment-friendly. Compared with fixed parcel lockers, SML-CBs move parcels closer to customers and provide them with options to choose pick-up locations.

The operational mechanics of SML-CBs can be delineated as follows: Specific bus routes are selected, predicated upon a multitude of criteria encompassing parcel delivery demand along these routes, individual bus stop ridership, and overall route profitability, among other factors. E-commerce parcels are initially conveyed via delivery trucks from distribution centers to terminals situated on the selected bus routes. The SML-CBs possess the flexibility to be allocated across various bus routes in distinct time slots, either affixed to or detached from buses at bus terminals, thereby enabling dynamic transportation between terminals in alignment with fluctuating delivery demands. Customer-parcel interactions are coordinated through an emergent online delivery platform that we are developing. This platform's core functionalities include (1) apprising customers of proximate bus stops for parcel retrieval, (2) furnishing anticipated parcel arrival timelines, and (3) offering real-time parcel tracking capabilities. The first two functionalities are underpinned by intricate mathematical models and algorithms elucidated in our separate scholarly contributions, while the latter is facilitated via the sharing of buses' GPS coordinates. The insertion of parcels into lockers is executed by bus drivers or dedicated platform personnel, contingent upon the specific operational strategy employed. As parcels near their designated pick-up locations, the platform disseminates notifications to customers as a prompt for impending pick-up preparation. Upon bus arrival, customers unlock the designated lockers to complete the retrieval process—a procedure augmented through advanced IoT technologies. The retrieval process strategically coincides with the bus's scheduled dwell time at stops, thus minimizing disruptions to regular bus operations. Safety is further enhanced by deploying overhead cameras on the lockers, enabling bus drivers to surveil the pick-up process. In instances where customers are unable to retrieve their parcels within the stipulated time window, alternative redelivery options are presented, such as rescheduling to the same bus stop at a later time using the same locker.

An alternative design for SML-CBs is depicted in Figure 3.1, with the help of Midjourney. The rationale for external locker placement on the bus is to mitigate disruptions between boarding or departing passengers and customers engaged in parcel retrieval. It also enables customers who are not transit users to access this service. Such an arrangement necessitates minimal structural alterations to the buses to facilitate the straightforward attachment and detachment of the lockers. Regarding design specifications, locker dimensions are meticulously calibrated to conform with road safety norms and to preclude any negative impact on the flow of adjacent traffic lanes. The lockers are equipped with an interactive display interface capable of both facial recognition and barcode scanning functionalities, thereby expediting the customer authentication process. Additionally, the locker compartments are designed with variable dimensions to accommodate parcels of diverse sizes. However, it is worth noting that the SML-CB system predominantly targets the transportation of small to medium, lightweight parcels to ease both the retrieval process for customers and the carrying burden subsequent to pick-up.

Amazon patented a mobile pick-up location technology that may be associated with a public bus [2]. Similar to our SML-CBs concept, they also share bus routes for parcel deliveries. Our proposed SML-CBs are different in several key aspects. Firstly, Amazon's concept uses stationery lockers. Secondly, in Amazon's system, the parcel is carried by individuals inside the bus. As such, SML-CBs allow for parcel distribution with minimal interference with passengers. Thirdly, we introduce a mobile app that interacts customers with transit agencies, locker operators, and e-commerce retailers. Finally, by using advanced modeling, algorithms and IoT technologies, the pick-up service time is minimized to diminish the delays to bus operations.

FIGURE 3.1: Concept of SML-CBs - a possible layout.

3.4 Research Methodology

We have designed and conducted a survey, as part of a larger survey of e-commerce consumer attitudes of online shopping in major Canadian Metropolitan Areas. The survey was conducted by the Smart Freight Centre. Below we describe the analysis methodology, survey design and major results from the analysis of the collected data on smart mobile lockers.

3.4.1 Technology Acceptance Model and Analysis

To analyze the potential customers' decisions regarding their acceptance or rejection of SML-CBs, we utilized the technology acceptance model (TAM). This dominant model investigates factors affecting customers'/users' acceptance of a certain technology [19]. The TAM model, initially defined by Davis [8], proposed that users' attitudes toward a system were dominant to whether the users would actually accept the system. This attitude can be further influenced by two beliefs: the perceived usefulness and the perceived ease of use, while the latter can influence the former. Both beliefs are assumed to be further influenced by the system design characteristics. In our case, we have six system characteristics that correspond to the survey questions: Top Motivating Factor, Top Concern, Expected Discount, Willing to Wait Time, Expected Walking Distance and Unsafe Feelings. The Top Motivating Factor, environmental friendliness, is mapped to Perceived Usefulness (PU). When participants indicate their top motivating factors for using SML-CBs, they are essentially revealing what they perceive as the benefits or enhancements provided by this technology. These benefits could range from convenience to time-saving, directly aligning with perceived usefulness. The Top Concern can impact both PU and Perceived Ease of Use (PEOU), as concerns about new technology can affect both how useful it is perceived to be and how easy it is to use. For example, if a concern is about the reliability of SML-CBs, it affects its perceived usefulness, or if the concern is about the complexity of operating the locker, it affects its perceived ease of use. The Expected Discount is mapped to PU. When users expect a discount, they likely perceive the technology as providing greater value or usefulness, particularly cost-effectiveness. The Willing to Wait Time impacts PU, as it can be seen as a trade-off against the perceived benefits of using SML-CBs. If users are willing to wait longer, it suggests that they find the system sufficiently beneficial to justify the wait. Expected Walk Distance is connected to PEOU. The distance users are willing to walk to pick up parcels from SML-CBs indicates the system's convenience and accessibility, key aspects of PEOU. The Unsafe Feelings are believed to affect the Attitude Toward Using directly. The feelings of safety or lack thereof directly impact the user's attitude towards adopting and using technology. If users feel unsafe, their overall attitude towards using SML-CBs becomes negative, regardless of their perceived usefulness or ease of use. This makes it a direct factor in shaping the "Attitude Toward Using" aspect of TAM. The TAM analysis is visualized in Figure 3.2.

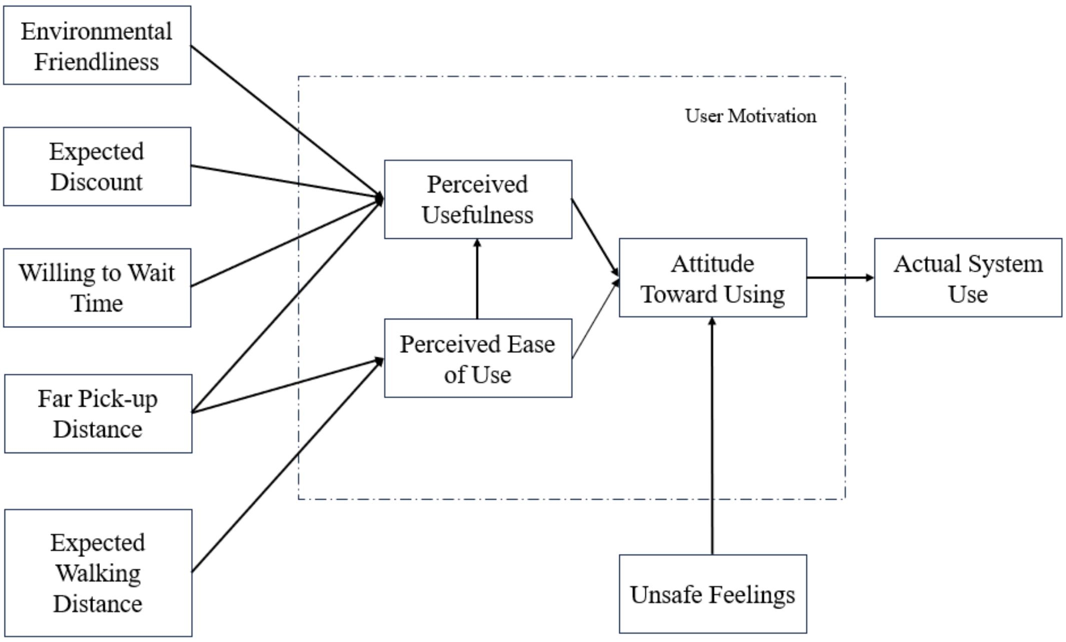

FIGURE 3.2: TAM Analysis of SML-CBs.

3.4.2 Survey Design

The McMaster Human Research Ethics Committee approved this survey. The survey included 2617 participants in nine major cities across Canada, including Edmonton, Halifax, Hamilton, Montreal, Saskatoon, St. John's, Toronto, Vancouver, and Winnipeg. Participants are 18 years or older, and their responses are recorded from the 8th to the 22nd of December 2022, with the aid of a market research team. The survey was designed to collect at least 2550 responses, ensuring that each of the surveyed demographics had a sample size that was large enough for statistical significance. In addition, our survey data is coded by forward sortation areas that can be used to get insights on differences between urban, suburban, and rural views on using SML-CBs.

The survey has multiple sections. In this paper, we focused on two sections: participant demographics (part one) and participants' perspectives on SML-CBs (part two). In part one, we included factors that allow as to analyze participants by different groups. Besides including factors such as basic demographic information of age and gender, we reviewed the literature on parcel locker deliveries and selected factors that are suitable as well as available in affecting the performances of parcel locker implementation. For example, Schaefer and Miguel [25] used multiple variable groups, including land use and house income, to study the spatial accessibility and equity of Amazon parcel locker facilities. We also found that the results of case studies in deploying parcel lockers in different cities for e-commerce deliveries could be different [26]. In addition, Iannaccone et al. [10] observed that online shopping frequency may explain customers' choice of parcel lockers. Furthermore, the price is proved to be the most important criterion for customers choosing parcel locker services [15]. Supported by these findings, we include six relevant factors to group the participants: Age, Land use, House type, City, Online shopping frequency, and Online Shipping payment preferences.

We classify the six factors into three types: 1. basic demographic information, 2. location and land information, and 3. online shopping and shipping information. For land use, we cover three types: urban, suburban, and rural. Considering possible concerns of revealing participants' real house income, we use the housing ownership to reflect the class of house income and include five ownership types of houses: apartment, condo, house, townhouse, and others (for example, university or college residency). To reflect the sensitivity of service price, we use customers' frequency of paying for parcel shipments.

There has been limited literature studying customers' acceptance and perspectives of mobile parcel lockers, according to our knowledge. In part two, we designed six questions to assess participants' acceptance and perspectives toward using SML-CBs for e-commerce last-mile deliveries. We generated these questions and the associated answer options based on a combination of literature reviews and the feedback we collected from academic and industry audiences when presenting the concept at various conferences. We kept the number of answer options from four to five for each question. The purpose is to balance providing enough options to reflect participants' perspectives and not lose their motivation by listing too many alternative options.

The first question focuses on the factors that may motivate participants to use SML-CBs, which include four answer options: 1. Encouragement to use more public rides, 2. Environmental friendliness, 3. Less traffic congestion, 4. Lower delivery costs.

The second question assesses the factors that may hinder participants from using SML-CBs, with four options available: 1. Operations to use this service is too complex. 2. The bus stop is too far away from your location. 3. You may miss the first delivery trial. 4. Your safety when picking up.

The third question explores the expected service prices of the participants for using SML-CBs. Considering that pricing is one of the most important factors that impact customers to adopt and use parcel lockers [5], we are interested in exploring how much discount the participants are looking for when comparing SML-CBs with existing parcel delivery services like Uber. Four levels of discounts are provided: 1. 10%, 2. 25%, 3. 50%, and 4. 75%.

The fourth question investigates participants' expected wait time when picking up parcels. Customers wait time for parcels is important for delivery service quality, and need to be optimized when operating SML-CBs. One of our critical concerns in running SML-CBs is that the reliability of the service may be weakened by the uncertainties of bus operations, leading to delays in bus arrivals and the possibility that customers have to wait at bus stops that exceed their expected time. If the customers wait more than their expected maximum threshold, they may be unsatisfied and unlikely to use the SML-CBs again. Since the SML-CBs will need to partner with the transit system and face the uncertainty of bus operations, we are interested in how much time the participants are willing to wait for the parcels, based on which we observe the participants' tolerance towards the service uncertainty in terms of time. Four answer options for the question are given: 1. 30 seconds. 2. 1 minute. 3. 3 minutes. 4. 5 minutes.

The fifth question relates to participants' expected walking distance using SML-CBs. The pick-up distance has been identified as another critical factor that impacts the customers' willingness to use both fixed and mobile parcel lockers [23, 28]. The walking distances are classified into four ranges: 1. less than 50m. 2. 50–100m. 3. 100–200m. 4. 200–500m.

The sixth question tests participants' attitudes toward the safety of using SML-CBs. There has been no research on customers' feelings of safety when using the service provided by mobile parcel lockers. However, this is one of the most common questions that we have received from the audiences being exposed to the SML-CB concept. The feeling of safety is divided into five levels from 0 to 4, with 0 representing absolute safety and 4 representing absolute lack of safety.

The seventh question tests the willingness of participants to use SML-CBs in different weather conditions. Though there is literature acknowledging that weather conditions affect users' decisions on how to get to the mobile parcel lockers [14], little is known about how customers react to mobile parcel lockers in different weather conditions. Since we are collaborating with the public transit system, we also test whether the willingness of public riders among the participants is more robust. We have considered three weather conditions and provided four options: 1. No, I will use it in any weather. 2. Yes, I will use it less in rainy weather. 3. Yes, I will use it less in very cold/snowy weather. 4. Yes, I will use it less in very hot weather.

3.4.3 Results

All 2617 participants reported their ages, cities, and residential types. Among these participants, 2285 participants reported their shopping frequency, and 2258 reported their shipping payment preferences. The distribution of participants' ages, cities, residential types, shopping frequency, and shipping frequency can be found in the appendix tables. The overview and detailed results are presented as follows.

3.4.3.1 Overview Results

We start by presenting an overview of the results that aggregates all the participants.

Options	Percentages (%)
Encouragement to use more public rides	17.76
Environmental friendliness	32.05
Less traffic congestion	20.00
Lower delivery cost	30.19

TABLE 3.1: The participants' top motivating factor for using SML-CBs.

The distribution of factors that motivate respondents is shown in Table 3.1. The top factor that motivates all participants is environmental friendliness. This suggests a high environmental awareness among Canadian e-commerce shoppers toward accepting new delivery technology. The lower delivery cost is identified as the second top motivating factor by all participants, falling behind environmental friendliness by only 1.86%.

Options	Percentages (%)
Operations to use this service is too complex	21.86
The bus stop is too far away from your location	28.2
You may miss the first delivery trial	25.71
Your safety when picking up	24.22

TABLE 3.2: The participants' top concern for using SML-CBs.

Compared with the distribution of factors that motivate participants, the distribution of participant concerns is more even, with the percentage of all options ranging between

20% to 30%. As shown in Table 3.2, the top concern is "the bus stop is too far away from your location."

Options	Percentages (%)
10% Discount	6.26
25% Discount	32.64
50% Discount	34.13
75% Discount	26.97

TABLE 3.3: The participants' expected discount of using SML-CBs.

The distribution of participants' expected discounts is shown in Table 3.3. The most selected expected discount is 50%. It can be observed that a small discount, like 10%, is not very attractive for participants to transfer into using SML-CBs since only 6.26% of participants select 10% as the favored discount they are looking for. However, the majority of participants are not looking for a reduction as aggressive as 75% in existing delivery service prices. It is observed that a 50% discount would attract as many as 73.03% participants to use SML-CBs.

Options	Percentages (%)
30 seconds	21.86
1 minute	18.32
3 minutes	30.13
5 minutes	43.72

TABLE 3.4: The time that participants are willing to wait.

In Table 3.4, the most selected wait time is five minutes. These results suggest a high tolerance of the participants for the parcel pick-up waiting time, rather than the case that participants allow a very narrow time window to pick up their parcels.

Options	Percentages (%)
Less than 50m	24.47
50-100m	26.02
100-200m	26.86
200-500m	22.64

TABLE 3.5: The self-pick-up distance that participants are willing to walk.

As for the distribution of the self-parcel pick-up walking distance, the most preferred walking distance for participants, as shown in Figure 3.5, is "100 - 200m."

Options	Percentages (%)
0	10.99
1	15.63
2	33.89
3	23.09
4	16.40

Table 3.6: The participants' unsafe feelings of using SML-CBs.

Regarding the participants' unsafe feelings, the top option is level "2", as shown in Table 3.6. As many as 83.60% participants did not feel absolutely unsafe (level '4'), and 60.51% participants felt neutral or safe (level '0', '1', and '2') in using SML-CBs.

Options	Percentages (%)
No, I will use it in any weather	15.32
Yes, I will use it less in rainy weather	17.73
Yes, I will use it less in very cold/snowy weather	58.44
Yes, I will use it less in very hot weather	8.51

Table 3.7: The weather impact on participants of using SML-CBs.

The results in Table 3.7 reveal that 15.32% participants can be regarded as robust potential customers who would use SML-CBs regardless of the weather conditions. However, weather conditions, including rainy days, hot days, and snowy/cold days, exert a strong impact on participants' willingness to use SML-CBs. The snowy/cold weather will impact the willingness of as many as 58.44% participants. We explored whether the participants taking public transit for work show stronger resistance to weather conditions in the next subsection.

We use the Z-test to better statistically measure the option significance for each question. In the absence of specific benchmarks, we assume an equal distribution among options, which is 25% for questions with four options (Q1, Q2, Q3, Q4, Q5, and Q7) and 20% for questions with five options (Q6). We first define the hypothesis. For example, the null hypothesis (H_0) of the proportion of respondents who chose a specific option (e.g., The bus stop is too far away from your location for Q1) p equals the hypothesized proportion (p_0): H_0: $p = p_0$. The alternative hypothesis (H_1) is defined as the proportion of respondents who chose the specific option is different from the hypothesized proportion: H_1: $p \neq p_0$. Next, the test statistic is calculated by the following formula, where p is the observed proportion of respondents who chose the option, p_0 is the hypothesized proportion, and n is the total number of survey respondents.

$$Z = \frac{p - p_0}{\sqrt{p_0(1 - p_0)/n}} \tag{3.1}$$

We determine a 95% confidence level, of which a two-tailed test has $\alpha = 0.05$ and the critical Z-values ± 1.96. The Z values of all options are summarized in the following Table 3.8.

Questions	**Option 1**	**Option 2**	**Option 3**	**Option 4**	**Option 5**
Q1 (Motivator)	-8.55	8.33	-5.91	6.13	na
Q2 (Concern)	-3.71	3.78	0.84	-0.92	na
Q3 (Expected discount)	-22.13	9.03	10.79	2.33	na
Q4 (Wait time)	-3.71	-7.89	6.06	22.12	na
Q5 (Walking distance)	-0.63	1.21	2.20	-2.79	na
Q6 (Safety feeling)	-11.52	-5.59	17.76	3.95	-4.60
Q7 (Weather impact)	-11.44	-8.59	39.51	-19.48	na

TABLE 3.8: Z-test results for the significance of all survey options.

The Z-test table provides the following managerial insights: For customer motivations, the highly positive Z-values of 'Environmental Friendliness' and positive Z-values of 'Lower Delivery Cost' suggest that we could enhance our value proposition by focusing on environmental benefits as well as cost savings, and tailor our marketing and operational strategies to these insights for better alignment with customer preferences. Regarding customers' concerns, the positive Z-value of 'The Bus Stop is Too Far Away' and a slightly positive Z-value of 'Miss First Delivery Trial' highlight customers' concerns over the service's convenience and reliability. On customers' expected price cut, the highest positive Z-value of 50% Discount and a lower positive Z-value of 25% Discount suggest our promotional planning to use the highly preferred 50% discount sparingly to maximize impact while relying more regularly on the 25% discount as an appealing yet sustainable option.When it comes to the customers' expected waiting time, the highest positive Z-value of 5 Minutes suggests that customers most accept the longest time period within the given wait time options. This indicates a significant tolerance, which presents an opportunity to manage expectations around service delivery times without significantly impacting customer satisfaction. A positive Z-value of '50-100m' and a higher positive Z-value of '100-200m' show lights on optimized service placement, which aims to place service points within the 50-200 meter range to align with the most preferred walking distances. The extremely high positive Z-value of 'I will use it less in very cold/snowy weather' indicates a strong tendency to use the service less in cold or snowy conditions, significantly more than expected. This motivates us to develop features or services that address weather-related concerns. A high positive Z-value of 'level 2' in the safety feelings suggests many more customers feel a neutral level of safety than would be expected if feelings were evenly distributed. This indicates a potential improvement; making safety features more visible or enhancing them could shift this perception toward feeling safer.

3.4.3.2 Detailed Results – Impact of Different Factors

By breaking the participants into different groups and analyzing the detailed results, we are able to focus on and answer critical questions that we are likely to encounter in implementing SML-CBs: 1. What are the top motivators for different participants? 2. What are the top concerns for different participants? 3. Who are our target customers if the discount level is low, medium, and high? 4. Who will wait longer for parcels and show stronger resilience to uncertainties in parcel arrivals? 5. Who has stronger preferences for shorter walking distances? 6. Who feels safer about using SML-CBs? 7. Who shows stronger resilience to cold/snowy weather? 8. Will the resilience to cold/snowy weather be stronger if we narrow down to participants who are public riders? Particularly, we would like to explore the segmented participants that show different results with the overall results.

Impact of Age The detailed results of participants in different age ranges are shown in Figure A1. In part a, it is observed that the top two motivating factors are "environmental friendliness" and "lower delivery costs" for participants across all ages. However, the top motivator varies between ages. For participants aged "46-55" and "66 or older," the option "lower delivery cost" is more appealing and thus becomes their top motivating factor. In part b, we found that the top concerns differentiate depending on the participants' ages. For young participants who are "18-25" and "26-35," the top concern is the option "miss the first delivery trial." For middle-aged participants, the top concern is "safety when picking up" for the group aged "36-45", while the group aged "46-55" and "56-65" identified the possible long pick-up walking distance as the top concern. For elderly participants, the option "complexity of operating the system" becomes their dominant concern. In part c, the most selected discount is "25%" for those aged "36-45" and "66 or older," and "75%" for participants aged "56-65." In part d, the percentages of "most patient" participants, identified as those who could wait for the parcels for five minutes, increased with age, except for participants aged "56-65," while the percentage of "impatient" participants, defined as those who are willing to wait for only thirty seconds for their parcels, increased with age except for participants aged "56-65." In part e, the preference for the shortest walking distance, reflected by choosing the option "less than 50m," increased with age. In part f, the feeling of being unsafe at "level 2" when using SML-CBs remains the most selected option for participants across all ages. Still, its significance compared to other levels of unsafe feelings decreased with age. With the increase in age, participants tend to feel more unsafe, reflected in higher percentages of participants choosing "level 3 " and "level 4". In part g, the oldest participants aged "66 or older" showed the strongest unwillingness to use SML-CBs in cold/snowy weather, while participants aged "36-45" showed the strongest resistance to cold/snowy weather. In part h, there is an overall decrease from 54% to 52% of participants choosing the option of "snowy/cold weather will impact" when we filter participants by public riders. The reduction is observed in participants aged "18-25," "36-45," "46-55," and "56-65," with the most significant reduction observed in participants aged "46-55."

Impact of Residential Types Figure A2 visualizes the detailed results for participants living in different residential types. In part a, the top motivating factor for all participants is "environmental friendliness." In part b, the top concerns for participants vary with residential types. The top concern switched to "operations to use this service is too complex" when the participants reside in "condos," "townhouses," and "other types." Participants living in "apartments" are more sensitive to usage safety and chose "your safety when picking up" as their top concern. In part c, condo residents are looking for less aggressive discounts and have the highest proportion compared to other participants in selecting 10% and 25% discounts. In part d, participants in "apartments" and "other types" showed stronger willingness, reflected by a higher proportion summing up three-minute and five-minute waiting times. In part e, the top selected walking distances vary for participants in different residential types. While the participants living in "other types" chose the longest walking option, "200-500 m," as their favorite option, the participants living in "house," "townhouse," "apartment," and "condo" chose "less than 50m", "50-100m", "50-100m" and "100-200m" as the most selected choices, respectively. It can be summarized that the denser the residential types are, the longer walking distance that residents tend to choose as their most selected option. In part f, participants in "townhouses" and "other types" chose "level 3" and "level 4" as their most selected feelings, showing more conservative attitudes toward using SML-CBs regarding usage safety. In part g, the option "use it less in cold/snowy weather" was dominant. The proportions range from 50% to 60% for all groups of participants. In part h, after filtering participants by using public transit for mobility, it is found that there was a significant reduction of participants living in "townhouses" that selected "use it less in cold/snowy weather" to below 40%.

Impact of Cities Coming to participants living in different cities, the top motivating factors vary, as shown in part a of Figure A3. The participants in Montreal showed the highest interest in "environmental friendliness," while Hamilton participants showed the highest interest in "lower delivery cost" compared to other participants. Other participants favoring "environmental friendliness" most are in Saskatoon and Hamilton, while Winnipeg and Saskatoon participants show comparatively stronger interest in “lower delivery costs.” In part b, only the participants in Montreal chose "operations to use this service is too complex." It is worth noticing the significant high and low rates of the participants in Montreal and St.John’s who selected the option "the bus stop is too far away from your location," which indirectly reflects participants’ confidence in the convenient accessibility of using the transit system in their cities. In part c, participants in Halifax and St. John’s showed stronger preferences towards lower discounts at "25%". In contrast, Saskatoon participants had the strongest preference towards a higher discount at "75%." In part d, "five minutes" was the top selection for participants in all cities. The participants from cities including Montreal, Toronto, and Vancouver with denser transit systems tend to be less patient, reflected by the lower rates of selecting wait time of "5 minutes." The participants from cities including St.John’s, Winnipeg, and Halifax can be more patient and have higher proportion in selecting the wait time of "5 minutes". In part e, different from the most selected option, "100-200m," of the overview results, "less than 50m" becomes the most selected for participants in most cities, including Edmonton, Halifax, Montreal, Saskatoon, and Winnipeg. Hamilton and St. John’s participants showed stronger tolerance to longer walking distances, reflected by a higher proportion in selecting "200-500m." In part f, participants in Saskatoon tend to be more conservative in the usage safety feeling, with "level 4" as the most selected option. In part g, "use it less in very cold/snowy weather" is a dominant option for participants in all cities. It is more significant (more than 60%) for participants in colder cities, including Edmonton, Saskatoon, and Winnipeg, while it is less significant (less than 50%) for warmer city participants, for example, in Vancouver. In part h, after filtering the participants by public transit riders, there is a large reduction (more than 15%) of "use it less in very cold/snowy weather" for participants in Halifax and Hamilton and a small reduction (less than 15%) in Montreal, St. John's and Winnipeg. Hamilton participants who are public riders showed a much stronger willingness to use SML-CBs in any weather, reflected by the shift of the most selected option to "will use it in any weather."

Impact of Land Types As for the impact of land types, the detailed results are visualized in Figure A4. In part a, the distribution is similar for all land types, with the options ranking being the same for urban and suburban participants. However, for participants in rural areas, the most attractive option becomes "lower delivery cost." In part b, the top concern shifted from the "bus stop is too far from your location" in the overview results to "your safety when picking up" for both urban and suburban participants. For rural participants, the percentage of choosing "bus stop is too far away your location" is significantly higher than other options in the same land type or the same option in other land types, showing the lack of confidence of rural participants in conveniently accessing the transit system. In part c, the suburban participants showed a stronger preference towards a lower discount at "25%." In part d, the distribution pattern is similar, and the options ranking is the same for participants across all land types. In part e, rural and subrural participants are looking for closer bus stops, though they might have lower transit density, which is reflected by their most selected option as"less than 50m". In part g, the option "use it less in very cold/snowy weather" is dominant among all participant groups. The urban participants appear to be slightly more sensitive to rainy weather, reflected by comparatively higher proportions in selecting "will use it less in rainy weather." In part h, after narrowing down the participants into public transit commuters, a large reduction (more than 15%) is observed in selecting "use it less in very cold/snowy weather" for participants in suburban areas.

