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Behavioural aspects, operational decisions, and strategic planning for crowd-shipping by public transport passengers

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# **Behavioural aspects, operational decisions, and strategic planning for crowd-shipping by public transport passengers**

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Transport Group

Department of Infrastructure Engineering

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## Abstract

The significant rise in e-commerce and the subsequent surge in home deliveries are recognized as the primary drivers of increased freight vehicle activity in urban areas, leading to various adverse effects. Consequently, academia and industry have put forth several innovative last-mile logistics solutions to tackle the growing concerns associated with heightened urban freight activity. Among these solutions, Crowd-shipping (CS) stands out. The delivery of parcels by crowdshippers is anticipated to play a crucial role in improving the environmental impact of urban freight operations. Initiatives like these can potentially decrease the circulation of delivery trucks, particularly in local and residential zones, resulting in reduced emissions, alleviated traffic congestion, and improved safety conditions. This, in turn, brings significant benefits to the general public.

For many years, industry and academia have predominantly concentrated on CS involving occasional drivers. Various CS platforms, such as Amazon Prime, Walmart Spark Delivery, DHL MyWays, Deliveroo, UberEATS, DoorDash, and PiggyBee, have been introduced by e-retailers and couriers within the industry (Alnaggar et al., 2021). However, from a sustainability standpoint, while CS initiatives can decrease dedicated van or truck trips for package delivery, relying on occasional drivers in these initiatives may not be ideal due to the introduction of additional car traffic. Evidence suggests that such initiatives could lead to increased traffic demand in transport systems, as many drivers may view it as a secondary job opportunity, and new immigrants in developed countries may find it to be a readily available employment option (The New York Times, 2020). Acknowledging this drawback, a novel and emerging area of CS research has emerged, focusing on CS utilizing Public Transport (PT) passengers (Marcucci et al., 2017; Serafini et al., 2018; Gatta et al., 2019a; Gatta et al., 2019b; Fessler et al., 2022). Referred to as Green CS, this terminology is used for PT-based CS, as such services may not lead to dedicated trips for package delivery (Gatta et al., 2019a). Even if they do, the utilization of capacity and revenue in PT systems is expected to be improved.

This study investigates the feasibility and performance of implementing PT-based CS initiatives. Before system implementation, a comprehensive assessment of its performance is essential. Crowdshippers constitute the primary stakeholders in CS systems, forming the supply side of CS platforms. Understanding the willingness of PT passengers to engage in PT-based CS systems and their probability of accepting CS tasks is crucial. With these inputs, it becomes possible to estimate participant demographics, CS supply size, and the acceptance of

CS tasks by PT passengers. These insights guide planning studies to optimize operational and strategic decisions, as well as evaluate the performance of PT-based CS systems.

Using survey data collected from 2208 PT passengers in the Sydney metropolitan area, this research explores the intention of PT passengers to participate as crowd-shippers in PT-based CS initiatives and their likelihood of accepting CS tasks. A binomial logit model is developed to identify variables influencing the intention to participate. Key findings indicate that women, full-time employees, elderly individuals, retirees, and low-income PT passengers exhibit limited participation, whereas the youth, those with a positive attitude towards sustainable freight initiatives, and individuals with experience working with Parcel Lockers (PLs) are more likely to participate. Additionally, factors related to time availability/flexibility and passengers' physical health condition/importance are found to be more significant than compensation levels in influencing PT passengers to participate in PT-based CS initiatives.

A Latent Class (LC) choice model is developed to explore different participant characteristics and preferences for accepting CS delivery tasks under varying levels of offered incentives, package weight, and required detour distance at the destination. The model identifies three classes: "leisurely," "avid," and "sceptical" users. Leisurely users, mainly employed with higher ages and lower PT trip frequency per month, express a potential desire to undertake CS tasks that are not logistically burdensome. Avid users, the largest class, are mostly younger PT passengers less sensitive to task difficulty and may accept tasks with minimal incentives. Sceptical users, with high PT trip frequency and income, are unwilling to accept CS tasks unless well-compensated.

At an operational level, a PT-based CS system is formulated to minimize parcel delivery costs for carriers. Three operational decisions are considered: (1) assigning parcels to selected lockers in the CS system or vans in the home delivery system, (2) routing delivery vehicles for visiting parcels assigned to home delivery and lockers, and (3) incentivizing PT passengers participating in the CS system. These decisions are simultaneously optimized to minimize the carrier's total delivery costs. The developed behavioural models are integrated into the design system. Strategic planning involves finding optimal locations for placing PLs in PT stations through sensitivity analyses, providing valuable insights.

A heuristic solution algorithm is proposed to optimize allocation, routing, and incentivization decisions, tested on a real case study from the GS area. Results show that for a small carrier, utilizing a PT-based CS system could save daily delivery costs up to 36%, depending on CS initiative familiarity and the number of PT stations equipped with PLs. Vehicle delivery costs in the CS-integrated delivery system are reduced by 50% to 65%

compared to the conventional vehicle-only system. The study suggests that a CS system should offer higher incentives initially, and as familiarity grows, figures could be reduced based on market and operational conditions. Simulated experiments indicate that denser PL networks enable carriers to reduce incentives even at earlier stages with lower familiarity rates.