Impact of E-commerce Shopping Frequency The detailed results regarding the impact of e-commerce shopping frequency are shown in Figure A5. In part a, "lower delivery cost" is most attractive for less frequent online shoppers, defined as participants who shopped "less than once in 3 months," "once in 2 to 3 months," and "once a month." For more frequent online shoppers, defined as those who shopped "once in two weeks," "once a week," and "more than once a week," the option "environmental friendliness" becomes the top motivating factor. In part b, in contrast to overview results, "the bus stop is too far away from your location" is not the top concern anymore for all groups, except participants who shopped online "once a month." Participants who shopped "less than once in 3 months "and "once in 2 to 3 months" seem to be more concerned about the complexity of using the system, while shoppers, including those who shopped "once in 2 weeks," "once a week," and "more than once a week," are more concerned about the quality of the service, reflected by selecting options including "may miss the first delivery trial" or "safety when picking up." In part c, more frequent shoppers, except participants who shopped "more than once a week," tend to accept a lower discount at "25%" as the most selected option, compared with less frequent shoppers at a favorite discount rate of "50%". In part d, the distribution of options' ranking is similar for all groups. In part e, the most selected walking distance varies depending on the participant group, showing no similar distribution between groups. Both the most and least frequent shopping participants preferred the shortest walking distance, "less than 50m." Participants who shopped "once in two weeks" favored the second shortest walking distance, "50-100m". Participants who shopped "once in 2 to 3 months" showed the strongest preference for the longest walking distance, "200-500m." In part f, the unsafe usage feeling at "level 2" (neural) is the leading option for all groups. The ranking of options is the same, and distributions are similar for participants across all groups except for the least frequent shopping participants. In part h, after filtering the participants by public transit commuters, there is a reduction in "use it less in very cold/snowy weather" for participants who shopped "once a month" and "once a week."

Impact of E-commerce Shipping Payment Preference Many useful observations can be obtained from Figure A6 of the detailed results regarding the participants' shipping payment preferences. In part a, the participants that are in two extremes, "I always pay for shipping" and "I never pay for shipping," showed a stronger preference towards "lower delivery cost" as the favorite option, while the rest of the participants chose "environmental friendliness" as the most selected option. In part b, participants who are willing to pay for shipping are more concerned over service qualities, with their top concerns being "your safety when picking up" and "you may miss the first delivery." We observe a more significant leading of "your safety when picking up" for participants who always pay for shipping and of the option "you may miss the first delivery trial" for participants who usually pay for shipping over other options in their respective groups. In part c of Figure A6, most participants who "never pay for shipping" seek the biggest discount at "75%". It can be summarized that the more likely the participant group pays for shipping, the more participants in the group accept low and medium (non 75%) discounts. In part d, while participants across all groups chose "five minutes" as the most selected option, it was found that shipment payers are more patient than non-payers. In part e, the participants of two extremes, "I always pay for shipping" and "I never pay for shipping," showed a stronger preference towards the shortest given walking distance. In part f, the participants who are frequent shipment payers (including "always pay for," usually pay for," and "sometimes pay for") felt safer using the SML-CBs, reflected by a higher proportion in summing up "level 0," "1, "and "2". The neural feeling of safety at "level 2" increases with the willingness to pay for shipment. In part g, the strong attitudes of using SML-CBs regardless of the weather condition ranges between 10% and 20% for participants across all groups. In part h, when focusing on public riders, there is an obvious increase (>15%) in the percentages of "robust" customers who chose to use SML-CBs in any weather conditions for participants who "always pay for shipping." In addition, a slight reduction in percentages of "use it less in very cold/snowy weather" is observed for participants who paid for shipping except "always pay for shipping."

3.5 Discussions

We are recommended to use "environmental friendliness" and "lower delivery costs" as top selling points for SML-CBs since they could be more appealing to all potential customers than other motivating factors in our survey. To address the top concern, "picking up bus stops may be too far," we suggest developing efficient optimization models for potential customers to guarantee they are assigned to bus stops within their accepted walking distances. In Chapter 4 we propose a quadratic assignment problem to address this concern. Another possible solution could be giving the potential customers who are more sensitive to parcel pick-up distances more weight in the customer-bus stop assignment. The second top concern, "may miss the first delivery trial," could be solved by developing convenient and cost-efficient re-delivery strategies. To clear the next common concern, "your safety when picking up parcels," we suggest adopting more human-centered designs and operating strategies to create a safe environment for customers' parcel pick-ups. For example, maintaining a safe distance between customers and traffic flow when customers conclude the parcel pick-up service. Lastly, the complexity of using the system, either from the hardware or software, could be relieved by various measures, including enhanced online customer service, offline product promotion, and accelerated parcel pick-up process through IoT technologies.

The distribution of the discounts that potential customers look for could act as pricing guidelines for SML-CBs to reach a target market penetration. For example, providing a 25% discount compared to existing delivery services would help us to reach a maximum of 38.9% market penetration. Knowing customers' accepted maximum waiting time at bus stops would help us choose the proper time to send notifications to customers to address the bus arrival uncertainty of the selected routes. Based on the observations from the distribution of customers' expected parcel pick-up distance, we found that participants could be more strict with the parcel pick-up walking distances, compared with walking distances accepted by the accessibility of fixed parcel lockers, for example, ranging from 0.25 to 0.5-mile [25]. This trade-off may be due to the more strict time constraints for using the service within certain time windows. The lack of usage safety feelings for some potential customers, could be due to the fact that shared mobility is an emerging technology, and potential customers, are unfamiliar with the mode of co-transportation of passengers and freight. This suggests that further work needs to be done through outreach activities such as vivid illustrations, for example, short videos, to potential customers. Regarding the weather impact, one possible solution is to choose warmer cities for early-stage implementation of SML-CBs to relieve the impact of snowy/cold weather. Another possible solution is to focus more on the existing public riders, who showed stronger resistance to snowy/cold weather to use SML-CBs. We could also target those cities where respondents where less sensitive to cold weather, such as St John as per Figure A3.

To better generate the assessment from the detailed results, we develop a performance matrix to rate the answers for questions three to six to systematically explore the potential of participants to accept SML-CBs in each group. The values in the matrix for questions three to five, shown in Tables 3.9–3.11, respectively, are the expected values, which are defined by:

$$\sum_{i=1}^{n} p_i(LB_i + UB_i)/2 \tag{3.2}$$

where n is the number of groups, p_i is the percentage of group i, LB_i, and UP_i are the lower and upper bounds of group i.

The expected value of answers for question six is defined by,

$$\sum_{i=1}^{n} p_i F_i \tag{3.3}$$

where F_i is the degree of safety feeling for group i. The overall score of each participant group is defined by

$$\sum_{i=1}^{n} R_i/n \tag{3.4}$$

where R_i is the rank of group i, and n is the number of groups.

For questions three and six, the lower the expected value that a participant group has, the higher the ranking the group is in. This is because the lower discount reflects that respondents are more tolerant of higher service prices, and the lower unsafe usage feeling reflects that participants feel safer using SML-CBs. For questions four and five, the higher the expected value that a group has, the higher the ranking the group is in. This is because the higher values show that the respondents are willing to walk further for parcel pick-ups and wait longer at bus stops. In addition, considering the critical impact that the parcel pick-up distance may have on potential customers, we visualize the expected parcel pick-up walking distance (EWD) for different participant groups in Figure 3.3.

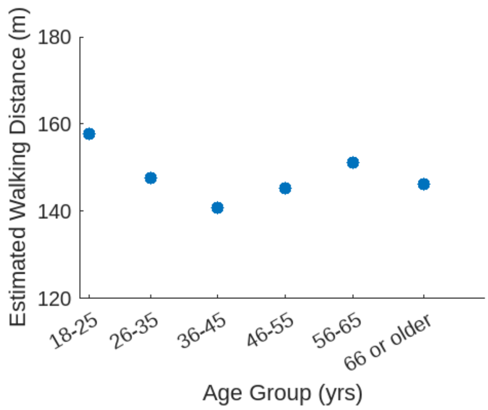

FIGURE 3.3: The expected walking distance for participants of different ages.

Questions/Groups	18-25	26-35	36-45	46-55	56-65	66 or older
Q3(E)	29.39	29.64	27.87	33.07	31.46	27.21
Q3(R)	3	4	2	6	5	1
Q4(E)	151.27	148.63	151.95	157.37	166.53	161.53
Q4(R)	5	6	4	3	1	2
Q5(E)	157.85	147.64	140.74	145.18	151.08	146.16
Q5(R)	1	3	5	6	2	4
Q6(E)	2.08	2.16	2.07	2.17	2.23	2.36
Q6(R)	2	3	1	4	5	6
Overall Score	2.75	4	3	4.75	3.25	3.25
Overall Ranking	1	4	2	5	3	3

TABLE 3.9: Assessment matrix of participants regarding ages.

Figure 3.3 shows that the young potential customers aged "18-25" have the longest expected walking distance, while potential customers aged "36-45" show the shortest expected walking distance. A "smile curve" is observed in EWD with the increase of participants' ages, except the oldest participants aged "66 or older". A more comprehensive assessment from the matrix in Table 3.9, where (E) represents the expected value and (R) represents the ranking, reveals that the young potential customers aged "18-25" had the highest ranking across all participants in terms of ages, suggesting their highest potential to adopt SML-CBs. We may target these potential customers and launch SML-CBs around university or college campuses to reach maximum users.

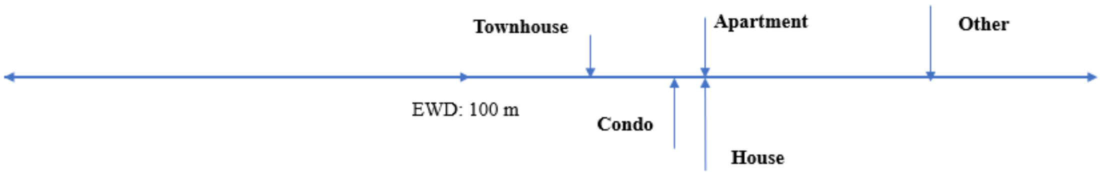

FIGURE 3.4: The expected walking distance for participants of different residential types.

Questions/Groups	**Apartment**	**Condo**	**House**	**Townhouse**	**Other**
Q3(E)	28.32	28.77	30.10	31.49	32.85
Q3(R)	1	2	3	4	5
Q4(E)	166.88	150.00	153.82	146.21	184.17
Q4(R)	2	4	3	5	1
Q5(E)	149.65	145.34	150.02	126.54	205.56
Q5(R)	3	4	2	5	1
Q6(E)	2.01	2.32	2.20	2.29	2.26
Q6(R)	1	5	2	4	3
Total Score	1.75	3.00	2.00	4.00	2.00
Overall Ranking	1	3	2	4	2

TABLE 3.10: Assessment matrix of participants regarding residential types.

Though the potential customers in "other types" residences had a significantly higher expected walking distance, as shown in Figure 3.4, the results from the assessment matrix in Table 3.10 reported that participants living in the apartment have the highest rating due to high performance of other indicators. This suggests that we may target apartment residents in the early stage to implement SML-CBs to secure the number of users.

Figure 3.5 shows that the potential customers in St.John's lead in the expected walking distance, followed by Hamilton customers. The potential to implement SML-CBs in different Canadian cities is reflected by the ranking shown in Table 3.11. The top three

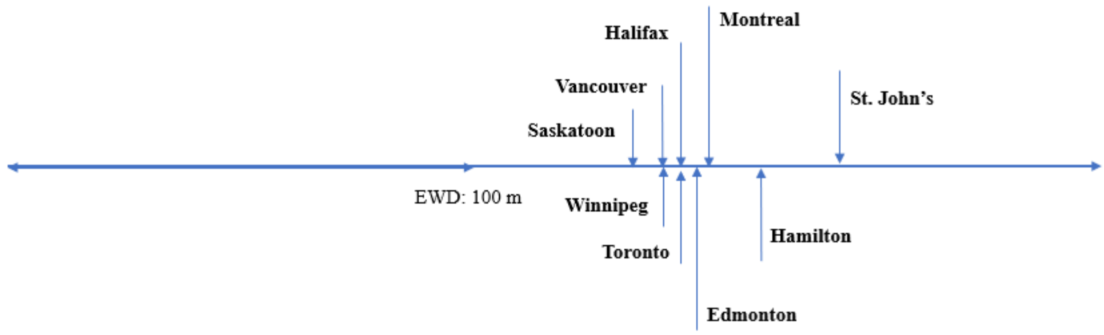

FIGURE 3.5: The expected walking distance for participants of different cities.

Questions/Groups	Edm	Hal	Ham	Mon	Sas	StJ	Tor	Van	Win
Q3(E)	29.73	29.55	28.00	30.78	32.41	24.83	29.72	30.17	26.76
Q3(R)	6	4	3	8	9	1	5	7	2
Q4(E)	161.46	166.76	160.36	151.91	136.53	191.11	150.51	158.41	167.12
Q4(R)	4	3	5	7	9	1	8	6	2
Q5(E)	148.74	146.95	162.94	150.75	136.11	183.00	145.18	142.28	142.13
Q5(R)	4	5	2	3	9	1	6	7	8
Q6(E)	2.27	2.38	2.23	1.95	2.49	1.78	2.24	2.26	2.26
Q6(R)	7	8	3	2	9	1	4	6	5
Total Score	5.25	5	3.25	5	9	1	5.75	6.5	4.25
Overall Ranking	6	4	2	4	9	1	7	8	3

TABLE 3.11: Assessment matrix of participants regarding cities.

cities are Saint John's, Hamilton, and Winnipeg. This suggests that we may approach the authorities of these cities to advertise and implement SML-CBs. It appears that Megacities, such as Toronto, do not necessarily have the highest ranking in this rating system, while the high rankings of some other cities put them into the advanced positions to reshape last-mile delivery infrastructures by implementing innovative supply chain technologies, like the SML-CBs.

From Figure 3.6, the ranking of expected walking distance is strongly correlated with the density of residential land. The expected walking distance decreases with the increase in residential density. In Table 3.12, the ranking results conclude that participants in the sub-urban area, though they may not have the easiest access to transit facilities, are most promising in using SML-CBs, followed by urban potential customers. This suggests that we focus on urban and suburban areas to initially implement SML-CBs.

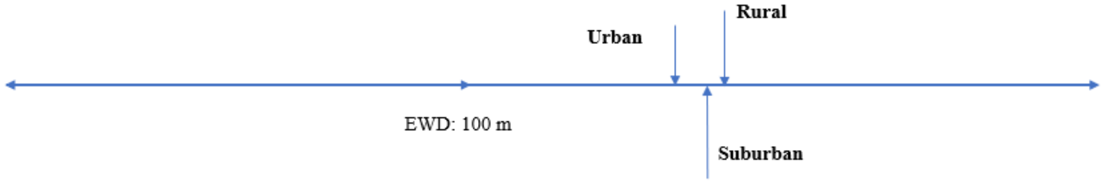

FIGURE 3.6: The expected walking distance for participants of different residential land types.

Questions/Groups	Urban	Sub-urban	Rural
Q3(E)	28.99	29.73	33.39
Q3(R)	1	2	3
Q4(E)	156.72	155.72	149.93
Q4(R)	1	2	3
Q5(E)	145.16	152.13	155.26
Q5(R)	3	2	1
Q6(E)	2.21	2.12	2.15
Q6(R)	3	1	2
Total Score	2.00	1.75	2.25
Overall Ranking	2	1	3

TABLE 3.12: Assessment matrix of participants regarding land types.

Questions/Groups	> 3 Month	2-3 Mon	1 Mon	Bi-week	1 Week	< 1 Week
Q3(E)	29.22	32.70	29.08	28.55	28.04	33.05
Q3(R)	4	5	3	2	1	6
Q4(E)	154.50	172.47	159.60	153.44	151.08	134.25
Q4(R)	3	1	2	4	5	6
Q5(E)	133.71	158.17	157.45	148.71	145.71	120.16
Q5(R)	3	4	1	5	2	6
Q6(E)	2.15	2.16	2.12	2.28	2.13	2.31
Q6(R)	3	4	1	5	2	6
Total Score	3.75	2.75	2.00	3.50	3.00	6.00
Overall Ranking	5	2	1	4	3	6

TABLE 3.13: Assessment matrix of participants regarding online shopping frequencies.

From Figure 3.7, we observe that the relationship between shopping frequency and EWD is similar to an inverted U shape. The monthly online shoppers, including potential customers who shopped once a month and shopped once in 2 to 3 months, have the

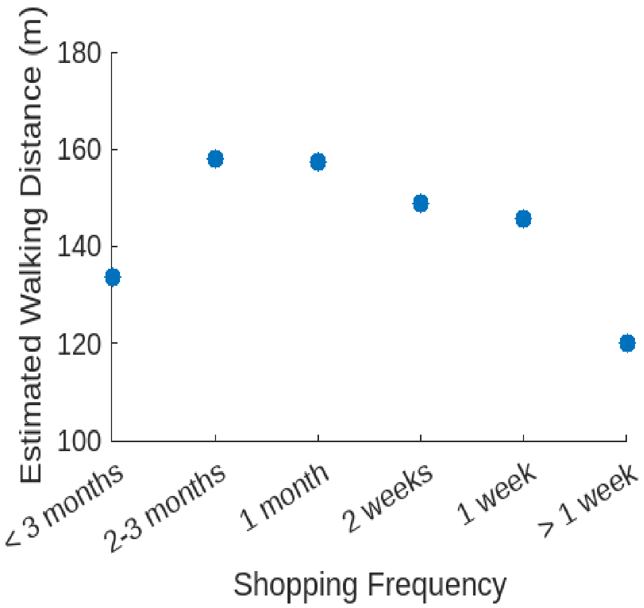

FIGURE 3.7: The expected walking distance for participants of different online shopping frequencies.

longest expected walking distance. Based on the results from Table 3.13, they are also the customers who appear to be most promising to adopt SML-CBs. The most frequent online shoppers, who shopped more than once a week, followed by the least frequent online shoppers who shopped less than 3 months, reported two nearest expected walking distances. These results suggest we may want to approach online shoppers with medium shopping frequencies (monthly) as our target customers.

Questions/Groups	**Always**	**Usually**	**Sometimes**	**Very rarely**	**Never**
Q3(E)	20.92	26.53	26.71	30.39	33.62
Q3(R)	1	2	3	4	5
Q4(E)	165.39	167.20	165.38	156.12	137.88
Q4(R)	2	1	3	4	5
Q5(E)	136.54	149.40	154.29	153.09	127.39
Q5(R)	4	3	1	2	5
Q6(E)	1.97	2.16	2.18	2.14	2.32
Q6(R)	1	3	4	2	5
Total Score	2.00	2.25	2.75	3.00	5.00
Overall Ranking	1	2	3	4	5

TABLE 3.14: Assessment matrix of participants regarding shipping payment behaviors.

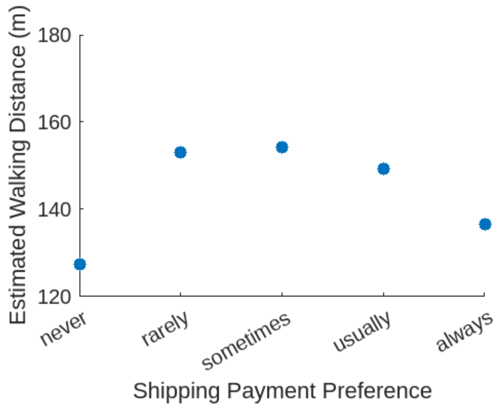

FIGURE 3.8: The expected walking distance for participants of different shipping payment behaviors.

In Figure 3.8, we observe that the relationship between shipping payment preference and EWD is also similar to an inverted U shape. It is found that the potential customers with two extreme shipping payment preferences, "never pay" and "always way," favored the shortest expected walking distance. From Table 3.14, a linear relationship between the willingness to pay for shipment and the ranking of the potential customers is observed. The more customers are willing to pay for shipment, the higher ranking they will possess in the rating system. We identify the potential customers who always pay for shopping as our target customers and prioritize them in advertising.

3.6 Conclusions

This study is seminal research that delves into prospective consumers' attitudes toward using SML-CBs for e-commerce parcel deliveries. We run a survey across nine significant Canadian municipalities, accruing over 2500 responses. Preliminary analysis reveals key preferences for each query, thereby guiding the initial deployment strategies for SML-CBs. Among the motivating factors, "environmental friendliness" emerged as the predominant factor, whereas geographical inconvenience, specifically "bus stop distance," was the primary deterrent. Interestingly, respondents demonstrated a high propensity for a 50% discount on existing delivery service fees, which could subsequently attract a wider customer base, accounting for an estimated 73.03% of interested prospective users. When evaluating the inconvenience associated with additional efforts, namely walking to and waiting at bus stops, respondents displayed a greater tolerance for extended wait times over longer walking distances.

When segmenting the overall findings based on multiple dimensions—such as age, housing type, cities, online shopping frequency, and shipping payment preferences distinctive and parallel patterns emerged. Utilizing a systematic rating system, we were able to pinpoint demographic clusters with the highest potential for early adoption of SML-CBs. Primary targets include younger individuals, apartment dwellers, residents of Saint John's, suburbanites, monthly online shoppers, and those who consistently opt for paid shipping. Secondary targets encompass the age group of 36-45, homeowners, residents of Hamilton, urban dwellers, infrequent online shoppers, and individuals who usually incur shipping fees.

To better compare the factors that impact customers' adoption of various types of parcel lockers and to identify the differences, we summarize such factors in Table 3.15. We found that there is an overlap between adopting fixed PL and SML based on factors including distance, dwell time, and weather. This suggests that the smart PLs, regardless of the mobility types, are influenced by these convenience-related factors. The literature on SMLs and fixed PLs addressed the impact of complexity, which could be due to acknowledging both delivery alternatives as emerging technologies and being aware of the usage challenge in terms of complexity. Within MPLs, the authors in this paper further extend the factors impacting customers to include sustainability and safety. The customers could embrace sustainability by sharing the bus transport resources while hesitating to pick up parcels near temporarily parked buses.

3.7 Acknowledgement

The authors acknowledge Heider Al Mashalah's for his support in designing the survey and data collection. We also acknowledge support from an Alliance Grant from the Natural Sciences and Engineering Research Council of Canada (NSERC).

Year	Papers	Fixed PL	Self SML	SML-CBs
2021	[13]	Security, Reliability, Timeliness	-	-
2021	[29]	Price, Reliability, Convenience, Fault handling capability, Diversity	-	-
2021	[30]	Convenience, Reliability, Privacy security, Compatibility, Relative advantage, Complexity	-	-
2024	[6]	Distance, Dwell time, Notification forms, Daily delivery frequency, Parcel type, Weather condition	Distance, Dwell time, Notification forms, Daily delivery frequency, Parcel type, Weather condition	-
2024	This chapter	-	-	Sustainability, Complexity, Distance, Price, Wait time, Safety, Weather

TABLE 3.15: The factors that impact customers' adoption of various types of parcel lockers

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Appendices

Options	**Percentages (%)**
18-25	12.72
26-35	17.12
36-45	16.47
46-55	15.44
56-65	16.47
66 or older	21.78

Table A1: The distribution of participants' ages.

Options	**Percentages (%)**
Edmonton	8.34
Halifax	4.72
Hamilton	4.61
Montreal	22.93
Saskatoon	3.16
St.John's	2.93
Toronto	33.87
Vancouver	13.87
Winnipeg	5.56

Table A2: The distribution of participants' locations.

Options	**Percentages (%)**
Apartment	21.78
Condo	12.72
House	53.36
Townhouse	8.22
Other	0.92

Table A3: The distribution of participants' residential types.

Options	**Percentages (%)**
< 3 months or only at specific times, e.g., Christmas	9.5
Once in 2 to 3 months	15.75
Once a month	24.51
Once in 2 weeks	22.89
Once a week	18.07
> once a week	9.28

TABLE A4: The distribution of participants' online shopping behavior (shopping frequency).

Options	**Percentages (%)**
I always pay for shipping	1.95
I usually pay for shipping	6.47
I sometimes pay for shipping	24.09
Very rarely do I pay for shipping	47.74
I never pay for shipping	19.75

TABLE A5: The distribution of participants' online shopping behavior (shipping payment).

FIGURE A1: Detailed results in terms of participant ages.

FIGURE A2: Detailed results for participant residential types.

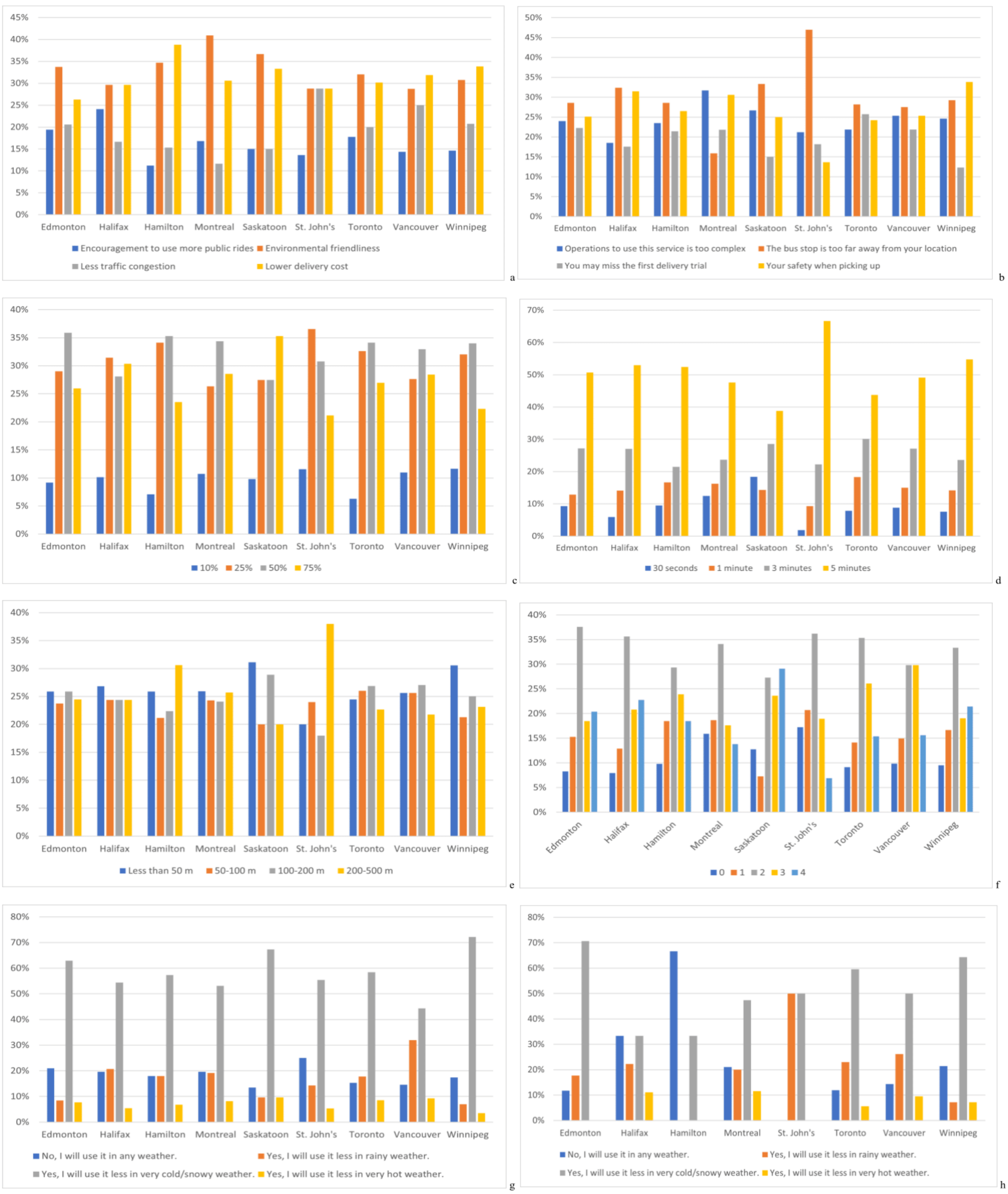

FIGURE A3: Detailed results for participant cities.

FIGURE A4: Detailed results for participant residential land type.

FIGURE A5: Detailed results for participant shopping frequency.

Figure A6: Detailed results for participant shipping payment.

Chapter 4

Operating Smart Mobile Lockers with City Buses for E-commerce Last Mile Deliveries

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Operating Smart Mobile Lockers with City Buses for E-commerce Last Mile Deliveries

Si Liu
DeGroote School of Business
McMaster University, Hamilton, ON, Canada
Email: lius278@mcmaste.ca

Elkafi Hassini
DeGroote School of Business
McMaster University, Hamilton, ON, Canada
Email: hassini@mcmaster.ca

Abstract

This paper introduces a novel last-mile delivery system where a smart parcel locker is operated in tandem with city buses. Smart parcel lockers are replenished at bus terminals, attached to city buses for mobilization, and the parcels are picked up by customers at bus stops. This system has the advantage of being economical by reducing delivery costs and being environmental by reducing emissions. We briefly explain the system and explore its operations in different scenarios, including optimal customer assignment, random customer assignment, and nearest bus stop customer assignment. We aim to motivate the system's adoption by minimizing the customers' total walking distances. Due to the complexity of the optimal customer assignment scenario, we optimize the problem of assigning customers to bus stops and assigning lockers to buses as a quadratic assignment problem with quadratic constraints (QAPQC). We propose a hybrid construction-greedy (HCG) heuristic to solve the QAPQC. Our numerical results show that HCG is efficient regarding solution quality and execution time in both small and large data instances and has good performance with various customer characteristics. Finally, we implement a case study in Mississauga City, Canada, to demonstrate the applicability of our models and solutions in real-world data.

Keywords: *E-commerce, Last mile delivery, Sharing economy, Parcel Lockers, Quadratic Assignment Problem*

4.1 Introduction

This paper addresses the challenges posed by the rapid expansion of e-commerce sales worldwide, with global e-commerce sales reaching 4.2 trillion U.S. dollars in 2020, a 27.6% increase over 2019, and over two billion people purchasing services or goods online, according to Statista data. The COVID-19 pandemic lockdown further accelerated this trend, as evidenced by the 42.85% increase in online grocery sales share of all grocery sales in 2020. According to the Mastercard Economics Institute, Canada's share of online retail sales more than doubled during the pandemic. While e-commerce offers convenience to customers and provides business opportunities, it also poses challenges, with the main one being delivering an unprecedented volume of parcels using existing supply chain infrastructure [19]. Adding flexibility to the supply chain network is recommended in steady-state business conditions to handle disruptions, but such flexibility is limited to 25% even under high disruption probabilities [3]. The recent upsurges in e-commerce volumes, such as the 75% increase in the number of parcels Canada Post had to deliver in June 2020 compared to June 2019 [8], far exceed reasonable, flexible network tolerances and necessitate new measures. In this paper, we propose one alternative last-mile e-commerce delivery system that leverages the sharing economy concept to avoid overburdening the existing supply chain network.

The e-commerce last mile delivery, which involves delivering parcels to customers, is the final stage of an e-commerce supply chain. It is also one of the most expensive parts of e-commerce delivery operations, accounting for anywhere between 28% [43] and 50% [22] of the total delivery cost. Furthermore, it is widely regarded as the least efficient as well as the most polluting phase of the supply chain [40]. Given the importance of last-mile delivery, numerous studies have focused on improving it to reduce costs, boost efficiency, and minimize environmental impact. However, simply increasing network capacity by adding more delivery trucks to deal with the surge in e-commerce volumes creates additional challenges [25]. Firstly, the movement of additional trucks causes extra traffic flow and congestion, particularly during peak times or in busy downtown areas, exacerbating the environmental impact. Secondly, city centers are not designed to accommodate numerous delivery trucks, resulting in illegal parking and increased costs. For instance, in 2018, UPS paid 33.8 million US dollars, while FedEx paid 14.9 million US dollars in New York City due to illegal parking and related expenses [29]. Consequently, some studies have explored innovative delivery alternatives as non-traditional solutions.

Innovative delivery alternatives such as automated parcel lockers (APLs), drones, and autonomous vehicles have been studied. Among these alternatives, APLs are favored due to their economies of scale [28]. APLs are lockers that are situated in various locations, such as apartment blocks, workplaces, and railway stations, with electronic locks that can be used by different consumers at their convenience [11]. By 2018, APLs had gained popularity and were used in more than 20 countries [11]. However, the fact that APLs are located in a fixed location has created some disadvantages. Firstly, land occupancy can incur a high cost, particularly if local land zoning prohibits locating APLs in certain city areas [23]. Secondly, the parcel lockers are stationed on the ground and cannot be relocated frequently to meet dynamic customer demands [54]. Thirdly, replenishment can be slow if customers do not pick up parcels within a short period [53]. Recently, a new kind of APLs called 'mobile parcel lockers' (MPLs) was introduced to address some of these issues. MPLs can change locations during the day, either autonomously or by human drivers, to increase their accessibility to customers. For the same service coverage, fewer lockers may be required. However, they also have limitations [27]. The construction cost of MPLs can be high if they are driven autonomously, while additional operational costs are incurred if they are driven manually. The movement of additional MPLs would cause extra traffic flow, and parking them would require specific parking lots that can be costly or unavailable.

To address the limitations of the above-mentioned alternatives, we propose a novel e-commerce last-mile delivery system using self-monitoring, analysis, and reporting technology (SMART): smart mobile lockers (SMLs) in conjunction with city buses (SML-CBs). This system leverages existing city transit to improve the efficiency and sustainability of last-mile deliveries. SMLs are attached to city buses, and parcels are delivered to customers by existing bus routes and stops. SMLs are equipped with artificial intelligence (AI) and internet of things (IoT) technology to operate efficiently and safely. This innovative system opens the door to rich operational problems. In this paper, we focus on assigning customers to bus stops and assigning lockers to bus routes to minimize customers' total walking distance. We summarize our main contributions as follows:

- This is one of the first studies to introduce the concept of coordinating smart parcel lockers with public transit systems as an efficient alternative to current last-mile delivery methods.

- We study one of the most critical problems in successfully operating the SML-CB, which is to motivate customers to use SML-CB by optimizing the assignment of customers and lockers to minimize the total customers' walking distance.
- We model the assignment problem as a quadratic assignment problem with quadratic constraints and develop a construction-based heuristic to efficiently solve the problem. We also compare the performance of different operating scenarios.
- We implement a case study in Mississauga City, Canada, to provide guidelines for real SML-CBs operations.

This paper is structured as follows: Section 4.1 presents an introduction. Section 4.2 delivers a brief literature review. Section 4.3 discusses the design and operational details of SML-CBs. Section 4.4 introduces our quadratic assignment problem with quadratic constraints (QAPQC) for assigning customers and lockers, formulates the problem, and discusses different operating scenarios. Our proposed heuristic solution and numerical implementations are included in Sections 4.5 and 4.6, respectively. The final two sections, Section 4.7 and 4.8, implement our models and heuristics on a real case in Mississauga City, Canada, and conclude our findings.

4.2 Literature review

This section briefly reviews three streams of literature most relevant to our proposed system, optimization models, and solution approaches.

4.2.1 Automatic lockers for last mile deliveries

The literature on using parcel lockers for last-mile deliveries focuses on operational logistics issues. Iwan et al. [20] assessed the usability of parcel lockers from the customers' perspective based on cases from the InPost company system in Polish cities. Orenstein et al. [38] developed a logistics model for delivering small parcels to service points (SPs). They found that the parcel recipients might have no strong preference among the SPs. The delivery tasks can be performed at lower cost and shorter times if some of these recipients can be flexible with delivery locations and provide the sender with multiple location alternatives.

More recent literature focuses on designing various efficient smart lockers. Faugère and Benoit [14] discussed various optimization-based design methods for smart locker banks, including fixed-configuration and modular tower-based locker banks in omnichannel business-to-customer logistics. Schwerdfeger and Boysen [47] proposed a mobile parcel locker that could change its locations autonomously or be driven by humans during the day. They optimized the locker's locations to satisfy all customers' demands.

4.2.2 Sharing economy for last mile deliveries

The sharing economy is defined as "an IT-facilitated peer-to-peer model for commercial or non-commercial sharing of under-utilized goods or service capacity through an intermediary without transfer of ownership" [46]. The main idea behind the sharing economy is to create additional services from under-utilized goods or services. Our proposed SML-CB coordinates the city transit system, where the average bus occupancy rate does not exceed 15% in the U.S. [57].

In freight transportation, the sharing economy concept has been mostly manifested in crowdsourcing activities, which use individual private vehicles to deliver parcels. Chen and Stanislav [9] investigated the service level of crowd-sourced last-mile deliveries and the performance of asset utilization through an agent-based simulation model. Devari et al. [12] explored the social networks of retail store customers for delivering online orders through crowdsourcing. Their study revealed that crowdsourcing deliveries could reduce delivery costs and total emissions while improving delivery speeds, delivery reliability, and privacy, as well as avoiding failing deliveries. Akeb et al. [2] proposed a collaborative crowd-based solution for collecting and delivering parcels through neighbors. The solution used circle packing to estimate the number of neighbors needed, the number of parcels, and the corresponding reward for drivers. Dupljanin et al. [13] studied the performance of three types of crowd-sourced delivery fleets: bicycles, cars, and both. Their comparison revealed that the bicycle-based fleets method outperformed the other two methods with the simulated conditions within an urban setting. Huang and Muhammad [18] compared the last-mile delivery with different crowdsourcing integration strategies. They showed that well-planned crowdsourcing integration benefited delivery flexibility and cost-saving. Cheng et al. [10] formulated a game between the crowdsourcing platform owner, sponsors, and participants. They found that using a single-prize mechanism and a fixed intermediary fee schedule is optimal.

A second research stream within the sharing economy is crowd-shipping. Although crowd-shipping and crowdsourcing delivery have been used interchangeably in some studies, crowd-shipping refers to cases when the drivers make personal trips and conduct deliveries in tandem with those trips. Behrend and Frank [4] investigated the integration of crowd-shipping and item-sharing. They proved that integration facilitated collaborative consumption and developed integrated models to maximize the platform's profit and the number of fulfilled requests. Behrend et al. [5] solved a crowd-shipping problem and a capacitated item-sharing problem using a set of packing formulations. They recommended providing incentives for drivers to access low-density delivery regions. Le et al. [24] reviewed the components of crowd-shipping services, including supply, demand, operations, and management. They suggested improving impacts, including behavioral and societal, to create a dynamic and sustainable crowd-shipping system.

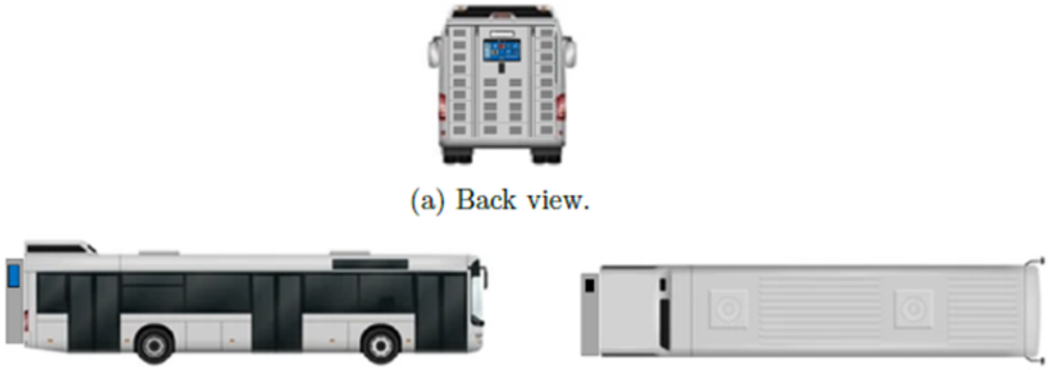
Other relevant studies have focused on shared mobility and shared routes. Qi et al. [41] evaluated the potential impacts of the transition to shared mobility from the perspective of logistics service providers and local governments. They found that though shared mobility was not scalable, it did lift some pressure off the traditional truck fleet and offered flexibility to their operations. Bergmann et al. [6] utilized shared routes to integrate first-mile pickup and last-mile delivery in urban e-commerce distributions.

4.2.3 Quadratic assignment problems and solutions

The quadratic assignment problem (QAP) was initially introduced by Tjalling and Martin [52] and was developed to minimize a cost function multiplied by the distance and the flow between each pair of facilities. Various formulations of QAP were covered in a recent literature review [49]. When solving QAP, the methods can be exact, meta-heuristic, or heuristic. The exact solutions generally consist of three methods or their extensions: cutting plane methods, branch and cut methods, and dynamic programming [42]. Various meta-heuristic approaches have been applied to solve QAPs (e.g., greedy randomized adaptive search procedure (GRASP) [50], tabu search [49], variable neighborhood search (VNS) [36] and Genetic algorithms [56]). Concerning that QAPs are NP-Hard problems, heuristic approaches warrant solving large instances. For example, Mihić et al. [32] developed a constructive heuristic method based on randomized decomposition (RD).

4.3 Operations of SML-CBs

The SMLs are connected to the back of transit buses, as shown in Figure 4.1, and are partitioned into multiple slots. The colored rectangular in Figure 4.1 (a) represents the locker display screen that may be used for advertising, the blue box in Figure 4.1 (b) depicts the touch screen for customers, and the black box in Figure 4.1 (c) represents a maintenance module for the locker. In addition, the SMLs are assigned to bus routes depending on customer demands, and customers are assigned to bus stops where their parcels are to be delivered. Figure 4.2 illustrates the operations of the SML-CB system. The SMLs are attached to or removed from buses at the bus terminals. Based on the service range, the locations of customers and retailers, some bus stops are selected as service points for parcel deliveries. The locker replenishment is done at terminals. While the bus is berthing, the customers and retailers approach the locker, feed, or pick up their parcels.



(a) Back view.

(b) Side view.

(c) Top view.

FIGURE 4.1: 2D illustration of SML-CB (modified on Shutterstock Real-Time Networks).

A mobile app that we are developing enables interactions between retailers, customers, transit systems and SML-CBs. Customers start ordering through our app or retailer's online system, and in the first case, the app will transfer the order to retailers. Supported by our models and algorithms, the app determines the bus routes and stops that provide services for retailers and customers based on their locations. Retailers reserve slots of SML-CBs that are on their assigned bus routes. According to the expected arrival time of buses, retailers wait at bus terminals and feed parcels into SML-CBs when buses berth. As soon as the parcels are in the SML-CB, customers will receive notifications from the app, which include the location of their parcels and the expected arrival time at assigned bus stops. Customers are able to track the in-time locations of parcels through the app. When SML-CBs are close to the service points, the app will send another notification to customers to remind them to prepare parcel pickup. Customers will need to wait at the assigned bus stops and open the locker using the App to conclude the delivery process.

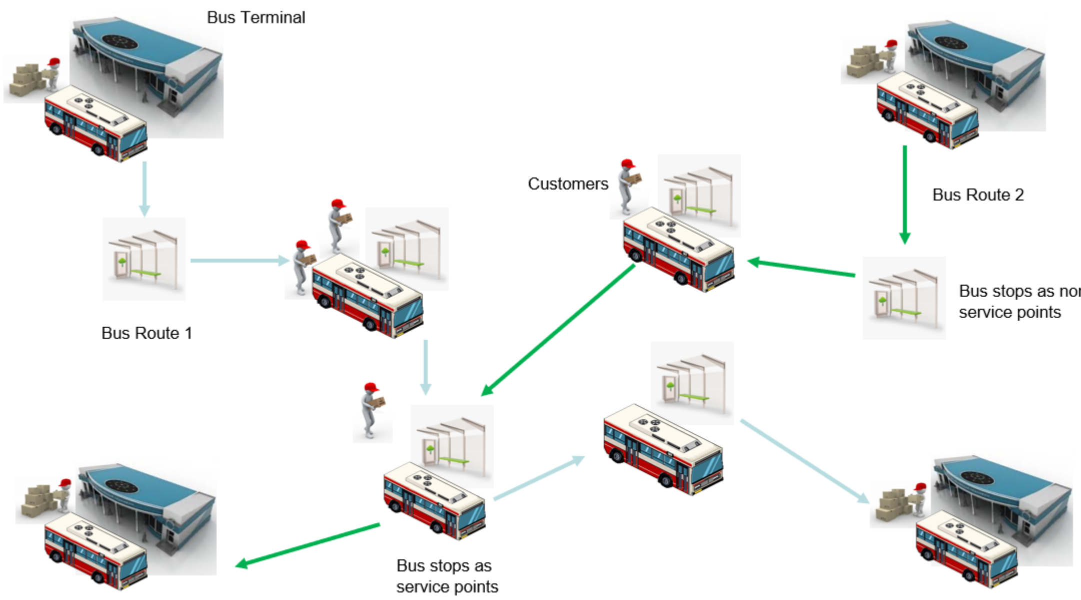


FIGURE 4.2: The illustrations of the SML-CBs Operations.

Our proposed system has several potential advantages. First, using the existing bus network does not require extra delivery trucks, which can reduce costs and traffic congestion. Second, parking at stops for buses is mandatory if passengers need to be on or off board. This idle time of berthing can be utilized for customers to pick up parcels if the interference with the bus passengers is minimized while no illegal curbside parking or reserved parking is needed. Additionally, customers have flexibility in choosing pickup time given that buses need to frequently stop at customers' nearby assigned bus stops. Lastly, it can contribute to local economic development by encouraging customer-to-customer business initiatives with an economical and environment-friendly distribution system.

4.4 Problems definition and optimization models

This section explains different operating scenarios for the SML-CB, states significant research problems and assumptions, and proposes mathematical formulations.

4.4.1 Operating Scenarios

It is unclear how to operate SML-CBs by the participating agency, considering that it is an emerging technology. To solve this problem, we propose and consider three operating scenarios:

- Optimal customer assignment scenario: The number of lockers is limited, and customers are assigned to a given number of available lockers. This scenario suits the early stage of operating SML-CB due to the limited resources, including lockers and bus routes, that are available.
- Random assignment scenario: Customers are randomly assigned to bus stops given a limited number of lockers. This scenario acts as a benchmark to test our proposed heuristic to solve the assignment problem of the optimal customer assignment scenario for validity and efficiency.
- Nearest bus stop customer assignment scenario: The number of available lockers is unlimited. All customers are assigned to the nearest bus stops, regardless of the cost associated with the number of occupied lockers and bus routes. This scenario acts as a benchmark that helps to explore the trade-off between the increase in the number of lockers and the reduction of customers' walking distances.

The optimization problem of the customers' and lockers' assignment for the optimal customer assignment scenario will be modeled as a quadratic assignment problem with quadratic constraints. We define this optimization problem due to its complexity.

4.4.2 Problem Assumptions

We assume that the information assigning parcels to lockers is known to start with a simpler model, which can be relaxed in our future work. It is also assumed that a locker can be assigned to precisely one bus route. Relaxing this assumption will require adding scheduling aspects to the model. Furthermore, we assume that each customer has a single parcel. Finally, we assume that customers pick up their parcels anytime and no re-delivery cases are considered. Some of these assumptions will be relaxed in future work.

4.4.3 Problem Statement

In addition to the findings from the literature on fixed parcel lockers, a nationwide survey delivered by our research team with 2465 participants on E-commerce last mile logistics in Canada found that the distance from the parcel pickup location is the most critical determining factor for customers' acceptance of parcel lockers. Thus, it is befitting to consider our goal to minimize the customers' total walking distance to bus stops where customers pick up their parcels. The customer and locker assignment (CLA) problem is thus defined as follows:

Problem 1 (CLA)**.** *Assign each locker to one and only one bus route and each customer to one and only one bus stop while minimizing the total customers' walking distance.*

4.4.4 Optimization Model

To formulate the CLA, we use the following notations:

Indices	
b	index for bus stops, $b = 1, 2, \ldots, B$.
k	index for customers, $k = 1, 2, \ldots, K$.
ℓ	index for lockers, $\ell = 1, 2, \ldots, L$.
r	index for bus routes, $r = 1, 2, \ldots, R$.
Parameters	
$a_{k\ell}$	1, if customer k is assigned to locker ℓ, 0 otherwise.
d_{kb}	distance between customer k and bus stop b.
s_{br}	1, bus stop b is on bus route r, 0 otherwise.
Decision variables	
x_{lr}	1 if locker ℓ is assigned to bus route r, 0 otherwise.
y_{kb}	1 if customer k is assigned to bus stop b, 0 otherwise.

The CLA problem can be formulated as follows:

CLA

$$\min \sum_{k=1}^{K}\sum_{\ell=1}^{L}\sum_{r=1}^{R}\sum_{b=1}^{B} a_{k\ell}x_{lr}y_{kb}s_{br}d_{kb} \tag{4.1}$$

$$\text{s.t.} \sum_{r=1}^{R} x_{lr} = 1 \qquad \forall \ell \in L \tag{4.2}$$

$$\sum_{\ell=1}^{L}\sum_{r=1}^{R}\sum_{b=1}^{B} a_{k\ell}x_{lr}y_{kb}s_{br} = 1 \qquad \forall k \in K \tag{4.3}$$

$$x_{\ell r}, y_{kb} \in \{0,1\}, \qquad \forall k \in K, \ell \in L, b \in B, r \in R. \tag{4.4}$$

The objective function (4.1) minimizes the walking distances of all customers when their parcels are already assigned to lockers. Constraint set (4.2) ensures that each locker is assigned to a single bus route. Constraint set (4.3) guarantees that each customer is assigned to a single bus stop. Constraint set (4.4) enforces the binary requirement for the decision variables.

Formulation CLA is a quadratic assignment problem (QAP) with a quadratic constraint (QAPQC). It is a generalization of the quadratic assignment problem [7, 31]. In Theorem 1, we show that CLA is $\mathcal{NP}$-Hard.

Theorem 1. *Problem CLA is $\mathcal{NP}$-Hard.*

Proof. We will show that CLA reduces to a QAP, which is shown to be $\mathcal{NP}$-Hard [45]. To do so, we consider the case when $s_{br} = 1, \forall b$, and r, i.e., all bus stops belong to all routes. Thus, CLA will be reduced to

$$\min \sum_{k=1}^{K}\sum_{\ell=1}^{L}\sum_{r=1}^{R}\sum_{b=1}^{B} a_{kl}x_{lr}y_{kb}d_{kb}$$

$$\text{s.t.} \sum_{r=1}^{R} x_{lr} = 1 \qquad \forall \ell \in L$$

$$\sum_{\ell=1}^{L}\sum_{r=1}^{R}\sum_{b=1}^{B} a_{kl}x_{lr}y_{kb} = 1 \qquad \forall k \in K$$

$$x_{\ell r}, y_{kb} \in \{0,1\}, \qquad \forall k \in K, \ell \in L, b \in B, r \in R.$$

Observing that

$$\begin{aligned}
\sum_{\ell=1}^{L}\sum_{r=1}^{R}\sum_{b=1}^{B} a_{kl}x_{lr}y_{kb} &= \sum_{\ell=1}^{L} a_{kl}\sum_{r=1}^{R} x_{lr}\sum_{b=1}^{B} y_{kb} \\
&= \sum_{\ell=1}^{L} a_{kl}\sum_{b=1}^{B} y_{kb} && (\text{ since } \sum_{r=1}^{R} x_{lr} = 1\ \forall \ell \in L \text{ as per } (4.2)) \\
&= \sum_{b=1}^{B} y_{kb} && (\text{ since by definition} \sum_{\ell=1}^{L} a_{kl} = 1) \\
&= 1 && (\text{ by } (4.3)\ ).
\end{aligned}$$

Therefore, CLA is reduced to

$$\begin{aligned}
\textbf{LCA}' \qquad & \min \sum_{k=1}^{K}\sum_{\ell=1}^{L}\sum_{r=1}^{R}\sum_{b=1}^{B} a_{kl}x_{lr}y_{kb}d_{kb} \\
& \text{s.t. } \sum_{r=1}^{R} x_{lr} = 1 && \forall \ell \in L \\
& \sum_{b=1}^{B} y_{kb} = 1 && \forall k \in K \\
& x_{\ell r}, y_{kb} \in \{0,1\}, && \forall k \in K, \ell \in L, b \in B, r \in R,
\end{aligned}$$

which is a QAP. □

Theorem 1 implies that CLA is at least as hard as QAP. The latter is known to be 'very hard', and even finding an ϵ-approximation is $\mathcal{NP}$-Hard [7]. While exact solution methods have been developed for QAPs, such as using branch and bound [15, 17, 33], finding optimal solutions for problems with K as small as 20 can take a long time [7]. In practical instances, K could be in the thousands. Thus, we consider developing heuristic methods to solve CLA. Several heuristic approaches have been developed for QAPs, including but not limited to construction methods, improvement methods, and metaheuristics [7].

4.5 Solution methodologies

The combination of construction-based and greedy heuristics enables us to leverage the strengths of both methodologies. For solving QAPs, the construction-based method provides flexibility in balancing the quality of solutions and computational effort [48], while the greedy method improves the qualify of the solution and enhances the diversity in the solution [1]. In addition, we opted to use the hybrid heuristic rather than other generic heuristic methods, such as metaheuristics [37], so we could benefit from the special structure of our problem for easier implementation and higher computational efficiency.

4.5.1 Heuristic for the optimal customer assignment scenario

Considering the computational complexity of CLA, we introduce a heuristic for the optimal customer assignment scenario. This heuristic leverages both a construction method and a greedy heuristic, with its pseudocode presented in Heuristic 1. Here's a step-by-step breakdown of the process: 1. Initialization: Begin by setting up the assignment solution. For each customer, select the closest bus stop and assign them to the route that encompasses it. If a bus stop is shared among multiple routes, the assignment to a specific route is made at random. 2. Route Review: Examine customer to route information for each locker, tallying route frequencies. Assign each locker to its most frequent route. For lockers with equally frequent routes, make a random choice. 3. Walking Distance Calculation: After updating route assignments, pinpoint the closest bus stop for each customer and determine their walking distance. 4. Switching Process: This comprises two stages: a. First Switch: Focus on route adjustments for lockers. Rank customers based on their walking distances, from longest to shortest, and identify the locker with the highest cumulative distance. In the event of a tie, select one locker randomly. Then, reassign this locker to the initial route. For customers in the chosen locker, reassign them to their nearest bus stop on the new route. Compare their total walking distance to the original; if it's longer, retain the original assignment and repeat the process for other routes. Otherwise, update the solution with the new details. This phase concludes when we've identified the minimum walking distance for the chosen locker. b. Second Switch: This stage is about swapping lockers. Again, rank customers based on walking distance and pick the locker with the maximum cumulative distance. After this step, revert to the first switch. The iteration between the first and second switch processes continues until all lockers have been re-evaluated for different routes. Ultimately, this heuristic identifies the minimal cumulative walking distance for customers and the corresponding route and bus stop assignments.

Heuristic 1 Optimal customer assignment scenario

1: Read problem input data: a_{kl},d_{kb} and s_{br}.
2: For each customer, k, find the bus stop with the shortest distance. Break ties arbitrarily.
3: For each customer, k, find the locker that is carrying his/her parcel. Assign that locker to the route with the bus stop identified in Step 2. Break ties by picking the route that is assigned the most frequently so far. Break further ties arbitrarily.
4: Rank the frequency of assigning lockers to routes from largest to smallest. Pick the highest L frequencies to determine the initial assignment of lockers to routes. Break ties arbitrarily.
5: For each customer, k, find the closest bus stop to them based on the route assigned in Step 4. Now we have a feasible solution and calculate its total distance.
6: Rank the customer travel distances from highest to lowest. From the highest distance, perform pairwise exchanges by switching the corresponding locker routes to other remaining routes. Keep the new bus stop assignment that reduces the total walking distance.

Heuristic 2 Random assignment scenario

1: Read problem input data: d_{kb} and s_{br}.
2: Randomly generate the customer-locker matrix a_{kl}.
3: Randomly generate the locker-route matrix m_{lr}.
4: Randomly generate the customer-stop matrix n_{kb} based on the generated a_{kl} and m_{lr}.
5: Calculate the total walking distance of customers.

4.5.2 Heuristic for the random assignment scenario

The heuristic randomly generates assignments with a fixed number of available lockers. This heuristic acts as a benchmark solution in terms of time efficiency. The pseudo-code is shown in Heuristic 2.

4.5.3 Heuristic for the nearest bus stop customer assignment scenario

The heuristic assigns customers to their nearest bus stops. Based on the bus stop-bus route information s_{br}, we classify the customers into the same group if they are assigned to the same bus route. Given a sufficient number of lockers, the customers on the same bus route are grouped into different lockers if the number of customers' parcels exceeds the capacity of one locker. We introduce a new matrix e_{kr}, which represents the assignment of customers to routes. The a_{kl} is then generated based on the number of customers assigned to each route. The pseudo-code is shown in Heuristic 3

Heuristic 3 Nearest bus stop customer assignment scenario

1: Read problem input data: d_{kb} and s_{br}.
2: For each customer k, find the bus stop with the shortest distance and generate. Generate e_{kr} based on s_{br}. Save the customer separately if the d_{kb} ties.
3: For each route r, calculate the number of assigned customers.
4: Cluster the customers' parcels on each route based on the bus stop sequence on that route.
5: Fill the customers' parcels separately into the available capacity of the lockers on the customers' assigned route. If there is no capacity, add more lockers for customers.
6: Generate a_{kl}.
7: Calculate the total walking distance of customers. Calculate the number of used lockers and compare the number with different threshold values.

4.6 Numerical results

We validate the proposed models and heuristics in this section. All computations are executed on a server with 32 GB RAM, Intel(R) CPU E5-2680 2.7GHZ processor.

4.6.1 Results of a small data instance

We conduct a small case study using the GAMS platform (version 38.1.0) based on real data from MiWay, the transit system in the City of Mississauga, Canada, to prove the applicability of our system and models. The solver we use is ANTIGONE, which is a deterministic, mixed-integer, nonlinear global optimization framework [34].

Example 1 (Cooksville Case)**.** *The area studied is in Cooksville, City of Mississauga, and is bounded by Dundas St W, Hurontario Street, Mavis Road, and the railway through Cooksville Go, as shown in Figure 4.3.*

The information on bus routes and stops in the target area is extracted from the MiWay website [35]. The customers' locations are assumed to be the parking tickets with the tag of 'illegal truck' from the 1st of January to the 14th of January in 2018. In Figure 4.3, the small red circles represent 45 ($= B$) bus stops, and the small green circles represent 11 ($= K$) customers' locations. Five ($= R$) Bus routes will be used: No.28, No.91, No.1, No.103, and No.19. Five ($= L$) lockers are available. The distance matrix d_{bk} is generated based on the coordinates from bus stops and customers' locations. Using the Antigone solver, the problem is solved in 3.5s. It is found that 11 customers are assigned to four lockers, four bus routes, and nine bus stops, and the utilization of the available lockers, bus routes, and bus stops are 80%, 80%, and 20%. Each of the four lockers is attached to a different bus route, and the capacity of four lockers is enough

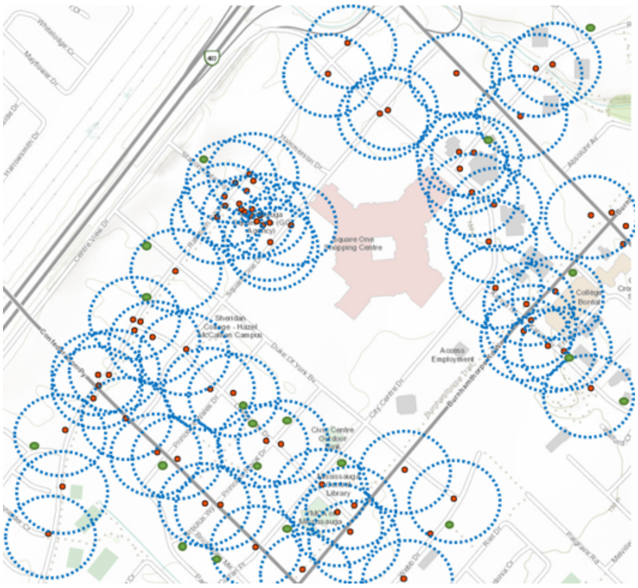


FIGURE 4.3: Bus routes, stops, and customers' location in a small data instance.

to serve all customers. Bus route No.19 is not selected since the majority of customers are not nearby its en-route stops. The fact that not all lockers, bus routes, or stops are selected helps to reduce possible impacts on bus operations. The detailed assignment information is shown in Table 4.1, and the total walking distance for customers is 1569 meters.

Customer	Locker	Bus route	Bus stop
1	No.1	No.91	Hillcrest Ave At Mavis Rd
2	No.1	No.91	Hillcrest Ave At Mavid Rd
3	No.2	No.1	Dundas St at Elmcreek Rd
4	No.2	No.1	Dundas St at Clayhill Rd
5	No.2	No.1	Dundas St at Clayhill Rd
6	No.1	No.91	Hillcrest Ave West of Pearwood Place
7	No.2	No.1	Dundas St at Confederation Pky
8	No.3	No.28	Confederation Pky at Hillcrest Ave
9	No.3	No.28	Confederation Pky at Dundas St
10	No.2	No.1	Dundas St at Hurontario St
11	No.4	No.103	Hurontario St at John St

TABLE 4.1: Customers' assignment in a small data instance in Mississauga City.

4.6.2 Results of larger data instances

We evaluate our models and heuristics on larger random data instances; for each evaluation, we generate ten random instances. The Cplex solver, which is capable of solving quadratically constrained programming problems quickly and with minimal user intervention, is used to derive the exact solutions.

4.6.2.1 Comparing the optimal customer assignment scenario heuristic and the exact solutions in medium-size data cases

Ten different medium cases are designed to compare the heuristic of the optimal customer assignment scenario with the exact solutions under different R, B, L, and K values. The locations of bus stops and customers are uniformly and randomly distributed, and the range of the x axis and y axis is set between 0 and 5000 m. The data a_{kl} and s_{br} are generated randomly. We record the average values of the exact solution run time, the average customers' walking distance using the exact solution, the heuristic run time, the average customers' walking distance using the heuristic, the difference in terms of average customers' walking distance calculated by both methods and the optimal gap. The results are summarized in Appendix A in Table A1. It is observed that with the increasing number of decision variables, the optimal gap has a trend to stabilize, bounded by 4.7% and 7.8%. In case No.10, the exact solutions can not generate any solutions due to the memory limit of our computation platform.

4.6.2.2 Results between the optimal customer assignment scenario heuristic and the exact solutions in large-size data cases

We extend the number of decision variables to the scale of an actual number of customers, lockers, bus stops, and routes in three Canadian cities: Hamilton, Mississauga, and Toronto. The number of bus routes and stops in three cities are extracted from movitapp. The number of potential customers for the SML-CB is estimated based on 1. population, 2. the digital buyer penetration rate, 3. online shopping frequency, and 4. the customers' willingness to use parcel lockers. The first three parameters are extracted from Statistia.com, while the last parameter is 38% according to our e-commerce shopping survey delivered in 2021. The distribution of online shopping frequency is from Statistica [51]. The locations of bus stops and customers are uniformly and randomly distributed, and the range of x axis and $y$axis is set between 0 and 5000 m. The data a_{kl} and s_{br} are generated randomly. All numerical tests on Cplex solvers are constrained to a run time limit of 3600 seconds. The results are summarized in Appendix A in Table

A2. It is found that the exact solutions can not be derived within the given time limit, while the heuristic will generate solutions in short time periods.

4.6.2.3 Comparing the optimal customer assignment scenario heuristic with different customer characteristics

Given the importance of the customers to the success in operating SML-CB, we test the performance of the optimal customer assignment scenario heuristic when customers' characteristics, including the density of customers and the customers' distribution pattern, are different.

For the customers' density (CD), we run eight cases with different CDs while the maximum range of customer location decreases from 50000 meters to 500 meters. The tests are implemented in three scenarios based on the size of the dataset: small, medium, and large, abbreviated as S, M, and L. The combinations of $R-B-L-K$ for the S, M, and L scenarios are 5-50-10-40, 5-100-10-160, and 5-200-10-400, with the number of bus stops and customers increasing while the number of bus routes and lockers keeps the same. The locations of bus stops and customers are uniformly and randomly distributed, and the data a_{kl} and s_{br} are generated randomly. The results are summarized in Table A3 in Appendix A. Figure 4.4 visualizes the trend for the optimal gap in different cases. It is observed that: 1. The heuristic performs better in terms of optimal gap when customers are distributed in denser patterns. 2. Among the S, M, and L cases, the L cases with higher K and B values have better performance regarding the optimal gap.

For the customers' distribution pattern (CDP), we run four cases with the size of decision variables K, B, and R increasing. For each case, we implement it in three scenarios of CDP: uniform, centered, and clustered. The centered distribution means that all customers are located randomly around a point, which is the center of the studied area. The clustered distribution refers to the distribution that all customers are located randomly around two points, on half of the y axis and 1/3, 2/3 of the x axis. The maximum value of the customers' location x axis and y axis is 5000 m. The locations of bus stops are uniformly and randomly distributed, and the data a_{kl} and s_{br} are generated randomly. The results are summarized in Table A4 in Appendix A. Figure 4.5 visualizes the trend of the optimal gap in different cases. It is observed that: 1. The heuristic performs best in terms of the optimal gap if the customers are clustered distributed, followed by centered distribution and uniform distribution. 2. With the increased size of decision variables (K, B, R), the heuristic performs better in terms of the optimal gaps.

We conclude that the heuristic for the optimal customer assignment scenario performs better in terms of optimal gap when: 1. the customers are denser distributed. 2. the customers are distributed in clusters. 3. the data instances are with larger K, R, B values.

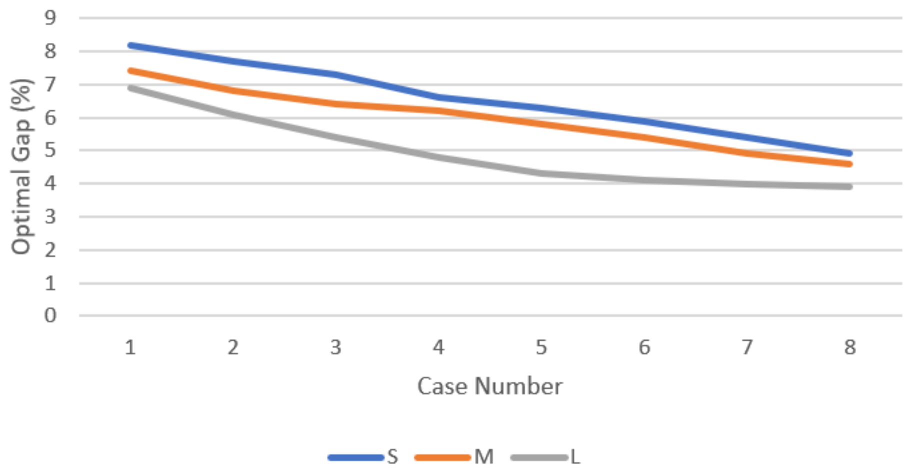


FIGURE 4.4: The effect of customers' density on optimal customer assignment scenario.

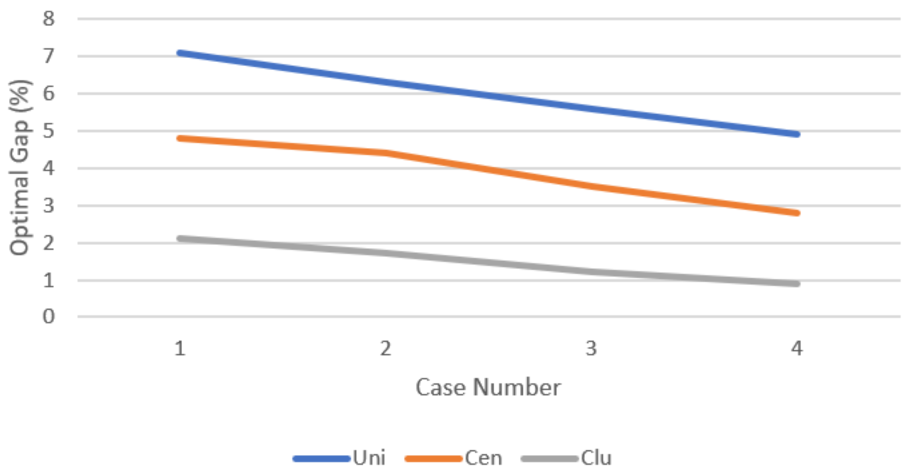


FIGURE 4.5: The effect of customers' distribution pattern on optimal customer assignment scenario.

4.6.2.4 Comparing the optimal customer assignment scenario heuristic and random assignment scenario heuristic

We design twelve cases with different sizes of decision variables to compare the solution results between the heuristics of the optimal customer assignment scenario and the random customer assignment scenario in terms of the optimal gap and the average customer walking distance. The customers are distributed in clusters. The maximum value of the customers' location x and y-axis is set as 5000. The locations of bus stops are uniformly and randomly distributed. The data a_{kl} and s_{br} are generated randomly. The results are summarized in Appendix A in Table A5 and visualized in Figure 4.6. It is found that the random customer assignment scenario heuristic gets solutions faster due to its simplicity, while the optimal customer assignment heuristic gets solutions with lower customers' walking distances. We use $M_T(\%)$ and $M_D(\%)$ to represent the time and distance multiplier of the random customer assignment scenario to the optimal customer assignment scenario. The average M_T is 0.255, while the average M_D is 2.78. The $M_T(\%)$ in all cases is lower than 0.5 and has a trend to stabilize after case No.10. The smallest M_D in all cases, cases No.1 and No. 2, is 2.07, meaning that customers need to walk at least 107% more than the optimal customer assignment scenario. From Case No.6 to Case No.7, the increase of M_D due to doubling the bus stops is steeper than doubling the customers (Case No.1 to No.2) and doubling the bus routes (Case No.8 to No.9). The gap between the customers' walking distances in the two scenarios tends to stabilize after Case No.11 while the sizes of decision variables increase.

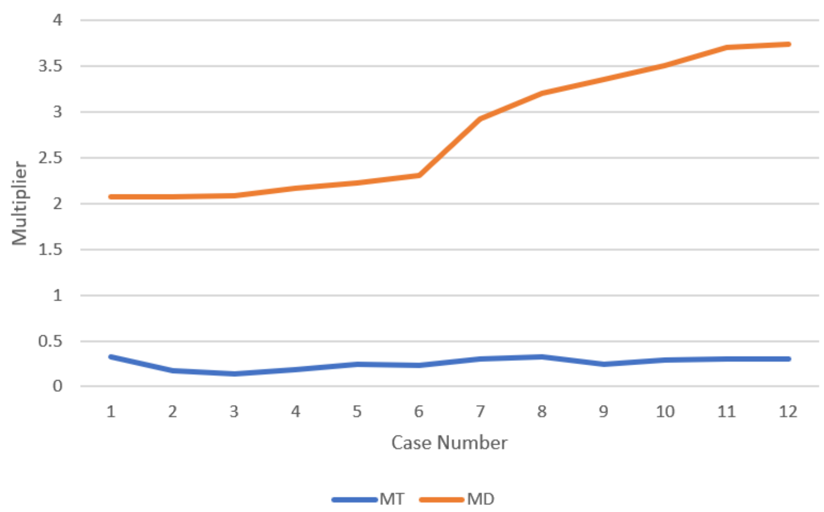


FIGURE 4.6: Comparison of optimal customer assignment and random customer assignment scenarios.

4.6.2.5 Comparing optimal customer assignment scenario heuristic and nearest bus stop assignment scenario heuristic

Ten cases are designed to compare the heuristic results regarding computation time, average customer walking distance, and the number of lockers between the two scenarios. We use M_T, M_D, and M_L to represent the multiplier in computation time, customers' walking distance, and lockers of the optimal customer assignment scenario to the nearest bus stop assignment scenario. All lockers are designed with the same capacity of 50 parcels per locker. The customers are distributed in a clustered pattern. The maximum value of the customers' location x axis and y axis is 5000 m. The locations of bus stops are uniformly and randomly distributed. The results are summarized in Table A6. M_T, M_D and M_L are visualized in Figure 4.7. It is observed that the nearest bus stop assignment scenario heuristic has advantages in computation time, with an average percentage of 20.7% time-saving. The comparative savings in customers' average walking distance by the nearest bus stop assignment scenario is 8.1%. However, such savings come with a high cost in the increased lockers needed. From case No.1 to case No.6, the customers are multiplied by 10, while the lockers needed compared with the locker prior operating scenario are multiplied by 11.4. The greatest change of M_L occurs from No.6 to No.7 when the available bus stops are doubled, which changes the trend of M_L. From case No.6 to case No.10, we found that increasing B and R will help decrease the ratio of lockers needed between two scenarios.

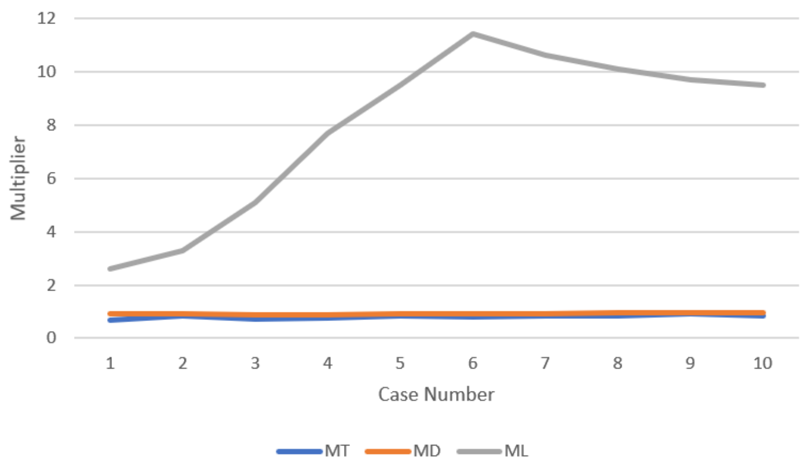


Figure 4.7: Comparison of optimal customer assignment and nearest bus stop customer assignment scenario .

4.7 A Case Study in Mississauga City, Canada

To test the applicability of the system, models, and heuristics on the actual addresses of customers, bus stops, and real bus route-stop information, we implement a case study in Mississauga City, Ontario, Canada.

4.7.1 Data and parameters

One of the most significant challenges in implementing a case study for operating SML-CB is determining the input data and parameters for the model, including customer data K, bus routes R, and bus stops B. The number and locations of transit bus stop B (=3346) and routes R (=139) are from geo2.scholarsportal[16]. The number of residents' locations (=454454) and their addresses are from the primary address point file from the Region of Peel [44].

All bus stops are visualized through ArcGIS in red points, while all residents' addresses are visualized in green points, in part (a), Figure 4.8. They are further clustered at the scale of 1:185795 through the density-based clustering in ArcGIS in part (b), Figure 4.8. It is observed that most bus stop cluster centers are in the neighborhood of residents' cluster centers. The number of customers K (=9805) is the same as in the previous section.

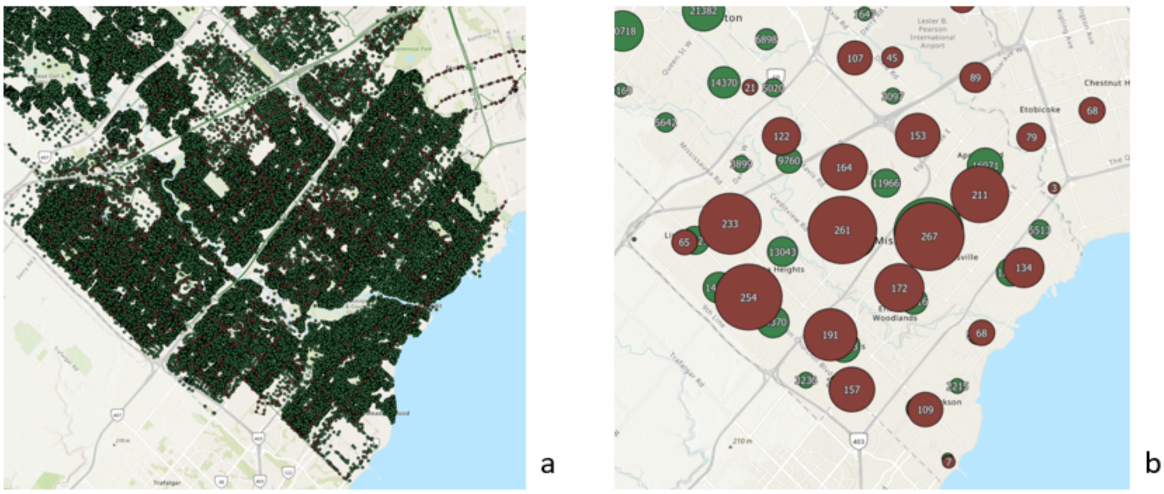


FIGURE 4.8: a: locations of residents (green) and stops (red) b: clusters of residents (green) and stops (red).

We further proceed to generate the parameters of a_{kl}, s_{br} and d_{kb} based on the values of K, B, and R. For the a_{kl}, it is generated based on neighborhood clustering, a method that fixed parcel lockers use for nearby customers [39]. We adopt the k-means clustering method to generate customers' clusters and define the number of such clusters equal to the number of lockers needed. For the s_{br}, it is generated by a search method we developed based on the locations of bus stops and available routes to generate s_{br}. The s_{br} is initialized as a zero matrix. The locations of every bus route are represented by a set of all points that construct the route in geo2.scholarsportal. The location of every bus stop is compared with the set of all point locations of every bus route. Once a stop location is within the predefined tolerance of 0.2 m of any location in a route set, the stop is considered to be on this route. The cell corresponding to the route and stop in the s_{br} is updated with 1. The iterations go through all bus stops and routes to generate the final s_{br}. The d_{kb} is generated through a multi-step process that strategically selects customers for better heuristic performance using the optimal customer assignment scenario while considering randomness in customers' selection from all available residents. The d_{kb} is initialized as a zero matrix, and each cell is updated with the distance between a resident and a bus stop calculated from the latitudes and longitudes reversely transferred from the geocodes. The first step is to select residents that are close to bus stops. We check the lowest distance between a resident and all stops for each resident and rank all residents in terms of such distance. We filter all residents by only selecting those in the lower 20% interval of distances among all residents, which results in 90891 residential addresses as potential customers' addresses. The second step is to select customers that are close to cluster centers. It has been proved that clustered and denser distribution gives better heuristic results for deploying the optimal customer assignment scenario. We identify the twenty busiest bus stops, defined as the stops that are joint with the most bus routes through the s_{br}, as the cluster center. Only the addresses within the radius of 400 m of the clusters are selected to guarantee a clustered and dense distribution pattern. The third step is to consider the randomness by randomly selecting 9805 addresses from the filtered addresses in step 2. The final d_{kb} is generated based on the customers' addresses from step 3 and bus stops.

Furthermore, two more important parameters need to be determined: the capacity of each locker C_L in all operating scenarios and the number of lockers L used for the locker-prior operating scenario. For C_L, the dimensions of some active bus fleets operated in Mississauga [55] are summarized in Table A7 to suggest constraints on the dimension of the lockers. In addition, we need to leave space in width for the bus turning and breaking lights, estimated as 0.6 m, and to leave space in height that is 1. away from the road, 2. for necessary mechanical checks, and 3. not a high place customers can't reach. Such height is estimated to be 0.8 m. After considering all the constraints, it is safe to assume the width and height of the locker as 1.8 $m \times 1.6$ m. For our reference, we summarize the parameters of slot dimensions of fixed smart parcel locker in Table A8. At the early stage of operating SML-CB, we focus on delivering small parcels, and for simpler manufacture, the dimensions of each locker slot are unified. The parameters of the locker slot are finally set as 0.23 m $\times$ 0.24 m. Thus, each locker will have 8 (in the row) $\times$ 6 (in the column), which equals 48 slots.

Secondly, we design a multi-step process to determine the number of lockers L for the optimal customer assignment scenario. In the first stage, we use the heuristic of the nearest bus stop assignment scenario to get the minimum average customers' walking distances and the maximum number of lockers we need. In the second stage, we utilize the heuristic of the optimal customer assignment scenario and gradually decrease the number of lockers from the maximum number in step one iteratively, at the cost of slightly increased customers' average walking distances. Such iterations will run until the average customers' walking distances reach a pre-defined threshold. Based on the results in the previous section and Table A6, customers' average walking distance savings is around 10%-12%, and we reasonably assume such a pre-defined threshold is 88%.

4.7.2 Results

The results from the nearest bus stop customer assignment scenario are summarized as follows: The computation time is 346 s. The number of lockers needed is 641. We define the average locker utilization rate as dividing the number of customers by the number of locker slots, so the average locker utilization rate is $9805/(48\times641) = 31.9\%$. The average customer walking distance is 112 m, which is reduced largely compared with all average walking distances from the numerical studies on random data in the previous section, and is reduced by 48.9% compared with the smallest walking distance of 219 m of D_{CP} with that section. This improvement could be due to two reasons. First, the real locations of bus stops have considered the convenience of nearby residents. Second, we have filtered and selected residents who are only close to bus stops as our customers. To better summarize the number of nearby customers, we classify them into A*, A+, A, and B customers, which are customers within 100 m, 200 m, 300 m, and 400 m of their assigned bus stops. The results are shown in Table 4.2. We found that 66.7% customers are within 100 meters of their assigned bus stops, within around 70.4 seconds of walking if the preferred walking speed is 1.42 m per second [26], and is the critical walking distance revealed in [30]. As many as 92.3% customers are within the range of

Distance classification	**A***	**A+**	**A**	**B**
% of customers	66.7%	79.5%	89.6%	92.3%

TABLE 4.2: Walking distance classification for the nearest customer stop assignment scenario

Distance classification	**A***	**A+**	**A**	**B**
% of customers	59.5%	74.3%	84.0%	85.5%

TABLE 4.3: Walking distances classification for the optimal customer assignment scenario

400 meters, which is a rough upper bound for slow local-stop service [21]. We also found that the augment of customers in percentages decreases when we proceed all the way from A* to B customers.

The results from the optimal customer assignment scenario are summarized as follows: The computation time is 487s. The average walking distance is 127 m, controlled per the 88% predefined threshold. The number of lockers is largely reduced to 236, and the locker utilization rate is increased to 86.6%. We have achieved a reduction of 63% in the number of lockers utilized at the cost of an increase of 12% of customers' walking distance. The decreased lockers and higher slot utilization rate align with our observations in the previous section. This can be explained by clustering nearby customers when replenishing the locker and assigning the customers in the same locker to bus stops that may not be nearest them. If we compare the average walking distances with the D_{LP} in the previous section, we achieve a reduction of 47.5% compared to the smallest walking distance of 233 m of D_{LP}. The results of A*, A+, A, and A- customers are summarized in Table 4.3. It is observed that there is a slight reduction ranging from 4.8% to 7.2% of every classification of the customers compared to the results of the nearest customer stop assignment scenario. The tail of the customer walking distance distribution, defined as the walking distance of more than 400 m, increases by 6.8%. This extra inconvenience due to long pick-up distance may lead to losing partial customers if they are not assigned to the nearest bus stops.

4.8 Managerial insights and conclusions

4.8.1 Managerial insights

From the Cookville case, it is observed that only certain bus routes and stops will be chosen when the number of customers does not exceed the capacity of available lockers. The criteria for selecting these routes and stops should encompass not only the proximity of customers but also the ridership metrics of the respective routes and stops. By focusing on busiest stops, parcel deliveries can leverage the natural dwell times during passenger boarding and alighting. This helps us prove to the city transit that the impact on bus operations can be minimized by strategically selecting bus stops and routes and building partnerships with the city transit for further implementing the SML-CBs.

In our numerical analysis, we demonstrate the influence of customer characteristics—namely customer density and distribution patterns—on the optimal gaps of the heuristic for optimal customer assignment scenarios. The proximity of heuristic solutions to exact solutions is more pronounced when customers exhibit higher densities and are clustered in their distribution. This implies that our proposed heuristic exhibits greater efficacy in urban contexts than in scenarios with sparsely and uniformly distributed rural customers in terms of optimal gaps. As one of the two benchmark operating scenarios, the random assignment scenario largely sacrifices customers' average walking distances for shorter computation time and is only suggested in operations with a very strict computation time limit. While the excessive walking distance of the random assignment scenario, compared to the optimal customer assignment, becomes more significant with the size of data instances increasing, adding bus stops will show more impact on such excessive distance, which further limits the application of this scenario in practices. As for the other benchmark scenario, the nearest bus stop customer assignment scenario, its savings on customer average walking distance are distinctive compared to the additional lockers to meet the demand of customers for assigning to the nearest bus stop. Adding bus stops and routes will help reduce the number of lockers slightly, while this could exert more impact on bus operations. An alternative strategy might involve utilizing the same locker multiple times, potentially diminishing the overall locker demand. In summary, we advocate for the adoption of the optimal customer assignment scenario, especially when resources—such as routes, stops, and lockers—are constrained.

Both the optimal customer assignment scenario and the nearest bus stop customer assignment scenario are tested on the large-scale case study in Mississauga City, Canada, and the results are encouraging. One primary observation is that both scenarios significantly curtailed the average customer walking distances compared to those in the artificial numerical outcomes. This reduction can be attributed to two main factors. Firstly, the design of bus routes and stops typically prioritizes urban passengers; our real-case analyses benefit from aligning with the underlying objectives of such pre-existing infrastructures. Secondly, the locker utilization rate is enhanced by clustering techniques instead of random assignments. Another salient finding pertains to our methodology for determining the locker count for the optimal customer assignment scenario. Based on our numerical observations, this methodology, which extrapolates from the locker counts of the nearest bus stop scenario, adeptly strikes a balance between reducing locker numbers and maintaining acceptable customer walking distances in real-world applications. Consequently, it provides a valuable heuristic for swiftly gauging the requisite locker fleet size. Our recommendation from the real case study resonates with that from the numerical results: the optimal customer assignment scenario is superior for operating the SML-CBs in the early stage, balancing satisfying customer walking distance and limited resources.

4.8.2 Conclusions

To conclude, we are among the first to introduce an innovative system named smart mobile locker in tandem with city buses (SML-CBs) to serve the last mile e-commerce parcel delivery. Rooted in the sharing economy, the system attaches smart parcel lockers to city buses to mobilize the lockers on existing transit systems. The parcels are replenished at bus terminals, and parcels will be delivered to customers at bus stops during bus service time, shared by both the transit and delivery systems.

We aim to study the optimization of the assignment of customers to bus stops and lockers to bus routes. We briefly introduce the design and operation details of SML-CBs and consider different operating scenarios for the SML-CBs. We mathematically formulate the assignment optimization problem associated with the optimal customer assignment scenario as a quadratic assignment problem with quadratic constraints and prove its hardness. Due to the complexity of the problem, we develop a hybrid heuristic to solve it efficiently. Additionally, we provide two heuristics to solve the nearest bus stop assignment scenario and randomly assignment operating scenario, which are considered benchmark operating scenarios. We solve the optimization problem associated with the optimal customer assignment scenario through the Cplex commercial solver on a small data instance to prove the validity of our model. Numerical tests are further implemented to compare the heuristic of optimal customer assignment strategy with Cplex solvers regarding computation time and optimal gap. The heuristic is proven to have significant savings with satisfying optimal gaps on all sizes of data instances and can solve the problem efficiently while the commercial solver can not. We test the performance of the optimal customer assignment scenario heuristic under different customer densities and distribution patterns to explore the effect of customer conditions. Finally, we apply the models and heuristics of optimal customer assignment and nearest bus stop assignment scenarios in Mississauga City, Canada, for a case study.

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Appendices

No.	R	B	L	K	$T_e(s)$[1]	Ave $D_e(m)$[2]	$T_h(s)$[3]	Ave $D_h(m)$[4]	ΔD[5]	Optimal Gap(%)[6]
1	5	50	10	40	40	401	0.03	431	30	7.6
2	5	50	10	80	95	406	0.06	437	31	7.8
3	5	50	10	160	413	432	0.14	459	27	6.3
4	5	50	10	240	470	427	0.16	454	27	6.5
5	5	50	10	320	550	431	0.17	457	26	5.9
6	5	50	10	400	1317	446	0.26	474	28	6.1
7	5	100	10	400	2353	314	0.27	333	18	5.6
8	5	150	10	400	2580	251	0.30	264	13	5.3
9	5	200	10	400	3340	223	1.08	233	10	4.7
10	10	100	10	400	3688	–[7]	1.2	343	–	–

[1] the computation time of the exact solution;

[2] the average customer pick-up distance of the exact solution;

[3] the computation time of the optimal customer assignment heuristic solution;

[4] the average customer pick-up distance of the optimal customer assignment heuristic solution;

[5] the gap between Ave $D_e(m)$ and Ave $D_h(m)$;

[6] the average optimal gap from case No.1 to No.9 is 6.2%;

[7] value not available due to memory limit;

TABLE A1: Exact and optimal customer assignment heuristic solutions in medium-size data instances.

No.	R	B	L	K	$T_e(s)$[1]	Ave $D_e(m)$[2]	$T_h(s)$[3]	Ave $D_h(m)$[4]	ΔD[5]	Optimal Gap(%)[6]
1	40	2270	20	4097	3600	–[7]	148	302	–	–
2	65	3084	33	9805	3600	–	411	318	–	–
3	192	8852	86	37544	3600	–	819	309	–	–

[1] The computation time of the exact solution, limited to 3600 seconds;

[2] The average customer pick-up distance of the exact solution;

[3] The computation time of the optimal customer assignment heuristic solution;

[4] The average customer pick-up distance of the optimal customer assignment heuristic solution;

[5] The gap between Ave $D_e(m)$ and Ave $D_h(m)$;

[6] The average optimal gap is not available;

[7] Value not available due to memory limit;

TABLE A2: Exact and optimal customer assignment heuristic solutions in large-size data instances.

N	Case	Max V[1]	$T_e(s)$[2]	$T_h(s)$[3]	Optimal Gap(%)[4]
1a	S[5]	50000	43	0.03	8.2
1b	M[6]	50000	596	0.11	7.4
1c	L[7]	50000	3109	0.77	6.9
2a	S	25000	40	0.03	7.7
2b	M	25000	487	0.1	6.8
2c	L	25000	2843	0.85	6.1
3a	S	10000	42	0.02	7.3
3b	M	10000	499	0.12	6.4
3c	L	10000	3089	0.72	5.4
4a	S	7500	40	0.03	6.6
4b	M	7500	483	0.1	6.2
4c	L	7500	2845	0.76	4.8
5a	S	5000	45	0.03	6.3
5b	M	5000	493	0.11	5.8
5c	L	5000	3910	0.7	4.3
6a	S	2500	36	0.05	5.9
6b	M	2500	667	0.09	5.4
6c	L	2500	3181	0.26	4.1
7a	S	1000	35	0.03	5.4
7b	M	1000	675	0.11	4.9
7c	L	1000	3187	0.39	4
8a	S	500	36	0.12	4.9
8b	M	500	506	0.18	4.6
8c	L	500	3199	0.79	3.9

[1] The maximum value of locations on x and y axis;

[2] The computation time of the exact solution;

[3] The computation time of the optimal customer assignment heuristic solution;

[4] The average optimal gap is 5.8%;

[5] Abbreviation of 'small'

[6] Abbreviation of 'medium'

[7] Abbreviation of 'large'

TABLE A3: The effect of customer density on the optimal customer assignment heuristic solutions.

N	R	B	L	K	Dist[1]	$T_e(s)$[2]	$T_h(s)$[3]	Optimal Gap(%)[4]
1a	5	50	10	50	Uni[5]	49	0.03	7.1
1b	5	50	10	50	Cen[6]	47	0.04	4.8
1c	5	50	10	50	Clu[7]	45	0.05	2.1
2a	5	50	10	100	Uni	126	0.06	6.3
2b	5	50	10	100	Cen	131	0.07	4.4
2c	5	50	10	100	Clu	128	0.06	1.7
3a	10	100	10	100	Uni	590	0.1	5.6
3b	10	100	10	100	Cen	552	0.16	3.5
3c	10	100	10	100	Clu	546	0.1	1.2
4a	10	100	10	150	Uni	3342	0.15	4.9
4b	10	100	10	150	Cen	3509	0.14	2.8
4c	10	100	10	150	Clu	3418	0.12	0.9

[1] The pattern of distribution;

[2] The computation time of the exact solution;

[3] The computation time of the optimal customer assignment heuristic solution;

[4] The average optimal gap is 3.8%;

[5] Abbreviation of 'uniform'

[6] Abbreviation of 'centered'

[7] Abbreviation of 'clustered'

Table A4: The effect of customer distribution pattern on the optimal customer assignment heuristic.

N	R	B	L	K	$T_{rand}(s)$[1]	$D_{rand}(m)$[2]	$T_{oc}(s)$[3]	$D_{oc}(m)$[4]	M_T[5]	M_D[6]
1	5	50	10	40	0.01	893	0.03	431	0.33	2.07
2	5	50	10	80	0.01	905	0.06	437	0.17	2.07
3	5	50	10	160	0.02	959	0.14	459	0.14	2.09
4	5	50	10	240	0.03	983	0.16	454	0.19	2.17
5	5	50	10	320	0.04	1015	0.17	457	0.24	2.22
6	5	50	10	400	0.06	1097	0.26	474	0.23	2.31
7	5	100	10	400	0.08	971	0.27	333	0.3	2.92
8	5	150	10	400	0.1	844	0.3	264	0.33	3.20
9	10	150	10	400	0.26	837	1.08	249	0.24	3.36
10	15	150	10	400	0.35	852	1.2	243	0.29	3.51
11	15	150	15	400	0.4	816	1.32	220	0.30	3.71
12	15	150	20	400	0.42	808	1.38	216	0.30	3.74

[1] The computation time of the random assignment heuristic solution;

[2] The average customer pick-up distance of the random assignment heuristic solution;

[3] The computation time of the optimal customer assignment heuristic solution;

[4] The average customer pick-up distance of the optimal customer assignment heuristic solution;

[5] The ratio of T_{rand}/T_{oc}, and the average value is 0.26;

[6] The ratio of $D_{rand}/\ D_{oc}$, and the average value is 2.78;

TABLE A5: Optimal customer assignment and random assignment heuristic solutions.

N	R	B	L_{oc}[1]	K	$T_{nb}(s)$[2]	$D_{nb}(m)$[3]	$T_{oc}(s)$[4]	$D_{oc}(m)$[5]	L_{nb}[6]	M_T[7]	M_D[8]	M_L[9]
1	5	50	10	40	0.02	393	0.03	431	26	0.67	0.91	2.6
2	5	50	10	80	0.05	398	0.06	437	33	0.83	0.91	3.3
3	5	50	10	160	0.10	409	0.14	459	51	0.71	0.89	5.1
4	5	50	10	240	0.12	401	0.16	454	77	0.75	0.88	7.7
5	5	50	10	320	0.14	417	0.17	457	95	0.82	0.91	9.5
6	5	50	10	400	0.21	434	0.26	474	114	0.81	0.92	11.4
7	5	100	10	400	0.23	310	0.27	333	106	0.85	0.93	10.6
8	5	150	10	400	0.25	252	0.3	264	101	0.83	0.95	10.1
9	10	150	10	400	0.98	219	1.08	233	97	0.91	0.94	9.7
10	15	150	10	400	1.02	231	1.2	243	95	0.85	0.95	9.5

[1] The number of lockers for the optimal customer assignment heuristic solution;

[2] The computation time of the nearest bus stop customer assignment heuristic solution;

[3] The average customer pick-up distance of nearest bus stop customer assignment heuristic solution;

[4] The computation time of the optimal customer assignment heuristic solution;

[5] The average customer pick-up distance of the optimal customer assignment heuristic solution;

[6] The number of lockers for the nearest bus stop customer assignment heuristic solution;

[7] The ratio of $T_{nb}/\ T_{oc}$, and the average value is 0.803;

[8] The ratio of $D_{nb}/\ D_{oc}$, and the average value is 0.919;

[9] The ratio of $L_{nb}/\ L_{oc}$, and the average value is 7.95;

TABLE A6: Optimal customer assignment and nearest bus stop customer assignment heuristic solutions.

Fleet Number	Model	Builder	Length(m)	Width(m)	Height(m)	Weight(kg)
0801-0844, 0901–0925	D40LFR	New Flyer	9.1-18	2.59	3.07-3.35	11100-19800
1730–1766	LFS	NOVA	12.19	2.59	3.2	–

TABLE A7: Dimensions of Miway Buses.

Country	Company	Slot Width(m)	Slot Height(m)	Slot Depth(m)
the U.S.	Amazon	0.41	0.3	0.36
Canada	Snaile	0.33	0.36	0.39
China	AITUO IoT	0.42	0.36	0.45

TABLE A8: Dimensions of Common Locker Slot.

Chapter 5

Powering E-commerce Last-Mile Delivery with Innovative Smart Mobile Parcel Lockers: A Sustainability Assessment

Partial content of this chapter is a manuscript under review by the journal Transportation Research Part D: Transport and Environment and under the following citation:

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Powering E-commerce Last-Mile Delivery with Innovative Smart Mobile Parcel Lockers: An Impact Assessment

Si Liu
DeGroote School of Business
McMaster University, Hamilton, ON, Canada
Email: lius278@mcmaste.ca

Elkafi Hassini
DeGroote School of Business
McMaster University, Hamilton, ON, Canada
Email: hassini@mcmaster.ca

Abstract

The exponential growth in e-commerce parcel volumes has spurred developing and implementing various innovative technologies in last-mile deliveries. Among these, smart fixed parcel lockers have gained international traction, offering enhanced parcel security and cost-efficiency compared to traditional door-to-door deliveries. However, their static nature limits accessibility and customer reach, constrained by the finite number of available lockers. In response, this paper introduces a novel concept of Smart Mobile Parcel Lockers with City Buses (SML-CBs), leveraging the ubiquity and routes of city buses to facilitate dynamic parcel delivery. Parcels are initially placed into intelligent lockers attached to city buses at bus terminals, then transported along bus routes, with customers coordinating pick-up at nearby stops through a dedicated mobile application within specific time windows. This study aims to comprehensively analyze the impacts, including economic, social, and environmental advantages of SML-CBs. We delineate the operational model of SML-CBs, followed by an economic assessment and a social assessment. We then present a hybrid Life Cycle Assessment (LCA) methodology to evaluate their sustainability profile. After establishing the system boundaries for this analysis, we detail the LCA parameters for both the manufacturing and operational phases of SML-CBs. The findings are threefold: 1) SML-CBs demonstrate markedly lower fuel consumption and emissions per parcel within urban environments, constituting just 2.91% of that of comparable delivery trucks. 2) Optimization of SML-CBs' parameters, including power source, capacity, and operational frequency, can reduce their GHG emissions per parcel by 53.923% from the highest recorded emissions level. 3) The lifecycle GHG emissions per parcel from optimized SML-CBs equate to only 9.801% of the most efficient delivery trucks reported in the literature. Collectively, these results substantiate the significant fuel and GHG emission reductions achievable through SML-CBs, positioning them as a sustainable and forward-thinking solution in the realm of last-mile delivery technologies.

Keywords: *Last-mile delivery, Sharing Economy, Mobile Parcel Locker, Sustainability Assessment, Life Cycle Analysis.*

5.1 Introduction

Last-mile delivery (LMD) is defined as the logistics activities related to freight deliveries to private customers in urban settings [7]. It stands as one of the most costly and environmentally burdensome segments within business-to-consumer (B2C) supply chains, with LMD costs potentially comprising up to 75% of the total supply chain expenses [20], and emissions from LMD activities reaching 158.4g CO_2 per km for each order when utilizing light vehicles or motorbikes [17]. Furthermore, LMD is responsible for 20% to 30% of urban road traffic [15], exacerbating congestion and pollution, especially in growing urban centers. As e-commerce continues to expand, these challenges are only magnified, necessitating innovative, sustainable, and efficient LMD solutions, such as smart parcel lockers (SPLs).

SPLs, integrated with internet of things (IoT) technology, offer a secure and cost-effective delivery option that enhances convenience and accessibility [58]. Traditional SPLs are permanently located in high-traffic areas such as apartments, transportation hubs, and post offices [40]. Yet, the fixed nature of these SPLs, coupled with urban land use policies, limits their availability and, thus, the scope of their service, potentially necessitating customers to travel, sometimes by car, to retrieve their parcels. This travel further adds to emissions and decreases the overall environmental benefit of using SPLs. The static nature of SPLs also limits their adaptability to fluctuating demand, leading to underutilization during off-peak times and potential overload during peak periods. The advent of mobile SPLs, capable of either human-driven or autonomous movement, has emerged to address some of these constraints, providing flexibility in location and the ability to meet dynamic customer needs [7]. However, their operation introduces additional traffic, parking challenges, and increased operational costs. In addressing the drawbacks of fixed and mobile SPLs, this paper introduces a novel delivery mechanism: smart mobile lockers in tandem with city buses (SML-CBs). This innovative approach, rooted in the sharing economy, involves attaching SPLs to city buses, thereby utilizing existing transit routes for delivery. This method strikes a balance between the permanence of fixed SPLs and the mobility of their mobile counterparts. SML-CBs are designed to adapt to the dynamic changes in parcel delivery demands by transferring between different bus routes at terminals. A specifically developed mobile application facilitates the coordination of parcels, transit systems, and customers, allowing for convenient parcel pick-up at bus stops and efficient transport of parcels from distribution centers to bus terminals. This system aims to reduce the environmental and traffic impact traditionally associated with LMD by leveraging existing urban infrastructure and technology. As SML-CBs represent a novel approach in the realm of last-mile delivery, there is a significant need for comprehensive research to understand their operational efficacy and impact.

To this end, this paper endeavors to fill a gap in the literature by being among the first to systematically assess the sustainability assessment, including the economic, social, and environmental impacts, of SML-CBs. The paper is structured as follows: Section 5.2 reviews the utilization of SPLs in last-mile deliveries and the application of LCA methods for assessing delivery technologies. Section 5.3 introduces the motivation behind and the operational details of SML-CBs. Section 5.4 and 5.5 assess the economic and social impacts. Section 5.6 elaborates on the environmental impact assessment research methodology, including LCA techniques, database sources, system boundaries, assumptions, and parameters for the assessment. It also presents the results, offering insights into the sustainability performance of SML-CBs, detailed LCA findings, and comparisons with traditional delivery trucks. Finally, Section 5.7 concludes with a summary of the findings and suggestions for future work, highlighting the potential of SML-CBs as a sustainable alternative in last-mile delivery.

5.2 Literature Review

This section reviews two research streams that are most relevant to our research topic: the utilization of SPLs in last-mile deliveries and the environmental impact estimation through life cycle assessments for last-mile deliveries.

5.2.1 The utilization of SPLs in last mile deliveries

Smart parcel lockers (SPLs) represent a revolutionary step in delivery logistics, leveraging advancements in the Internet and IoT technologies to offer secure, efficient, and accessible package storage solutions [58]. SPLs are broadly categorized into two types based on their mobility: fixed SPLs and mobile SPLs. Each type has spurred a distinct line of research, focusing on optimizing their deployment and usage. For fixed SPLs, a significant body of research has concentrated on determining optimal distribution locations. In Dublin, Ireland, a study employed a fuzzy decision-making model to rank various location alternatives for SPL placement [46]. Elsewhere, researchers have developed bi-level programming (BLP) models to balance the interests of different stakeholders involved in the placement of SPLs. For instance, one BLP model aimed to minimize planners' costs in choosing locations while also reducing consumers' pick-up costs [66]. Another study extended this approach to community settings, maximizing profits for SPL suppliers and user satisfaction simultaneously [67]. Further investigations have delved into network integration, such as combining SPLs with city crowd logistics networks, aiming to minimize total operational costs or maximize operating profits through strategic locker placement [39, 69]. Additionally, research has been conducted to assess the performance of existing SPL locations, studying the growth, collection patterns, and location characteristics of SPLs in specific regions [32, 37]. Conversely, research on mobile SPLs extends beyond just locating the optimal spots for lockers due to their inherent mobility. Studies have focused on minimizing locker fleet sizes to meet customer demands [51] and integrating location with route optimization to minimize operating costs in a comprehensive non-linear integer programming model [63]. This stream of research highlights the dynamic nature of mobile SPLs, emphasizing the need for advanced logistical models that account for both location flexibility and efficient routing to meet customer pick-up points.

5.2.2 Sustainability assessment of emerging last-mile delivery technologies through LCA

Sustainable development (SD) is defined as a path that balances the present and future needs so that the ability of future generations is not to compromise meeting their needs to the present generation's needs [8]. Industries and companies are embracing the concept of SD [50] and are relying on indicators and composite indicators to assess SD, which is known as sustainability assessment (SA) [6]. The purpose of SA, according to Ness et al. [47], is to assist decision-makers in evaluating nature-society systems from global to local perspectives, both in the short and long terms, and finally determine the actions that should or should not be taken to maintain the society sustainable. Singh et al.

[52] provided a comprehensive classification and evaluation of SA methodologies and recognized life cycle assessment (LCA) as a product-based decision support methodology that assesses various design and technological considerations of products considering their entire life cycle attributes. The SA is considered comprehensive on the inclusion of three pillars' assessment: economic, social, and environmental [6]. In this chapter, we will cover all such pillars.

LCA can evaluate the environmental impacts associated with all stages of a product's life cycle, encompassing raw material extraction, production, use, and waste management phases [23]. In the realm of emerging last-mile delivery technologies, the application of LCA is relatively nascent, with a few studies exploring its implications for various innovative delivery methods. Among these, some researchers have focused on specific emerging technologies. For instance, Koiwanit [29] conducted an LCA on drone delivery services in Thailand, utilizing the CML2001 life cycle impact assessment (LCIA) methodology to translate inventory data into environmental impact metrics. Similarly, Lemardelé et al. [35] investigated the life-cycle implications of autonomous delivery robots within two-echelon distribution strategies. In the vehicle analysis sector, the well-to-wheel (WTW) approach is increasingly employed to examine the complete fuel life cycle of vehicles, subdivided into the well-to-tank (WTT) phase—covering fuel production and distribution—and the tank-to-wheel (TTW) phase, which focuses on fuel consumption during vehicle operation [5]. However, WTW analyses are typically limited to fuel-related aspects and do not extensively cover the environmental impacts of delivery equipment. Comparative assessments form another critical area of research, evaluating various emerging delivery technologies against each other. For example, Li et al. [38] conducted an LCA of automated vehicles and delivery robots to measure life cycle greenhouse gas emissions. Andrea et al. [2] compared different logistics vehicle options in an urban context, analyzing the environmental footprints of electric cargo bikes, electric vans, plug-in hybrid vans, and diesel vans. Beyond simple environmental assessments, some studies have integrated economic considerations into their LCAs. Notably, Chiara et al. [12] compared electric and internal combustion engine vehicles in business-to-consumer e-commerce last-mile deliveries from both economic and environmental perspectives, utilizing LCA for environmental evaluation and total cost of ownership for economic analysis. Similarly, Apoorv et al. [3] provided a comprehensive assessment of light commercial vehicles, including internal combustion engine, battery electric, and hydrogen fuel cell electric vehicles, considering both their life cycle environmental impacts and total cost of ownership in different geographical contexts. These studies collectively highlight the growing importance and application of LCA in evaluating the environmental and, in some cases, economic impacts of last-mile delivery technologies. As these technologies evolve, LCA serves as a critical tool in understanding and mitigating their environmental footprint, thereby aiding in the transition to more sustainable delivery methods.

5.3 Introducing SML-CBs to Urban Logistics

This section elucidates the conceptual generation of SML-CBs and delineates its operational mechanics. Observations by Erhardt et al. [18] revealed a 15% decline in US bus ridership from 2012 to 2018, a trend exacerbated by the COVID-19 pandemic, as evidenced by an 88% reduction in ridership for the Toronto Transit Commission amid early pandemic business closures [1]. This downturn has led to underutilized transit system capacities and fiscal pressures for transit agencies [34].

The advent of the sharing economy, which promotes the utilization of underused assets for enhanced system efficiency and sustainability [26], offers innovative avenues for leveraging public transit systems in freight transportation. Existing studies have explored integrating public transport modalities—such as buses, subways, or trams—with delivery networks to partly employ the transit system's capacity for freight movement [7]. Ghilas et al. [21] devised a multi-modal transport chain linking traditional delivery vans with public transport, creating a complex system that involves transferring parcels between vans and public transit multiple times, ultimately leading to operational intricacies and potential transit delays. Similarly, Masson et al. [44] proposed a system where city buses transport parcels from depots to city-center micro hubs, followed by green technology-assisted deliveries to customers. Despite these innovative approaches, challenges persist, including complex coordination between different transport modes and the potential disruption of passenger services.

SML-CBs, underpinned by the sharing economy principles, represent a novel integration of smart parcel lockers with city buses to facilitate efficient last-mile delivery. Customized smart lockers are affixed to the rear of transit buses, mobilizing the lockers along established bus routes. Parcels are initially transported from distribution centers to bus terminals via delivery trucks, after which bus drivers or logistic personnel load them into the lockers. For retailers located en route, staff may directly load parcels at nearby bus stops. Customers, coordinated through a dedicated mobile application,

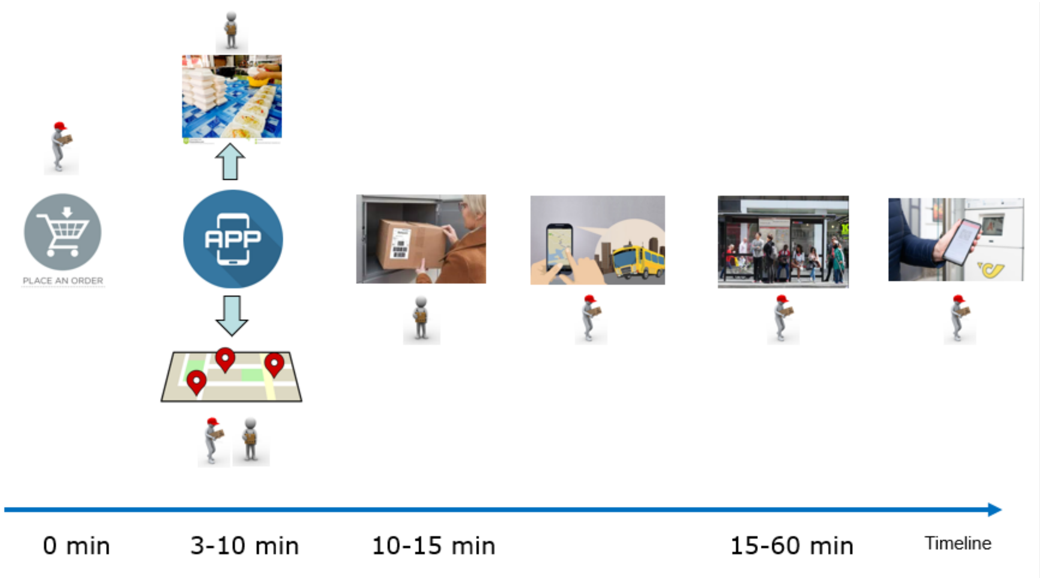

FIGURE 5.1: Operations of SML-CBs.

collect their parcels from lockers during the buses' scheduled stops. Advanced IoT technologies, such as facial or voice recognition, expedite the pick-up process within the constrained time windows of bus stops. In cases where customers miss initial delivery attempts, the system allows for subsequent pick-ups based on bus schedules. The whole service process of the SML-CBs is illustrated in Figure 5.1.

Compared to systems that require multiple interactions between delivery trucks and public transit, SML-CBs streamline the process by limiting interactions to bus terminals, thereby mitigating delays and reducing operational complexity. Moreover, by centralizing parcel distribution to bus stops rather than distributing them throughout the city center, SML-CBs effectively shorten total delivery routes and reduce the number of stakeholders involved. This approach not only simplifies the delivery system but also leads to decreased delivery costs and enhanced system efficiency.

5.4 Sustainability Assessment - Economic Assessment

5.4.1 Cost of operating SML-CBs

5.4.1.1 Models

Rooted in the sharing economy, the SML-CBs are expected to lower the delivery costs compared to traditional truck deliveries, which benefit from fewer truck deliveries and labor costs. To model this system characteristic, we construct a mathematical model for the pricing analysis to estimate the delivery cost during the operational phase of SML-CBs. Certain assumptions should be set as follows: Only one warehouse is considered in the SML-CBs delivery network. One customer only orders one parcel at a time and can choose only one available time slot. For simplicity, all customers are assumed to show up in their preferred time slot, and no re-delivery is needed at this stage. The locations of customers, bus stops, and warehouses are known. To formulate the problem, we use the following notation. The jth terminal and jth bus route are used interchangeably. To differentiate terminals on the same bus route, we use j^+ and j^-. We then develop a quadratic programming model for the cost estimate of deliveries through SML-CB.

Indices

i	index for parcels/customers, $i = 1, 2, \ldots, I$.
j	index for terminals/bus routes, $j = 1, 2, \ldots, J$.
ℓ	index for available lockers, $\ell = 1, 2, \ldots, L$.
s	index for bus stops, $s = 1, 2, \ldots, S$.

Parameters

Ca	capacity for each locker.
c_1	unit cost of transporting parcels between warehouses and terminals.
c_2	unit cost for operating lockers ℓ on bus routes j.
c_3	unit transportation cost of parcels in running lockers.
d_{wj}	distance between the warehouse and jth terminal.
d_j	length of jth bus route.
d_is	distance matrix between ith customer and sth bus stop.
M_{js}	binary matrix, equals to 1 if stop s is on route j, 0 otherwise.
d_{js}	distance between stop s and route terminal j.
d_{is}	distance between stop s and customer i.

Decision variables

x_{ij}	1 if parcel i is transported from the warehouse to terminal j, 0 otherwise.
y_{lj}	1 if locker l is at terminal j, 0 otherwise.
z_{il}	1 if parcel i is assigned to locker l, 0 otherwise.
w_{is}	1 if parcel i is assigned to stop s, 0 otherwise.

$$\min \quad c_1 \sum_{i \in I, j \in J} d_{wj} x_{ij} + c_2 \sum_{\ell \in L, j \in J} d_j y_{lj} + c_3 \sum d_{js} M_{js} x_{ij} w_{is} \tag{5.1}$$

$$\text{s.t.} \quad \sum_{i \in I} x_{ij} \leq Ca \sum y_{lj} \ , \forall j \in J \tag{5.2}$$

$$\sum_{i=1,\ldots,I} x_{ij} w_{is} d_{is} M_{js} \leq D_{max} \ , \forall i \in I, j \in J, s \in S \tag{5.3}$$

$$\sum_{i=1,\ldots,I} z_{il} \leq Ca \ , \forall \ell \in L \tag{5.4}$$

$$\sum_{l=1,\ldots,L} z_{il} = 1 \ , \forall i \in I \tag{5.5}$$

$$\sum_{j=1,\ldots,J} y_{lj} = 1 \ , \forall \ell \in L \tag{5.6}$$

The objective function (5.1) aims to minimize the total cost TC_1 operating the SML-CBs. The first term is to calculate the transportation cost of parcels from the warehouse to bus terminals. The second term is the lockers running cost once they are attached to buses. The third term is the transportation cost of parcels through SML-CBs on bus routes. Constraint (5.2) indicates that the parcels delivered to any terminal can not exceed the total capacity of lockers assigned to the same terminal. Constraint (5.3) limits the distance between customers and their assigned bus stops to less than the pre-defined threshold value. Constraint (5.4) constrains the total number of parcels assigned to any locker within the locker capacity. Constraint (5.5) guarantees that each customer is supplied with one locker. Constraint (5.6) guarantees that each locker is assigned to only one bus terminal.

For truck delivery costs, we use the following notation to formulate the problem:

Indices

h	index for customers clusters, $k = 1, 2, \ldots, H$.
i, j	index for customers clusters and the warehouse, $i = 1, 2, \ldots, I$, $j = 1, 2, \ldots, J$.
d	index for terminals/bus routes, $d = 1, 2, \ldots, D$.
c	index for customer locations, $c = 1, 2, \ldots, C$.

Parameters

Ca_T	capacity for each truck.
N_t	Number of trucks.
c_o	unit cost for truck operations.

Decision variables

x_{ij}	1 if the truck travels from node i to node j or from j to i, 0 otherwise.
x_{0j}	from the depot/warehouse to other nodes, =2 indicates a single-customer route.

Having the notations defined, we use the following formulation based on a revision of the VRP formulation [53], where S is a subset of H (customer nodes), and $v(S) \geq 1$ is the minimum number of trucks required to serve all nodes in S.

$$\min \quad c_o \sum_{i,j \in K} d_{ij} x_{ij} \tag{5.7}$$

$$\text{s.t.} \quad \sum_{i \in I} x_{ik} + \sum_{j \in J} x_{kj} = 2 \text{ , } \forall k \in K \tag{5.8}$$

$$\sum_{k \in K} x_{0j} = 2N_t \tag{5.9}$$

$$\sum_{i,j \in S} x_{ij} \leq |S| - v(S) \text{ , } \forall S \subseteq H : S \neq \varnothing \tag{5.10}$$

$$x_{ij} \in \{0, 1\} \text{ , } \forall i, j \in H \tag{5.11}$$

$$x_{0j} \in \{0, 1, 2\} \text{ , } \forall j \in J \tag{5.12}$$

The objective function (5.7), which is defined as TC_2, calculates the truck operation cost on the road. Constraint (5.8) requires two edges to be connected to each customer cluster. Constraint (5.9) requires $2N_t$ edges to be incident to the depot. Constraint (5.10) is the capacity constraints that are generalized sub-tour elimination constraints. Constraint (5.11) and (5.12) guarantee the integrity and bounds on x_{ij}.

5.4.1.2 Numerical illustration

We implement a numerical study for model validation and illustration. Firstly, we explain the numerical settings and estimate the parameters used in the models. In the test, we study a rectangular zone of 2 km times 6 km, the shape and area of which approximate that of Hamilton downtown, Ontario, Canada. There are 1000 customers are included in the test, and each customer has only one parcel to be dispatched from the last-mile distribution center. All customers are located within a predefined threshold of 200 m of bus routes. In addition, these customers are distributed in clusters, the centers of which are randomly selected from all bus stops, to imitate the real-world residency distribution [49]. This is because the SML-CBs focus on customers near bus stops. As for bus routes, we include eight routes; four are horizontal, while the rest are vertically oriented. The number of bus stops on each bus route is random, between 20 and 30. To simulate the turnovers of bus routes at crossroads, there are mutations on the route that change its direction. By setting the left-down rectangle corner point as the origin point, the down edge as the x-axis, and the left edge as the y-axis, the locations of the horizontal bus routes on the y-axis are constrained within the range of 0.5 km and 1.5 km, while the locations of the vertical bus routes on the x-axis are constrained within the range of 2 km and 4 km. The purpose of this constraint is to create a denser network of bus routes for deliveries. The customers, bus terminals, stops, and routes are visualized in Figure 5.2, where the blue dots represent bus terminals, the pink dots represent the customers, the red squares represent the bus stops, and green dashed lines represent bus routes.

The model parameters are estimated as follows. The unit cost of transporting parcels between warehouses and terminals, c_1, is set as 1.72 per km [54]. The additional weight of lockers and parcels will incur additional fuel costs for bus operations. The data from our manufacturer indicates the weight of SML-CBs is 155 lbs, and a typical TTC bus is 23170 lbs [10]. According to the data in [60], a city bus's typical fuel economy is 3 mpg, which equals 0.784 liters per km. Since the electrification of the bus fleet is a trend in many cities, the c_2 could be different or even lower if the buses to be operated are electric buses. The parcel transportation cost coefficient c_3 is defined as the weight per parcel divided by the bus weight times the fuel. We will deliver lightweight parcels at our start phase, ranging from 0.5 to 1 lbs, and the average parcel weight is set at 0.75 lbs. Thus, c_2 is 0.009$ per km and c_3 is 0.0004$ per km per parcel. The capacity of delivery trucks is set as 50 parcels, the same as our settings in the previous chapters.

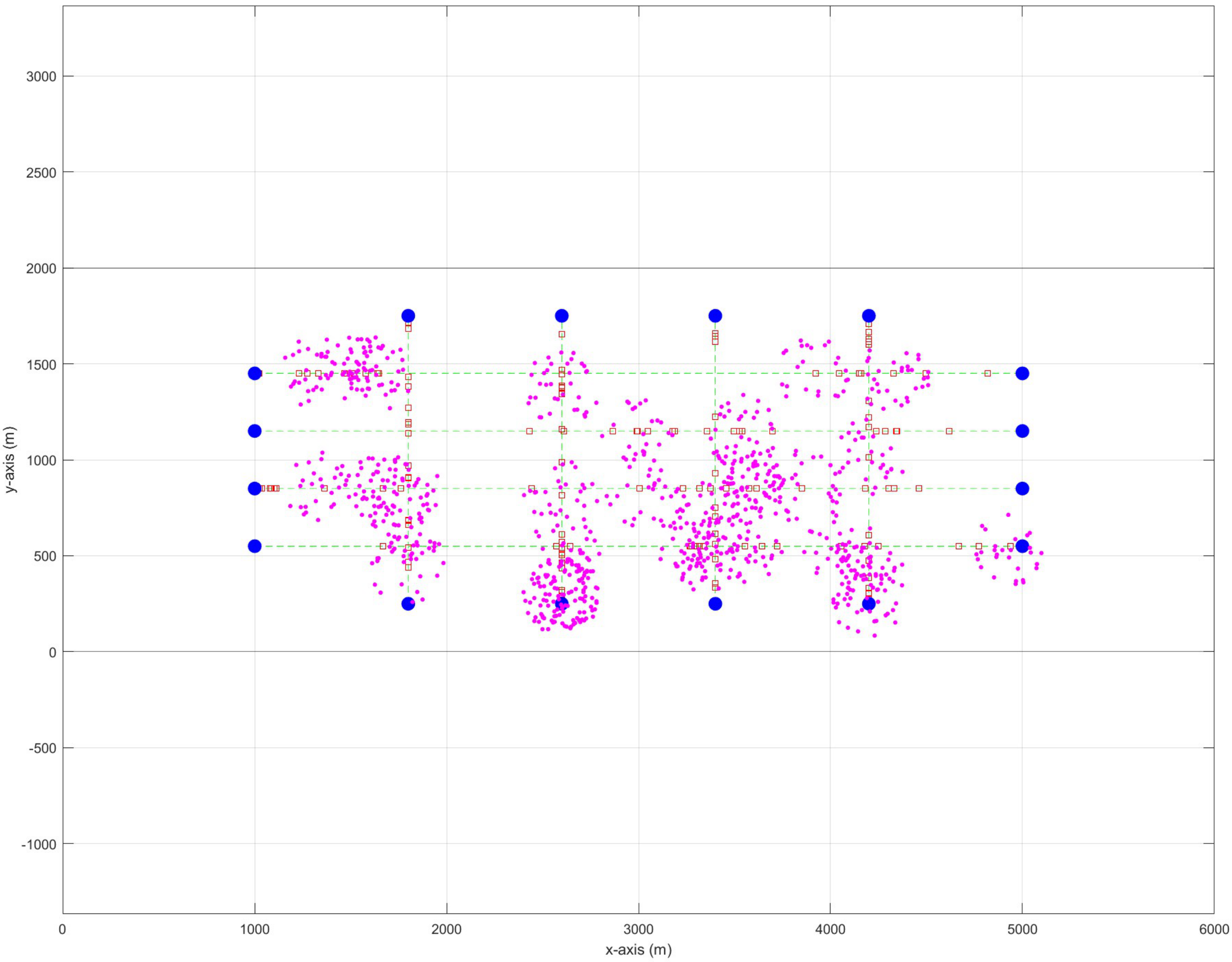

Figure 5.2: Visualizing customers, terminals, stops and routes

To solve the cost model for SML-CBs, which is a quadratic programming problem with quadratic constraints, we first linearize Equation (5.3) to make the model a quadratic programming problem with linear constraints. Considering the size of the input data which is not huge, we solve the problem using the MATLAB solver 'quadprog' for quadratic objective functions with linear constraints. For truck deliveries, the vehicle routing problem is further modified to incorporate the truck capacity constraint [53] as a capacitated vehicle routing problem (CVRP). The CVRP is solved by a hybrid solution method using a quantum annealer [19] in MATLAB. We found that the total traveling distances for truck deliveries is 180779 m. Through using SML-CBs, the truck delivery distance is largely reduced by 68.15% to 57577 m.

The total cost of truck delivery is \$310.94. The total cost of SML-CBs delivery is \$137.6, in which \$99.03 accounts for the truck delivery and \$38.57 accounts for transporting SML-CBs and the parcels inside. We reduce the delivery cost by 55.75% through using SML-CBs in the numerical test.

5.4.1.3 Parametric analysis

To test the robustness of the SML-CBs cost advantage, we compare the results of both SML-CBs and truck delivery costs under different parameters. We consider two important parameters that might impact the cost performance of SML-CBs and truck deliveries: the truck capacity for the courier and the parcel missed rate for the SML-CB operator and customer. For trucks, the more capacity the truck has, the fewer returning routes are required to the remote depot for the trucks, which contributes to shorter truck traveling distances and lower truck delivery costs. For SML-CBs, more re-delivery is required if the customers' parcel missed rate is higher, which leads to higher delivery costs.

In our parametric analysis, P_m is defined as the parcel missed rates for SML-CBs customers, and a maximum of three re-deliveries are provided by SML-CBs operators. The total delivery cost is $(1 + P_m + P_m^2 + P_m^3)$ of the initial delivery cost regardless of SML-CBs re-delivery. To reflect the increase in truck capacity, we define T_r as the truck ratio, which is the new truck capacity divided by the initial truck capacity, which is 50. The parametric analysis of the SML-CBs' cost advantage is shown in Figure 5.4. The areas where the SML-CBs are more cost-advantageous are highlighted in pink color, while the areas where truck deliveries are cheaper in cost. We found that SML-CBs are more cost-effective for the majority of cases. The areas that support truck deliveries are divided by $T_r = 6$. In the first area, the P_m first decreases and then increases at $T_r = 4$,

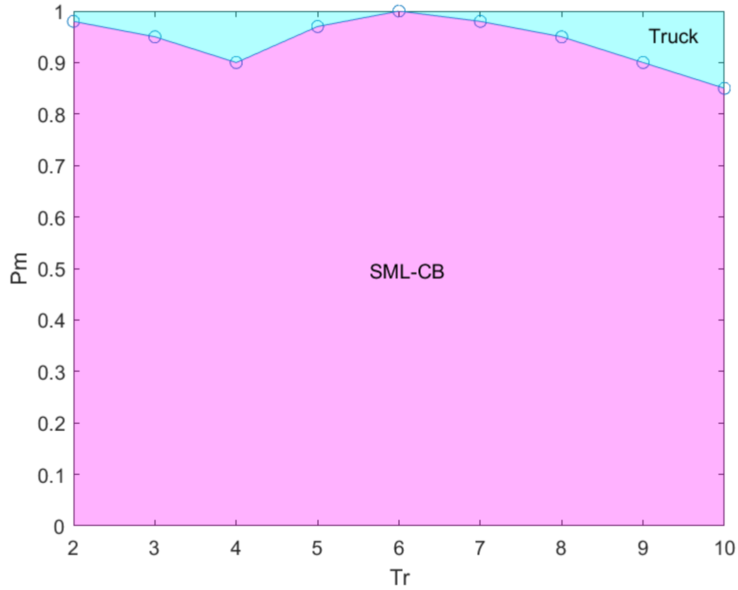

FIGURE 5.3: Parametric analysis of the SML-CBs' cost advantage

with the increase of T_r. In the second area, the P_m decreases with the increase of T_r. We conclude that truck deliveries are only cheaper in extreme P_m values.

5.4.2 Shares of SML-CBs stakeholders

5.4.2.1 Models

In e-commerce last-mile delivery, there are different scenarios for sharing the last-mile shipping cost. The first is that the e-retailers charge the customers per order for shipment and transfer the payment to couriers. Another possibility is that customers are charged a monthly fee for free shipping of whatever number of orders they place per month, similar to Amazon Prime. A third possibility is that e-retailers provide free deliveries over certain amounts of purchase if the placed orders are within a certain weight. In this chapter, we choose the first scenario for further analysis considering all stakeholders' shares. We assume that all customers are available and all parcels are delivered through SML-CBs. The parameters are defined as follows:

Parameters

lp	revenue per parcel for customers using SML-CBs.
LP	revenue for the SML-CBs operators.
r_1	commission rate from the SML-CBs operators to the couriers as incentives.
r_2	compensation rate to customers .
r_3	compensation rate to bus operators for possible impacts on bus operations.
ΔC_i	saved cost through operating SML-CBs in the i scenario .
CH_c	final cost for SML-CBs customers

The savings from using the SML-CBs, ΔC_1, are calculated in (5.13) and are shared by locker operators, couriers, bus transit, and customers. The shares of different stakeholders are calculated as follows, where R_1 is the commission income of couriers, R_2 is the compensation to customers for their extra efforts to pick up the parcels, and R_3 is compensation to bus transit for possible impact on bus routes. n is the number of customers, which equals the number of parcels since we are assuming each customer is only assigned one parcel.

$$\Delta C_1 = TC_2 - TC_1 \tag{5.13}$$

$$R_1 = \Delta C_1 \times r_1 \tag{5.14}$$

$$R_2 = \Delta C_1 \times r_2 \tag{5.15}$$

$$R_3 = \Delta C_1 \times r_3 \tag{5.16}$$

$$LP = \Delta C_1 \times (1 - r_1 - r_2 - r_3) \tag{5.17}$$

$$lp = LP/n \tag{5.18}$$

To summarize, the e-commerce platform initially charges per customer TC_2/n and fully transfers it to the courier. For each parcel, the courier will pay the SML-CBs operator lp, the customer R_2/n, the bus transit R_3/n, and reserve R_1/n as commission income to cover its own coordination costs. The final cost for customers for the last-mile delivery is calculated as(5.19):

$$CH_c = (TC_2 - R_2)/n \tag{5.19}$$

5.4.2.2 Numerical illustration

Based on the results from solving cost models of both delivery modes, TC_2 = \$310.94 and TC_1 = \$137.6 and so ΔC_1 = \$173.34. The values of r_1, r_2, r_3 are respectively set as 15%, 50%, 15%, as per [68]. In delivering 1000 parcels through SML-CBs, the delivery couriers share \$26 (R_1) if there is no customer surcharge for delivery couriers while the bus operators share is \$26 (R_3). The revenue for the SML-CB operators is thus 20% of the cost savings, which is \$34.67. All customers are rebated with R_2, equal to \$86.67. Based on the truck delivery cost, each customer is charged \$0.31 by the delivery couriers and then is rebated \$0.086 for using SML-CBs, which is 27.74% of the initial charge.

5.5 Sustainability Assessment - Social Assessment

Defined by Burdge and Vanclay [9], the social impact assessment is to create a more sustainable biophysical and human environment by analyzing and managing the consequences on the human environment of social change. Such impact assessments cover assessing resource issues, including access to resources, such as e-commerce delivery services. In any given city, not all residents enjoy the same level of accessibility to these services, and online shoppers with marginal income levels may not use these services due to the increasing cost of traditional delivery modes. By utilizing bus routes, we extend the delivery network to under-served populations with cheaper delivery modes. Several studies have established the fact that constrained routes (short or long commutes) are often frequented by marginalized communities, such as those with gender inequalities and low-income households [43].

This section includes pioneer research to validate the SML-CBs' advantages of promoting delivery accessibility over smart parcel lockers (SPLs) that are installed at transit facilities through a case study in Portland, Oregon, the U.S. The reason that we compare SML-CBs with SPLs rather than delivery trucks is due to the lack of direct data on the accessibility of truck deliveries of any major couriers, and the comparison between SML-CBs delivery and truck deliveries will be made once such data are available to authors.

5.5.1 Accessibility analysis

The ridership is important for evaluating the potential of transit sites for hosting SPLs, and transit sites with higher ridership are prioritized over others due to the potential to serve more people [27]. For SML-CBs, the ridership is vital since the authors found that regular transit users show a stronger willingness to adopt SML-CBs and are more robust to conditions that are not ideal when using SML-CBs. While there are different dimensions to assess ridership, in this research, we choose the passengers on/off as the indicator for such an assessment due to its ease of acquisition, accuracy in measuring demand, and effectiveness of public transport [59].

For fixed SPLs operated with transit facilities, it is more common that they are installed within transit centers rather than nearby outdoor bus stops [11, 13, 61], due to there being fewer or no municipal land occupancy permit issues, more connectivity, as well as ideal pick-up conditions for bad weather. As a result, we choose SPLs in transit centers to benchmark with SML-CBs. We use the direct data of passengers on/off from TriMet rather than using the aggregated ridership to ensure that the site selected on bus routes or at transit facilities is at stop level, which guarantees that the distance between fixed SPLs and riders is comparable to the distance between SML-CBs and riders.

To compare the ridership between the two delivery modes, we introduce the metric route-stop ridership ratio (RSRR):

$$RSRR = \sum_i Rr_i \bigg/ \sum_j Rt_j \tag{5.20}$$

where Rr_i is the ridership of ith bus route, and Rt_j is the ridership of jth bus stop.

We assume that 16 bus routes, with the most ridership, are used for the SML-CBs. This makes the number of transit centers in Portland equal to the selected bus routes and offers a fair comparison between SML-CBs and SPLs. To consider the impact of workdays and weekends, we classify the ridership into weekdays, Saturdays, and Sundays. To assess the impact of COVID-19, which was not considered in [27], we compare the ridership for both delivery modes in 2019, pre-COVID time, and 2022, post-COVID time. In addition, we include both spring and fall periods to differentiate ridership data between seasons. If the ridership of transit centers is set as a baseline, the multipliers of bus route ridership to transit centers are shown in Table 5.1. In Tables 5.1–5.3, 'TC' and 'BR' are the abbreviations of 'Transit Center' and 'Bus Route', 'SP' and 'FA' represent spring and fall, 'WD','SA', and 'SU' represent Wednesday, Saturday, and Sunday. Our first observation is that the bus route multiplier is more than two in all years and seasons, which shows that by utilizing the stops on bus routes, the public ridership can be increased by more than 100% in all selected cases, reflecting a much more size of potential customers of SML-CBs than SPLs within transit facilities.

		Season				Season	
Year	**Day**	**Spring**	**Fall**	**Year**	**Day**	**Spring**	**Fall**
2019	WD	2.19	2.27	**2020**	WD	2.07	2.15
	SA	2.16	2.19		SA	2.13	2.37
	SU	2.20	2.24		SU	2.14	2.17

Table 5.1: Bus route multiplier of bus route stop ridership to transit center ridership.

If we analyze the results between years, we find that the weekly gap, including the weekday, Saturday, and Sunday, decreases in the year 2022 compared to that of the year 2019, with an outlier in 2022 Fall Saturday. This shrinkage of multipliers is possibly due to the disruption of COVID-19 and reflects a slighter reduction of riders near transit centers than selected bus routes. However, in 2022, this gap further increases in 2022 Fall compared to 2022 Spring, suggesting the continuous superiority of bus route ridership to transit center ridership. If we analyze the results by season, the average multipliers of the 2019 Spring and the 2022 Spring are 2.18 and 2.11, respectively, while the values of the 2019 Fall and the 2022 Fall are 2.23 and 2.23, respectively. We find that the fall multipliers, regardless of before or after COVID-19, are higher than the spring multipliers in the same year, showing the superiority of bus routes to transit centers in the fall season. To further validate better ridership performance in the fall season, we take the ridership data in the spring season as the baseline and show the fall data to spring data in Table 5.2 for both delivery modes. The seasonal multiplier for bus route ridership outperforms transit center ridership both before and after COVID-19. While both multipliers increased from the year 2019 to 2022, the increase in bus route multiplier is higher than that in transit centers. These results suggest that the possible seasonal impact favors the bus route ridership over that of transit centers, and we may consider launching SML-CBs in the fall season. As for the differences between weekdays and weekends in Table 5.3, the multiplier pattern after COVID is more regular compared to pre-COVID time, reflected by the continuous higher multipliers on weekends. We further define the day multiplier: the ridership on Saturday or Sunday divided by Weekday ridership, to further analyze the change of multipliers. Before COVID, the day multipliers of bus routes are less than or equal to that of the transit centers. However, after COVID, both the day multipliers of the transit center and bus routes increased, while the increase for bus routes is more significant, which enables bus route multipliers to outperform transit center multipliers. This suggests a higher utilization rate of transit infrastructure by bus route riders than transit center riders on weekends after

		Modes				Modes	
Year	**Day**	**TC**	**BR**	**Year**	**Day**	**TC**	**BR**
2019	WD	0.99	1.03	**2022**	WD	1.11	1.15
	SA	0.96	0.97		SA	1.01	1.12
	SU	0.99	1.00		SU	1.09	1.10

TABLE 5.2: Season multiplier (Fall to Spring) of bus route stop and transit center ridership

			Modes					Modes	
Year	**Season**	**Day**	**TC**	**BR**	**Year**	**Season**	**Day**	**TC**	**BR**
2019	SP	SA	0.65	0.64	**2022**	SP	SA	0.78	0.81
	SP	SU	0.53	0.53		SP	SU	0.65	0.67
	FA	SA	0.63	0.60		FA	SA	0.71	0.78
	FA	SU	0.52	0.52		FA	SU	0.64	0.65

TABLE 5.3: Day multiplier of bus route stop and transit center ridership

COVID-19.

5.6 Sustainability Assessment - Environmental Assessment

5.6.1 Research Methodology

We visualize the process of implementing environmental assessment in Figure 5.4. We first define the goal of environmentally assessing various SML-CBs. Then, we approximate the processes and system boundaries of SML-CBs, which are nascent because SML-CBs are an emerging technology. Having these defined, we proceed to estimate the parameters involved in various processes, which builds the foundation for compiling life cycle inventory. Based on all the previous steps, we can employ our chosen LCA and interpret the assessment results.

5.6.1.1 Life cycle assessment technique

LCA employs three predominant methods: Process-based, Input-Output, and Hybrid [70]. Each approach has distinct strengths and limitations. Process-based LCA, aimed at encapsulating a product's life cycle impacts, inevitably overlooks certain system elements due to the complexity inherent in even the simplest products' upstream systems [22]. For instance, Pomponi and Lenzen [48] highlighted that process-based LCA might

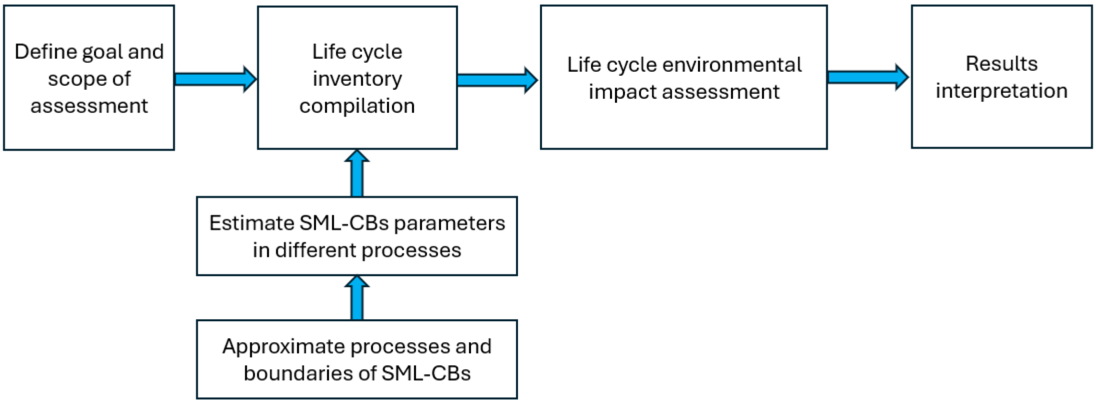

FIGURE 5.4: Research methodology process for the environmental impact assessment of SML-CBs

introduce significant inaccuracies, as evidenced by studies comparing truncation and aggregation errors, where hybrid LCA yielded more accurate results. Input-Output LCA, on the other hand, categorizes products into industry sectors to capture emissions and impacts across the entire supply chain, offering a more holistic perspective [31]. Despite its comprehensive approach, the technique's broad categorization can lead to allocation issues and representational inaccuracies, particularly for diverse products lumped into the same industry category [45, 57]. The multi-region input-output (MRIO) LCA, an extension of Input-Output LCA, addresses some of these limitations by estimating environmental impacts on a global scale, accounting for the complexity of international trade and supply chains [30, 70], enabling precise material footprint calculations for various products and sectors [62]. Wiedmann [65] showcased MRIO's extensive global applicability, detailing its use in emission and resource accounting across several countries. To amalgamate the strengths of individual LCA techniques while mitigating their limitations, Hybrid LCA has emerged as a significant branch of life cycle assessment. Hybrid LCA combines two or more LCA methods to leverage their collective advantages. For example, Malik et al. [41] developed an input-output-based hybrid LCA by merging process-based LCA with input-output analysis (IOA) to alleviate truncation errors inherent in process-based approaches, utilizing IOA's capability to trace extensive supply chains. Building upon this concept, our study employs the hybrid LCA methodology advanced by Zhao et al. [70], formulating an environmentally extended multi-region hybrid LCA (EE-MR-LCA). This innovative approach integrates the precision of process-based LCA with the comprehensive environmental data of EE-MR-LCA, capturing the benefits of both methods and providing a robust framework for environmental impact assessment.

5.6.1.2 Database and system boundaries

Several databases are utilized for comprehensive Life Cycle Assessment (LCA) through Multi-Region Input-Output (MRIO) models, as noted by Zhao et al. [70]. These include the Global Resource Accounting Model (GRAM), the Global Trade Analysis Project (GTAP), EORA, World Input-Output Database (WIOD), and Externality Data and Input-Output Tools for Policy Analysis (EXIOPOL). GRAM is renowned for estimating indirect material flows of traded products in their raw material equivalent, facilitating global material flow-based indicator calculations while maintaining comprehensive material balances on a national level [55]. GTAP, established by Horridge et al. [25], encompasses balanced economic, input-output, trade, and protection data harmonized across regions and sectors [16]. The EORA database has a detailed global coverage, featuring data for 189 individual countries [36], while WIOD provides national IO tables across 56 sectors in 43 countries, spanning from 2000 to 2014 [14].

In this study, we choose the EXIOBASE database, which is part of EXIOPOL. The latest version of EXIOBASE (version 3) is distinguished by its detailed MRIO tables, covering 200 products and 163 industries across all EU-28 countries, their 16 most important trading partners, and five aggregated "Rest-of-the-World (RoW)" regions. We have selected EXIOBASE for its comprehensive coverage, particularly for our target area of North America, and its alignment with the comparison framework utilized by [70], enabling us to update and build upon their findings with the latest data.

Our comparison of Smart Mobile Lockers with City Buses (SML-CBs) extends to various delivery truck modes, including diesel, hybrid, Compressed Natural Gas (CNG), and class 3 electric trucks. Unlike Zhao et al. [70], we exclude class 5 electric trucks due to their relatively higher environmental impacts from previous studies. The SML-CBs are categorized into bus-powered and self-powered types. Bus-powered SML-CBs derive electricity from the connected buses, whereas self-powered variants are equipped with their own battery systems. Depending on the power source of the bus, these SML-CBs are further differentiated into diesel, hybrid, CNG, and electric types.

The system boundaries for delivery trucks, as established by Zhao et al. [70], provide a framework reference for our assessment. For SML-CBs, the system boundaries encompass both the manufacturing and operation phases. The manufacturing phase includes the production of SML-CBs, the mounting system, maintenance and repair activities, diesel and natural gas production, electricity generation, and the infrastructure required for charging or refueling. The operation phase encompasses the consumption of diesel,

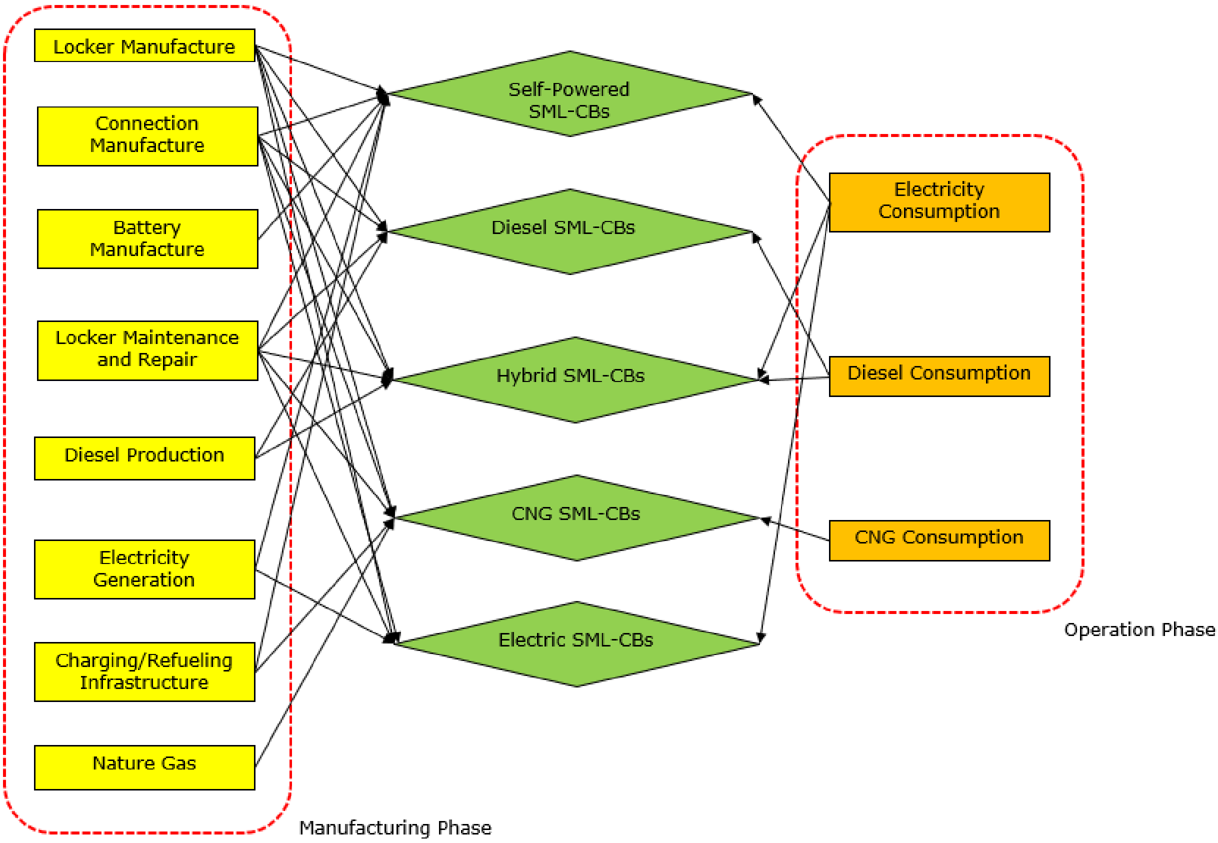

FIGURE 5.5: System Boundaries for the LCA of SML-CBs

CNG, and electricity. Currently, no data is available for recycling SML-CBs. Thus, similar to the approach in Zhao et al. [70] with delivery trucks, the end-of-life phases are not included in our assessment. The system boundaries of SML-CBs and the interconnections between components are elucidated in Figure 5.5. This comprehensive approach ensures a holistic understanding of the environmental impacts of SML-CBs compared to traditional delivery methods, contributing valuable insights into the sustainability of these innovative last-mile delivery solutions.

5.6.2 Assumptions and Parameters

5.6.2.1 Characteristics of buses, lockers, and trucks

Table 5.4 shows the characteristics of the city buses incorporated in our analysis. To ensure a uniform passenger capacity across different bus models, we have selected those

Model	Fuel Type	Weight (kg)	Seats	Average Fuel Economy	B-Capacity	B-Weight
Nova LFS[1]	Clean Diesel	12000	33	0.53 L/km	-	-
Orion VII[2]	Hybrid	13200	38	0.48 L/km	6 kWh	34.29 kg
Orion V[2]	CNG	13150	36	0.42 L/km	-	-
XE 40[2]	Electric	14601	42	0.99 kWh/km	525 kWh	3000 kg

TABLE 5.4: Bus Basic Characteristics

[1] Source: Réseau de transport de Longueuil.
[2] Source: Canadian Public Transit Discussion Board.

with analogous weights and seating arrangements. Given the proprietary nature of detailed bus specifications, we have sourced characteristic estimates from various available data. For diesel city buses, our focus is on the Nova LFS model, manufactured in 2018, with a fleet of 270 serving the Toronto Transit Commission (TTC). Its fuel economy is deduced from TTC eBus Errata data [56]. The Orion VII, from the 2008 production line with 160 units in the TTC fleet, represents the hybrid bus category. The Montreal Gazette has been utilized as a reference for hybrid bus fuel economy estimates. The average weight of this model is 13200 kg and ranges between 12700 and 13700 kg. In the absence of specific battery capacity (B-capacity) data for our selected hybrid bus model, we have employed an average B-capacity of 6 KWh, derived from CALSTART's database. To calculate the battery (B) weight, we have used the average specific energy density of 175 Wh per kg [4], resulting in a calculated B-weight of 34.29 kg. The Orion V has been selected to represent Compressed Natural Gas (CNG) buses, with an average weight of 13150 kg computed from the extreme weights of 11900 and 14400 kg from the Orion V series. The fuel economy for the CNG buses is estimated to be 20% lower than that of the diesel buses based on results from the National Renewable Energy Laboratory (NREL). The XE 40, produced by New Flyer Industries, has been chosen as our electric bus model and is part of the TTC fleet with 25 units. NREL data indicates its fuel economy at 0.99 KWh per km. The battery capacity of the XE 40 is reported as 525 kWh in New Flyer brochures, and with the specific energy density of 175 Wh per kg, the battery weight is calculated to be approximately 3000 kg. By meticulously standardizing the capacities and using diverse and credible sources for characteristic estimations, this study ensures a robust and comparative framework for analyzing the environmental impacts of different city bus models, contributing to a comprehensive understanding of the potential for sustainable urban transit systems.

The characteristics of the lockers, the mounting system, and parcels integral to the

Component	**Material**	**Weight 1**	**Weight 2**	**Weight 3**
Locker	Polycarbonate	29.5 kg	41.5 kg	57.5 kg
Parcel (Full)	-	24 kg	32 kg	48 kg
Mount	Stainless Steel	32.4 kg	48.1 kg	69.0 kg
Capacity (Slots)	-	12	16	24
Total	-	85.9 kg	121.6 kg	174.5 kg

Table 5.5: Specifications of Lockers

SML-CBs initiative are articulated in Table 5.5. As the SML-CBs initiative is not yet at the stage of uniform scaling with fixed standards, the outlined specifications are derived from preliminary design drafts and quotations from prospective manufacturers. The thickness of the smart lockers is tailored to our specifications, with a preference for polycarbonate material over traditional metals to achieve a lighter construction, conducive to the dynamic environment of city buses. The SML-CBs system incorporates a tower module, featuring a control unit. Three capacity variants have been proposed, with the dimensions of each SML-CB calculated to align with the height and width constraints of standard city buses. The mounting system is a critical component, designed to securely affix the SML-CBs onto the buses. Constructed from steel, this system requires minimal alterations to the buses, ensuring that the added weight is evenly distributed and does not compromise the vehicle's balance or operational capabilities. The strength of this system is robust enough to support the total weight of the SML-CBs and resist the dynamic forces encountered during bus movements. A simple yet effective rectangular steel frame, 5 mm in thickness, is conceived for mounting the SML-CBs [64], with the weight of the frame scaling with the locker capacities. The operational scope of the SML-CBs is primarily targeted at the transportation of small to medium-sized light parcels, with a maximum weight limit of approximately 2 kg per parcel. This constraint ensures that the system remains efficient and viable within the operational and structural limits of the city buses. The specifications provided in Table 5.5 represent a balance between functionality, safety, and efficiency, underpinning the innovative and sustainable ethos of the SML-CBs project.

The power consumption for SML-CBs is estimated based on the requirements of the control unit and individual smart locker slots, consuming 30 W and 0.5 W, respectively. One of the advantages of SML-CBs is their ability to operate continuously outside typical delivery hours, such as early mornings or late nights to align with the bus schedules. We consider two operational scenarios for the SML-CBs: full-day operation (case F), which runs 24 hours daily, and non-full-day operation (case N), which spans 18 hours a day. The

Power	Capacity 1	Capacity 2	Capacity 3
Case F (kWh)	0.84	0.92	1
Charging cycle (day)	2.14	1.95	1.8
Case N (kWh)	0.63	0.68	0.76
Charging cycle (day)	2.85	2.64	2.36

TABLE 5.6: Locker Power Consumption

daily power consumption for different SML-CBs types under these scenarios is detailed in Table 5.6. In instances where SML-CBs are self-powered, a 1.8 kWh Lithium battery equipped with a 110 V AC outlet, commonly available in the market and weighing approximately 11 kg, is proposed as the power source. Consequently, the total weight of the SML-CBs increases to 96.9 kg, 132.6 kg, and 185.5 kg, respectively. The battery's life cycle is anticipated to be around 2000 cycles, as suggested by Battery University [4]. With operational days set at 360 per year and the minimum cycling days from Table 5.6 at 1.8 days, battery replacements for the SML-CBs would be necessary approximately every 10 years. Currently, specific and reliable data on the longevity of smart parcel lockers are scant. For city buses, the lifespan is typically considered to be around 12 years according to Federal Transit Administration. However, the modular nature of SML-CBs and their mounting systems allows for their reattachment to new buses once the original bus is retired. For the purposes of this study, and to facilitate a standardized comparison, we assume the lifetime of SML-CBs to mirror that of delivery trucks, which Zhao et al. [70] posits to be 15 years. The models of delivery trucks utilized in this study are kept consistent with those used by Zhao et al. [70] to maintain comparability. This approach ensures a coherent and systematic evaluation of the power consumption and operational longevity of SML-CBs, reflecting their potential as a sustainable alternative to traditional delivery mechanisms.

5.6.2.2 Data and parameters for LCA

We classify SML-CBs into sectors based on the Environmentally Extended Input-Output Database, known as Exiobase 3 as of the 2022 version. All types of SML-CBs have the manufacturing and operation phase, which cover the component life cycle. Considering that the delivery truck and locker models were built in different years, we set 2019 as a base year to eliminate the effects of COVID-19.

The SML-CBs retail, installation, maintenance, and mounting system (manufacture and installation) prices are estimated on our potential manufacturers' quote prices and

Cost	**Capacity 1**	**Capacity 2**	**Capacity 3**
Retail	2120	2600	3240
Shipping and Installation	400	480	560
Mounting system and installation	1140	1692	2427
Maintenance (Per day)	10	12	14
Total (Except Maintenance)	3660	4772	6227

TABLE 5.7: SML-CBs Cost Estimation

market prices of similar products, shown in Table 5.7. The retail price of SML-CBs covers a central control unit and slots, the latter of which could be scaled up. The difficulty of installing SML-CBs of various capacities to the mounting system is reflected by the differentiated price. The maintenance price covers software support, charged daily regardless of the SML-CBs type, and hardware support, which varies depending on the size and weight of lockers. We estimate the cost of the mounting system and installation based on the cost of 304 stainless steel (0.55 \$ per lb), and the machined metal component, which is 16.4 \$ per lb, considering the cost of the process, including turning, milling, plating, handling, and installation [24]. All costs are in Canadian dollars and are transferred into US dollars in the assessment.

For the total GHG emissions, we include CO_2, CH_4, and N_2O, and use the CO_2-CH_4 equivalent multiplier and the CO_2-N_2O equivalent multiplier to transfer all emissions into CO_2.

The capacities regarding the number of parcels are different between delivery trucks and SML-CBs. For delivery trucks, the UPS average driver makes about 120 deliveries per day [42], so we assume the capacity of a delivery truck is 120 parcels, considering that most delivery trucks can implement a single delivery tour per day in the downtown area [28]. For SML-CBs, the parcels are transported on bus routes from terminal to terminal, and a 2-hour time window is assumed to travel between terminals as a service cycle. For full-day and non-full-day schedules, the SML-CBs can be operated 12 times and 9 times per day. We assume that the SML-CBs are able to reach the same customer service level as delivery trucks by utilizing as many bus routes as possible. However, the capacity of SML-CBs may not be fully utilized due to seasonal or insufficient demand, so we assume the utilization rate of SML-CBs is 90%. In addition, it is possible that the customers may miss their first delivery trial due to stricter pick-up time windows, and the parcels will be delivered to them in the same locker at a later time. We take this customer pick-up behavior into consideration and assume that 90% parcels are delivered successfully

Power	Capacity 1	Capacity 2	Capacity 3
Case F	98	156	235
LTR	1.25	0.77	0.52
Case N	73	118	177
LTR	1.65	1.02	0.68

TABLE 5.8: Locker-Truck Capacity Ratio

for the first time, while the remaining 10% parcels are delivered the second time. The valid delivered parcel volume for the SML-CBs is calculated as in Equation (5.21), where V_{ij} is the volume of SML-CBs with ith capacity and jth operating schedule, UL is the utilization rate, F is the operating frequency, Ca_i is the ith capacity of SML-CBs, and ul is the successful first-time delivery rate. For example, the valid parcel volume for the SML-CBs (Capacity 1) with a full-day operating schedule is calculated as 0.9*[10+(12-1)*10*0.9] = 98. The valid parcel volume for all other SML-CBs is calculated similarly, with the results of different capacities and operation schedules summarized in Table 5.8.

$$V_{ij} = UL * [Ca_i + (F - 1) * Ca_i * ul] \tag{5.21}$$

In Table 5.8, we also define the locker-truck ratio (LTR) to represent how many SML-CBs are required to serve the same volume of parcels that can be delivered through a truck. It is worth noticing that in all six given cases, there are three cases where the LTR is less than 1, requiring a lower number of SML-CBs than trucks.

We estimate the travel distance per bus per year by dividing the total bus travel distances of TTC, which is 143 million km, by the active bus TTC fleet, which is approximately 2100 [10]. The final annual travel distance per bus is thus calculated as 68095 km. Given the assumption that the operations of buses and delivery trucks are both 360 days per year, the daily bus traveling distance (DBTD) is calculated as 68095/360 = 189.15 km/day for full-day schedule operations. For non-full-day schedule operations, the DBTD is calculated as 189.15*(9/12) = 141.86 km/day.

The fuel economy of non-battery-supported SML-CBs consists of two sections: the additional power that buses consume to carry the SML-CBs together with parcels and the additional power to support the regular operations of SML-CBs, calculated in Equation (5.22). The fuel-electricity conversion rate is defined as Cr_i, which is the amount of fuel to generate 1 kWh of electricity for ith fuel type buses, approximated as 0.251 liter of

Power	Capacity 1	Capacity 2	Capacity 3
Diesel (L)	0.00913	0.00786	0.00710
Hybrid (L)	0.00743	0.00652	0.00594
CNG (L)	0.00718	0.00618	0.00555
Electric (kWh)	0.01746	0.01419	0.01216

TABLE 5.9: Fuel Economy of Operating SML-CBs per Parcel

diesel, 0.188 liter of diesel, and 0.249 cubic meters of CNG, for diesel, hybrid and CNG buses according to the U.S. EIA. It is important to note that these are rough estimations. The actual amount of fuel needed can vary based on several factors, including engine design, bus model, driving conditions, and maintenance.

$$F_{ij} = DBTD * FE_{ij} * (W_l/W_b) + P_{ij}/Cr_i \tag{5.22}$$

The fuel economies (per parcel) of non-battery-supported SML-CBs are summarized in Table 5.9, and all fuel economy values are calculated based on the assumption of a full-day schedule. For self-battery-supported SML-CBs, the fuel economy is the same as the non-battery-supported ones.

Manufacturing phase To proceed with the assessment of the SML-CBs manufacturing phase, we require the retail-manufacturing rate for the SML-CBs, which is unavailable. We estimate the manufacturing of SML-CBs by the sector "Manufacture of electric machinery and apparatus." We approximate the mounting system's manufacturing phase by the sector "manufacture of machinery." For SML-CBs supported by self-batteries, the manufacturing phase of Lithium-ion batteries is assessed by recent LCA data on Lithium-ion batteries [33] for GHG emissions.

Operation phase We assess this phase of SML-CBs by considering two sectors: the maintenance sector and the powering sector. For the maintenance sector, we calculate the total monetary value of maintenance by multiplying the maintenance cost per day in Table 5.7 and the days of operations in the lifetime. Since there is no specific sector in the Exiobase for the SML-CBs maintenance and repair, we approximate it by the sector of "maintenance, repair of motor vehicles parts."

For the powering sector, we consider direct and indirect impacts. The direct impact consists of tailpipe GHG emissions due to consuming diesel, natural gas, or electricity. The total emissions are calculated by considering the total CO_2 emissions and other emissions, the latter of which are estimated by the equivalent GHG emission multipliers of CH_4 and N_2O [70]. The indirect or the 'upstream impact' refers to the impact when producing various types of fuels. After obtaining the monetary values for every type of fuel, each value is entered into the Exiobase model to derive the total equivalent emissions separately. For SML-CBs powered by diesel/hybrid city buses, the direct emission impact (DEI) is finally calculated in Equation (5.23), while the indirect emission impact (IEI) is calculated through a similar method in Equation (5.24). Note that the FE is defined as per km liter diesel. LVM is defined as the life vehicle miles.

$$DEI = \sum GHG^{d}_{multiplier} * LVM * FE \tag{5.23}$$

$$IEI = \sum GHG^{i}_{multiplier} * LVM * FE \tag{5.24}$$

For the SML-CBs connected with CNG city buses, the GHG emission can be calculated following Equation 5.23 and 5.24 by replacing the $GHG_{multiplier}$ with equivalent CNG multipliers $GHG^{CNG}_{multiplier}$, as well as replacing the FE of diesel by the equivalent fuel economy FE_{CNG}. The SML-CBs powered by electric city buses only have IEI, and the total emissions can be calculated based on Equation 5.24 by replacing the diesel economy FE to equivalent electricity generation fuel economy FE^{e}, the unit of which is per km kWh.

No refueling or recharging infrastructure is needed for non-battery SML-CBs. The charging for battery-supported SML-CBs uses existing charging infrastructure (110 V) at bus terminals, and no additional charging infrastructure is required.

5.6.3 Results

We present the results in three subsections: the first section compares the fuel economy of SML-CBs with delivery trucks of the same power type. It estimates the GHG emissions of operating SML-CBs within cities and the savings of GHG emissions by replacing partial delivery truck fleets with SML-CBs. The second subsection analyzes the environmental impacts of SML-CBs with different power sources, capacities, and operation frequencies.

The third subsection compares the environmental impacts of the best-performance SML-CBs with the best-performance delivery trucks in our referred literature [70]. The results in all subsections reveal that the SML-CBs have substantial savings potential for GHG emissions.

5.6.3.1 Assessing the sustainability performance of operating SML-CBs

In this subsection, we assess the sustainability performance of operating SML-CBs and compare it with truck delivery. The fuel economy of truck delivery is shown in Table 5.10. It is observed that given the same capacity of parcels, the hybrid delivery trucks have the lowest fuel economy among the diesel, hybrid and CNG delivery trucks.

Power	Fuel/Electricity per Parcel
Diesel (L)	0.16594
Hybrid (L)	0.13686
CNG (L)	0.20522
Electric (kWh)	0.41758

TABLE 5.10: Fuel Economy of Truck Deliveries per Parcel

Let RST be the ratio of the fuel used to deliver a parcel by SML-CBs to that by a trucks. The RST values as well as the average values under different capacities and bus power types are shown in Table 5.11. We found that SML-CBs are sginificantly more fuel efficient than trucks. The mean value of the RST is 4.06%, and all RST values range from the lower bound of 2.7% of SML-CBs with CNG buses and the largest available capacity (capacity 3), to the upper bound of 5.5% of SML-CBs with diesel buses and the smallest capacity (capacity 1). Our first observation is that for SML-CBs attached to buses with the same type of power, more capacity will lead to lower SML-CBs fuel

Power	Capacity 1	Capacity 2	Capacity 3	Average
Diesel (L)	5.50%	4.74%	4.28%	4.84%
Hybrid (L)	5.44%	4.76%	4.34%	4.85%
CNG (L)	3.50%	3.01%	2.70%	3.07%
Electric (kWh)	4.18%	3.40%	2.91%	3.50%
Average	4.66%	3.98%	3.56%	-

TABLE 5.11: RST for Different City Buses and Capacities

-	Case 1	Case 2	Case 3
Number of Total Parcels	57,820,000 [1]	1,065,754 [2]	1,920,000 [3]
Parcels to be Delivered	5,782,000	106,575	192,000
Total Truck Emissions (ton)	2556.82	47.13	84.90
Total SML-CBs Emissions (ton)	85.52	1.58	2.84
Total Emission Savings (ton)	2471.31	45.55	82.06

TABLE 5.12: Sustainability Assessment Operating SML-CBs

[1] Source: The Load Star.
[2] Source: Statista.
[2] Source: Zenodo.

economies, reflected by the decreasing trend of the average fuel economy values from capacity 1 to capacity 3. This suggests increasing the capacity of SML-CBs within the size constraints and focusing more on delivering small parcels for better fuel economy performance. Our second observation is that for SML-CBs of the same capacity, the SML-CBs with CNG buses have the best fuel economy performance, followed by diesel, hybrid, and electric city buses. This suggests that we may focus on cities with a greater proportion of CNG buses in the city bus fleet for better performance.

To assess the savings of GHG emissions brought by the greatly reduced fuel economies, we propose operating the SML-CBs with CNG buses, which have the best fuel economy, in three cases: 1. Deliver for the big four in the U.S. delivery market (FedEx, UPS, US Postal Service, and Amazon) in the year 2021. 2. Deliver for Canada Post in the year 2020. 3. Deliver for the whole New York City Area in 2021. The number of parcels per day in each case is summarized in Table 5.12. Considering that the SML-CBs are an emerging delivery technology and are expected to serve as an alternative delivery technology to truck deliveries in the early stage, we assume that 10% parcels in each case are delivered through SML-CBs. The total emissions are calculated by summing up the total CO_2 emissions and equivalent CO_2 emissions from CH_4 and N_2O of parcel deliveries per day. We found that the SML-CBs can reduce 2471.31 tons, 45.55 tons, and 82.06 tons of GHG emissions compared to diesel truck deliveries daily.

5.6.3.2 LCA of SML-CBs

The SML-CBs cost of each phase is identified and calculated, and the life cycle cost data is used as input data for the EE-MR-HLCA model from the 2022 version of Exiobase 3.

Comparing Power Source Impact for SML-CBs In this subsection, we keep the capacity as capacity 1 and the operating frequency as non-full-day operating for all SML-CBs. Figure 5.6 and Table 5.13 show the GHG emission impacts of all types of SML-CBs.

The highest overall environmental impact comes from the battery-supported SML-CBs, based on the U.S. national average electricity price. Though there are no tailpipe emissions, the GHG emissions are moved to the fuel consumption phase from a life cycle phase. For SML-CBs powered by electricity, including the battery-supported and electric SML-CBs, the biggest impact is the fuel consumption, which is even higher than the sum of fuel consumption and tailpipe of all other non-electricity SML-CBs. A similar finding has been reported for electric delivery trucks in [70]. However, compared with the electrification of delivery trucks that have higher environmental impacts than non-electrification delivery trucks included in [70], we found that the electrification of SML-CBs becomes more competitive, with the LCA environmental impact of electric SML-CBs only 0.03% higher than diesel trucks. This is due to the transition towards a more sustainable electricity power generation structure in the U.S. Compared to the electricity power sources in 2015, there is an increase of 1.3% of hydro and 12.8% of renewable energies. If we compare battery-supported SML-CBs with electric SML-CBs, the LCA environmental impact performance of battery-supported SML-CBs is higher than the electric SML-CBs due to the manufacturing phase of batteries, though having batteries makes SML-CBs more independent of the bus power supply and resistant to failures of bus operations.

The lowest environmental impact among all SML-CBs is the CNG SML-CBs, followed by hybrid SML-CBs and diesel SML-CBs. The CNG SML-CBs are 23.03% lower than the diesel SML-CBs. While the LCA environmental impacts are the same as the locker manufacture and maintenance & repair for diesel, hybrid, and CNG SML-CBs, the CNG SML-CBs benefit from lower fuel consumption and tailpipe impacts. For fuel-supported SML-CBs, the biggest environmental impact is the tailpipe for diesel and hybrid SML-CBs, which is the same as diesel and hybrid delivery trucks, while the biggest environmental impact for CNG SML-CBs is the maintenance and repair. We identify the CNG SML-CBs to be the most promising SML-CBs in sustainability compared to other SML-CBs concerning power sources, the environmental impact of which is 34.03% lower than the battery-supported SML-CBs.

Power	Battery supported	Electric	Diesel	Hybrid	CNG
Locker Manufacture (g)	3.193	3.193	3.193	3.193	3.193
Battery Manufacture (g)	4.434	0	0	0	0
Maintenance and repair (g)	19.714	19.714	19.714	19.714	19.714
Fuel Consumption (g)	27.099	27.099	2.756	2.363	1.214
Tailpipe (g)	0	0	24.330	19.800	16.513
Total Emissions (g)	54.460	50.005	49.992	45.069	40.634

TABLE 5.13: LCA of SML-CBs with Different Power Sources (Per parcel)

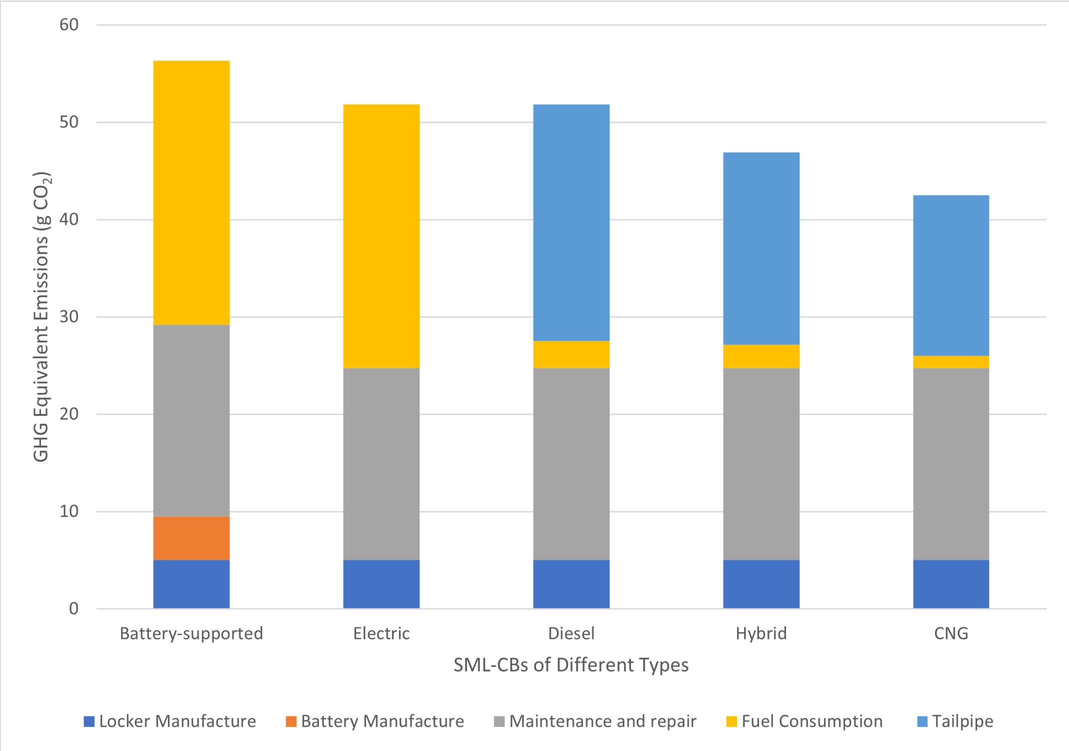

FIGURE 5.6: LCA of SML-CBs with Different Power Sources (Per Parcel)

Component	Capacity 1	Capacity 2	Capacity 3
Locker Manufacture (g)	3.193	2.612	2.308
Maintenance and Repair (g)	19.714	14.635	11.383
Fuel Consumption (g)	1.214	1.045	0.939
Tailpipe (g)	16.513	14.214	12.765
Total Emissions (g)	40.634	32.506	27.394

TABLE 5.14: LCA of SML-CBs with Different Capacities (Per Parcel)

Comparing Capacity Impact for SML-CBs We chose the CNG SML-CBs and the non-full-day operating frequency as power type and operation parameters to explore the impact of capacity. The emissions of three different capacities are depicted in Table 5.14 and Figure 5.7. With an increase of 4 slots (33% of capacity 1), the emissions of capacity 2 are reduced by 20.003% than capacity 1. Another increase of 8 slots (50% of capacity 2) reduces emissions by 15.726% compared to capacity 3. The biggest environmental impact for SML-CBs of capacity 1 and capacity 2 is maintenance and repair, and it changes to tailpipe for SML-CBs of capacity 3. We observe that all components are reduced by increasing the capacity. The most significant reduction is in maintenance and repair (42.459%), followed by locker manufacture (27.727%), tailpipe (22.697%), and fuel consumption (22.652%). The increase in capacity is more effective in reducing environmental impacts for the phase of manufacture and maintenance compared to the phase of fuel consumption and tailpipe. From the results in this subsection, we can conclude that SML-CBs with more capacities would generate better LCA environmental impact performance, and an increase of 100% capacity from capacity 1 to capacity 3 lowers the environmental impact by 32.584%.

Comparing Operation Frequency Impact for SML-CBs We compare the impact of two operation frequencies by fixing the capacity as capacity 3 and the power source as CNG. By increasing the frequency by 33.333% from 9 times per day (non-full-day frequency) to 12 times per day (full-day frequency), we have observed a 12.335% reduction in total emissions. The emissions of the operational phase, including the fuel consumption and tailpipe. The reduction from locker manufacture (24.697%) is almost the same as that of maintenance and repair (24.686%). Overall, by optimizing the parameters of power source, capacity, and operation frequencies, we have achieved the best environmental impact for SML-CBs per parcel to 24.015 g GHG emission per parcel.

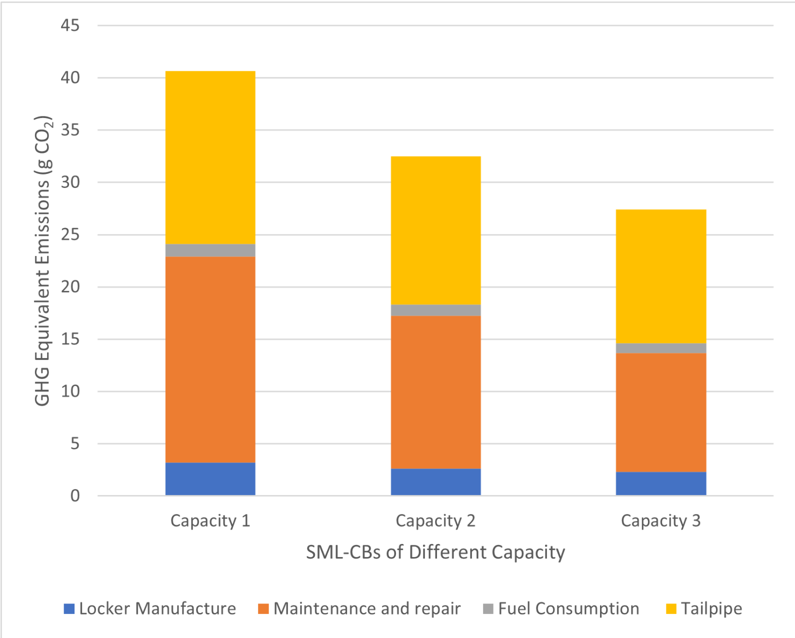

FIGURE 5.7: LCA of SML-CBs with Different Capacities (Per Parcel)

Component	Non Full-day Operations	Full-day Operations
Locker Manufacture (g)	2.308	1.738
Maintenance and Repair (g)	11.383	8.573
Fuel Consumption (g)	0.939	0.939
Tailpipe (g)	12.765	12.765
Total Emissions (g)	27.394	24.015

TABLE 5.15: LCA of SML-CBs with Different Operating Frequencies (Per Parcel)

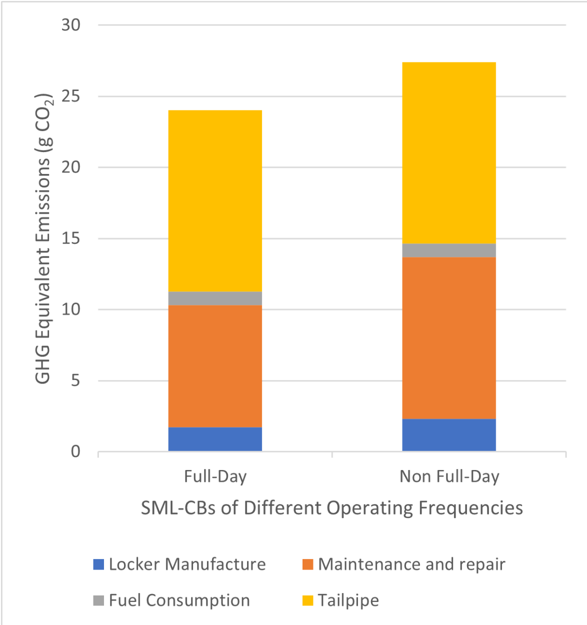

FIGURE 5.8: LCA of SML-CBs with Different Operating Frequencies (Per Parcel)

5.6.3.3 Comparing Sustainability between SML-CBs and Delivery Trucks

We use the GHG emissions per parcel to compare the sustainability performance, considering that the capacities are different between SML-CBs and delivery trucks. The comparison is between the SML-CBs with the lowest GHG emissions, which are powered by CNG, have a capacity of 3, and have full-day operating frequency, and the hybrid truck in [70], which has the lowest total emissions among all the researched trucks included in the literature. The capacity of the delivery trucks is set as 120 parcels, the same as our previous setting. The results are depicted in Table 5.16 and Figure 5.9. For easier comparison, we combine the truck manufacture and battery manufacture for hybrid delivery trucks into the manufacturing phase. For delivery trucks, the highest emissions are from the tailpipe phase, far more than all other phases. The total life cycle GHG emissions of SML-CBs are only 9.801% of the hybrid delivery trucks per parcel. The smallest emission proportion of SML-CBs to delivery trucks is in the manufacturing phase, which is 3.944%. This is because of the much smaller size and weight of SML-CBs compared to delivery trucks, as well as the comparative simplicity in manufacturing SML-CBs. The fuel consumption and tailpipe emissions of SML-CBs are only 6.897% and 7.043% of delivery trucks. This great saving is due to the way that SML-CBs gain

Component	Truck (Hybrid)	SML-CBs (CNG)	Proportion
Tailpipe (g)	181.235	12.765	7.043%
Fuel Consumption (g)	13.611	0.939	6.897%
Maintenance and Repair (g)	6.111	8.573	140.291%
Manufacturing (g)	44.074	1.738	3.944%
Total Emissions (g)	245.031	24.015	9.801%

Table 5.16: Comparing Sustainability between Delivery Truck and SML-CBs (Per Parcel)

mobility by rooting in the sharing economy in a much more sustainable way than delivery trucks. Most of the power in delivery trucks is to support mobilizing the trucks themselves rather than parcels in the last-mile deliveries. In contrast, the SML-CBs greatly lower the weight of the parcel delivery platform and significantly increase the power utilization for parcel transportation.

5.7 Conclusions

The increasing e-commerce economy has led to explosive growth of last-mile delivery activities. While fuel-based delivery trucks are still the mainstream method to deliver parcels, simply scaling up the truck fleet to meet the increased delivery demands causes various issues, including but not limited to the increased GHG emissions that conflict with the net zero emissions of many cities, and the traffic congestion due to insufficient transportation infrastructures. These emerging issues drive researchers and practitioners to explore the applications of innovative technologies in last-mile deliveries and quantify their benefits. The authors of this paper are the first to propose a delivery technology that harnesses the unused transportation capacity of city buses through externally attached smart parcel lockers, named smart mobile lockers with city buses (SML-CBs). Instead of delivering parcels from delivery centers to customers by trucks, the SML-CBs transport parcels from bus terminals, where the parcels are loaded into the lockers, to bus stops that are nearby customers for parcel self-pick-ups. SML-CBs share the bus routes with the city bus network and remove traditional delivery platforms like trucks from the deliveries. The customers' self-pick-up time windows share the bus dwell time at stops to avoid frequent braking and illegal parking due to implementing deliveries through trucks. Rooted in the sharing economy, the SML-CBs are expected to bring advantages including but not limited to lower delivery costs as well as less emissions.

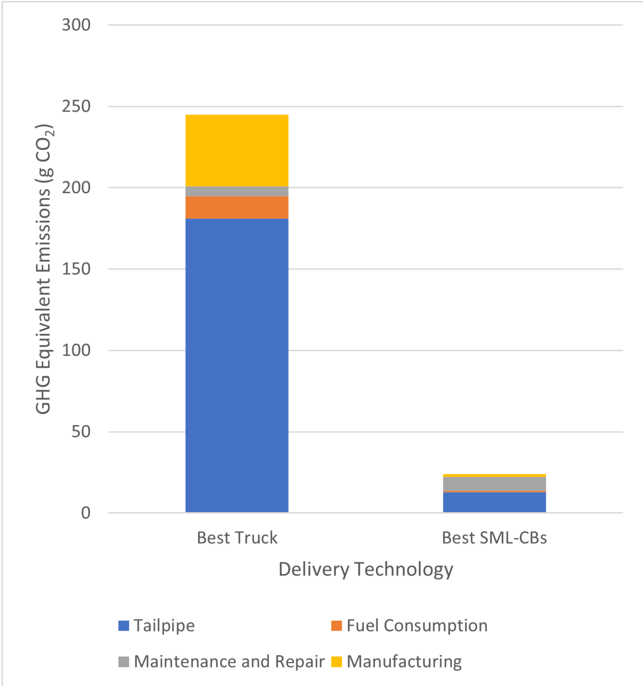

FIGURE 5.9: Comparing Sustainability between Delivery Truck and SML-CBs (Per Parcel)

The motivation of this research is to pioneer in analyzing the impact of operating SML-CBs, including the economic, social, and environmental impacts, emphasizing the last impact. In the economic impact assessment, we employ optimization models for the SML-CBs cost model and truck delivery cost model. Through a numerical test, we find that a reduction of as much as 55.75% is achieved through using SML-CBs compared to truck deliveries. We also model the pricing of SML-CBs and the shares of different stakeholders. Customers can receive a 27.74% discount/rebate on their initial charge. Our social impact assessment shows that compared to SPLs at transit facilities, the accessibility of SML-CBs in ridership is increased by 100% in all cases we have studied. Our last sections focus on quantifying the sustainability of SML-CBs and choosing the optimized parameters for SML-CBs in terms of sustainability. We adopt the hybrid life cycle assessment technique proposed by Zhao et al. [70] to systematically assess the sustainability performance of SML-CBs. We utilize the latest version of the EXIOPOL database for the hybrid LCA and define the system boundaries. We provide details of SML-CBs in the manufacturing and operation phase, which can not only be used in the LCA but also provide references for prototyping. We propose SML-CBs with different power sources, capacities, and operation frequencies and provide details of the buses and delivery trucks from different information sources. We define new parameters like the truck-locker ratio and valid parcel volume in terms of capacity for SML-CBs and SML-CBs fuel economies. The first part of our results compares the environmental impact indicators of operating SML-CBs and operating delivery trucks with the same power source. The proportion of fuel economies between SML-CBs and delivery trucks of the same type ranges from 2.91% to 5.50%, which shows the tremendous potential of operating SML-CBs in GHG savings within cities. The performance of SML-CBs' fuel economy becomes better with the increased capacity. Among all the power sources, the CNG-based SML-CBs have the most promising fuel economy compared to CNG-based trucks, followed by electric, diesel, and hybrid, given the same capacity (capacity 1) and operation frequency (non-full-day operation frequency). The second section of results explores the LCA performance of SML-CBs with different changeable parameters, including power source, capacity, and operation frequencies. By comparing the power source, we observed that the CNG-based SML-CB has the lowest LCA emissions, followed by hybrid, diesel, electric, and battery-supported electric. Our second observation is that the gap in emissions between electric SML-CBs and diesel-based SML-CBs is much smaller than the electric and diesel-based delivery trucks in previous literature. The power comparison results suggest we focus on the CNG bus fleet for operating SML-CBs at the current stage, and confirm that electric SML-CBs are more competitive in sustainability comparatively than electric delivery trucks. For CNG-based SML-CBs, increasing the capacity lowers the emissions in all life cycle phases, while increasing the operation frequencies lowers the emissions in the manufacture and maintenance phases. The results of exploring the relationship between CNG SML-CBs parameters and LCA performance provide guidelines for designing the capacity and proposing operating frequencies for the best performance of emissions. The last section of our results compares the life cycle emissions of the optimized CNG-based SML-CBs and those of the delivery trucks (hybrid trucks) with the lowest emissions in previous literature. The overall emissions of the chosen SML-CBs are only 9.801% of the selected trucks' emissions, which shows the great potential of SML-CBs in contributing to sustainability from a life cycle perspective. The lowest proportion of SML-CBs emissions to truck emissions comes from the manufacturing phase, followed by fuel consumption and tailpipe, all of which are below 7.5%. In contrast, the maintenance and repair emissions of SML-CBs are higher than that of trucks, due to more complexity in maintaining the lockers' advanced functions like uploading data to the cloud and collecting data through IoT sensors, which are not required by trucks.

This research acknowledges certain limitations that might introduce deviations in our results. Firstly, the potential interplay between alterations in transit ridership and the usage of SML-CBs was not examined. Specifically, there exists a scenario wherein certain SML-CB users may transition to public transit owing to their engagement with the transit system. In such instances, the consequent increase in emissions attributable to augmented ridership requires consideration. However, this situation lies in the fact that this transition to public transit by these users signifies a shift towards a more sustainable mode of transportation, consequently diminishing emissions associated with their commute. Comprehensive research employing an LCA approach to encompass both the modification in parcel delivery methods and the alteration in travel modes would be advantageous for a more nuanced analysis of emissions in future studies. Another potential oversight is the neglect of supplementary emissions from missed deliveries, caused by potential delays in bus operations and stricter time constraints for parcel collection as opposed to traditional truck deliveries. Subsequent research would be instrumental post-implementation of SML-CBs to refine the accuracy of emission estimates, particularly considering the impact of missed deliveries.

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Chapter 6

Conclusions and Future Work

This Ph.D. thesis is a pioneer research to integrate the sharing economy with smart parcel lockers, an emerging alternative for e-commerce last-mile deliveries, named smart mobile lockers with city buses (SML-CBs). We aim to build a theoretical foundation for SML-CBs by providing empirical and analytical evidence to support the feasibility and advantages of SML-CBs. This final chapter summarizes the main contributions of the thesis and sheds light on future research that extends this thesis.

To help identify the research gaps within the last-mile deliveries that SML-CBs contribute to filling in, we provided a comprehensive literature review on commercial and humanitarian freight last-mile deliveries in Chapter 2. We distinguished our review from other reviews on similar topics by constructing a conceptual framework, unifying key definitions in the area, implementing a bibliometric analysis for research clusters of 313 papers, and considering the impact of COVID-19. The review included 158 papers pre-COVID, with three research clusters identified: humanitarian last-mile operations, commercial last-mile operations, and last-mile technologies. Another 155 papers appeared during the COVID, clustered into two main streams: humanitarian last-mile operations and commercial last-mile operations. For pre-COVID research, we further classified the clusters into 12 areas of research based on the focus of the reviewed papers. Within each area, we summarized the literature by topics, objectives, and main innovations as guidelines for readers based on their needs. Our discussions emphasized emerging technologies for last-mile commercial deliveries and called for future research avenues that encourage multi-model deliveries, multiple delivery systems, and impact on local communities. We found that SML-CBs are in perfect alignment with these discussions and avenues.

Since SML-CBs are an emerging last-mile delivery technology, little is known about the potential customers' perceptions. Chapter 3 serves as a first step that helps us understand the attitudes among Canadian e-commerce consumers toward adopting SML-CBs and target the suitable consumers as early SML-CBs adopters. We analyzed the section dedicated to SML-CBs in a nationwide e-commerce customer survey with 2617 participants. Our overview results showed that the leading allurement for survey participants was the possible environmental sustainability of SML-CBs. In addition, our overview results showed respondents are sensitive to the distances for parcel self-pick-ups since around 50% of respondents were willing to accept a 100 meter as their maximum walking distance. Other overview results are also encouraging, reflecting that survey respondents were comparatively patient for parcel arrivals at bus stops and expected reasonable discounts compared to mainstream delivery services. Our detailed analysis systematically studied the impact of different factors on customers' perceptions, including ages, residential types, cities, land types, online shopping frequency, and online shipping payment preferences. We further analyzed the responses of various participant groups and rated the groups that are our target customers. However, this study is not without limitations. One such constraint is the dependence on self-reported data, whose subjectivity could impede the precision of the findings. Future inquiries should consider integrating objectively acquired customer usage metrics. A second limitation originates from our performance rating system's structural design, as it is solely based on survey results and may fail to encompass all possible factors affecting customer willingness. Further research is warranted to identify these variables' significance and relevance, thereby refining the system for a more nuanced implementation of SML-CBs. For subsequent research avenues, one potential direction involves examining customer dimensions more granularly to target customer subsets effectively. Another avenue could incorporate theoretical frameworks, such as the Unified Theory of Acceptance and Use of Technology, alongside empirical hypothesis testing to discern influencing factors systematically.

After identifying the importance of customers' walking distance for parcel self-pick-up towards the adoption of SML-CBs in Chapter 3, Chapter 4 aims to optimize the total customers' walking distances to motivate maximum SML-CBs customers during SML-CBs operations. We modeled two critical binary assignment variables: the assignment of customers to bus stops and the assignment of SML-CBs to bus routes. We formulated the problem of operating SML-CBs to minimize the total customer walking distances as a quadratic assignment problem with quadratic constraints, defined as the customer-locker-assignment (CLA) problem. Given the NP-hard nature of the CLA problem, we proposed a hybrid construction-greedy heuristic for efficient solutions. Additionally, we developed two other operating scenarios and corresponding solution heuristics to prioritize the computation time and the individual's walking distance to benchmark with our optimal customer assignment heuristic. The optimal heuristic proved its strong advantages in computation time and satisfying optimal gaps in different numerical cases. We chose Mississauga, Ontario, Canada, for a case study to simulate the SML-CBs operations in real-life settings. We pre-solved the case study problem by grouping customers' parcels into lockers based on customer neighborhood clustering and filtering the customers that are not near bus stops. Finally, we applied the optimization model, the optimal customer assignment heuristic, and the nearest customer stop assignment heuristic in the case. The results showed that the number of SML-CBs required for the optimal customer assignment heuristic was largely reduced by 63% at the cost of a slight increase of 12% of customers' walking distance, compared to the nearest customer bus stop assignment heuristic. For the optimal assignment heuristic, the average customer walking distance is 127 m, and 63% customers are within the critical distance of 100 meters in Chapter 3, reflecting the promising feasibility of SML-CB operations. As for future work, one interesting future research direction would be to add constraints that can reflect more realistic operations in developing the mathematical models, including the weight, dimension, and time constraints for the parcels. For example, the number of lockers can be decreased by running the lockers attached to the same bus multiple times to meet the delivery demands with different time requirements. This will add more complexity to the problem and require new solution heuristics. A second future direction could be exploring the optimum number and capacity of lockers in different operating scenarios by adding the capacity of lockers and the number of lockers as decision variables, which requires developing new mathematical models from the perspective of SML-CBs operators.

To validate the environmental advantages of SML-CBs, the most attractive allurements for customers to embrace this innovative technology recognized in Chapter 3, Chapter 5 systematically quantifies the sustainability performance, based on up-to-date life cycle assessment (LCA) technique and a modern comprehensive LCA database. In addition, we include an analysis of the economic and social impact assessments to validate the superiority of SML-CBs in terms of cost and accessibility over benchmark delivery technologies. As for the environmental impact assessment, after defining the system boundaries of SML-CBs by different LCA phases, we provided detailed SML-CB design parameters for LCA input based on various data sources. These parameters could act as baseline parameters for largely manufacturing SML-CBs at late scaling-up stages.

The first part of the results compared the fuel economy of SML-CBs. The fuel consumed per parcel for the SML-CBs with the best fuel economy is only 2.91% of the fuel consumed by delivery trucks of the same power source. The second part of the results optimized the life cycle sustainability performance of SML-CBs, in terms of emissions per parcel, by adjusting SML-CB parameters, including power source, locker capacity, and operating frequency. The final part of our results compared the emissions per parcel from the best-performance SML-CB with the best-performance delivery trucks in the literature. From a life cycle perspective, we revealed that SML-CBs delivery emissions are only 9.801% of truck delivery emissions. These results strongly supported that SML-CBs have the potential to be a game changer in the transition toward more sustainable last-mile deliveries. However, we also recognized the limitations of this study, especially in estimating parameters and developing assumptions for LCA. Since the SML-CBs are still in the prototyping phase, the first limitation is that some parameters for SML-CBs are based on estimation rather than experimental results, for example, the weight and price of SML-CBs. We have recently been awarded funding to run a pilot for SML-CBs that will allow us to collect real-time data to overcome this limitation. The second limitation is that we did not consider uncertainties in parameters, for example, the fuel economies. Another limitation is that we assumed the service levels of SML-CBs and delivery trucks are equivalent. With the gradual implementation of SML-CBs, the estimations of these parameters and assumptions can be improved to reflect more realistic cases, which can support the reliability of calculating SML-CBs' sustainability performance. One future extension of this research can study how to optimize the number of SML-CBs needed to reach the same service levels of delivery trucks while maintaining good sustainability performance. A second possible future research is to implement a multi-regional comparison of SML-CBs that helps us target the most promising region to scale up SML-CBs for best sustainability performance. Another future research direction is to compare the energy demands of different types of SML-CBs as well as compare them with delivery trucks.