## **Declaration**

This is to certify that:

- the thesis comprises only my original work towards the PhD except where indicated in the Preface,
- due acknowledgement has been made in the text to all other materials used,
- the thesis is fewer than 100,000 words in length, exclusive of tables, maps, bibliographies, and appendices.

**Seyed Sina Mohri**

Melbourne, May 2024

## Preface

This thesis presents my own research undertaken under the supervision of Dr Neema Nassir, Dr Patricia Sauri Lavieri, and Professor Russell Thompson. It was conducted within the Transport Group in the Department of Infrastructure at the University of Melbourne. This thesis is mainly based on five original journal papers that I have written during my candidature (2021-2024). These papers serve as the basis for Chapters Two to Five. Therefore, these chapters have been presented as standalone research studies in a journal publication format. I was the lead author and contributed more than 50% in all papers. Following are the papers and chapters associated with these papers:

- **Chapter 2:** Mohri, S.S., Ghaderi, H., Nassir, N. and Thompson, R.G., 2023. Crowdsipping for sustainable urban logistics: A systematic review of the literature. *Transportation Research Part E: Logistics and Transportation Review*, 178, p.103289. <https://doi.org/10.1016/j.tre.2023.103289>
- **Chapter 3:** Mohri, S.S., Nassir, N., Thompson, R.G., Lavieri, P.S., Public Transportation-Based Crowd-Shipping Initiatives: Are Users Willing to Participate? Why Not?, *Transportation Research Part A: Policy and Practice*. ([Status: Under revision](#))
- **Chapter 4:** Mohri, S.S., Nassir, N., Lavieri, P.S. and Thompson, R.G., 2024. Modeling package delivery acceptance in Crowdsipping systems by Public Transportation Passengers: A latent class approach. *Travel Behaviour and Society*, 35, p.100716.. <https://doi.org/10.1016/j.tbs.2023.100716>
- **Chapter 5:** Mohri, S.S., Nassir N., and Thompson, R., Lavieri, P.S., Crowd-shipping with Public Transportation Passengers: Operational Planning, *Transportation Research Part E: Logistics and Transportation Review* ([Status: Under review](#))

Some parts of this PhD research were also presented at international conferences. Following are the peer-reviewed conference papers:

- Mohri, S.S., Vijay, A., Kahalimoghadam, M., Stokoe, M., Nassir, N. and Thompson, R., 2022. Evaluating initiatives for improvement of urban freight deliveries: A case study of Sydney metropolitan area. *Australasian Transport Research Forum*. ([Link](#))

- Mohri, S.S., Nassir, N., Thompson, R.G., 2021. The impacts of COVID-19 Pandemic on The Volume and Pattern of Public Transport Trips in The Greater Sydney Area. Australasian Transport Research Forum, Brisbane, Australia. ([Link](#)).
- Mohri, S.S., Nassir, N., Thompson, R., 2023. Behavioral Modelling of Public Transport Passengers Participating in Last-Mile Freight Delivery, IPIC 2023 - 9th International Physical Internet Conference, Greece, Athens. ([Link](#))

In addition to the journal and conference papers, the findings of this PhD research were communicated as oral presentations in different forums including:

- Infrastructure Engineering Postgraduate Conference 2021/2022, hosted by the Department of Infrastructure Engineering, University of Melbourne, February 2022.

## Acknowledgment

Completing a doctoral program mirrors embarking on an extensive expedition, replete with exhilarating and testing episodes. It entails a rollercoaster ride of highs and lows. Throughout this odyssey, I confronted numerous hurdles, yet I am exceptionally fortunate to have been accompanied by some remarkable individuals whose steadfast support proved pivotal.

Foremost among them is my primary mentor, Dr. Neema Nassir, to whom I owe profound gratitude for his unwavering backing and mentorship throughout this research pursuit. His expertise, patience, and unwavering commitment played a pivotal role in shaping not only this thesis but also my evolution as a researcher. Equally deserving of appreciation are my co-mentors, Dr. Patricia Sauri Lavieri and Professor Russell Thompson, whose invaluable guidance, insightful suggestions, and constructive critique significantly enriched the quality of this PhD research. I must extend my thanks to Associate Professor Kourosh Khoshelham, the chair of the advising committee, for his invaluable feedback and support throughout my doctoral journey.

The University of Melbourne also merits my gratitude for awarding me the Melbourne Research Scholarship (MRS), which not only alleviated the financial strain of this academic venture but also underscored the university's belief in my potential.

To my family, the bedrock of my existence, I offer my deepest appreciation. Their boundless love, encouragement, and understanding have served as my sanctuary during moments of stress and uncertainty. To my friends, whose laughter and companionship alleviated the burdens of academia, I extend my thanks for reminding me of the beauty found in simplicity. A special debt of gratitude is owed to my wife, Atefeh Rahmatinezhad, for her unwavering support, understanding, and patience during this demanding period. Her unconditional love and encouragement have been my anchor, and I am profoundly thankful for her presence in my life.

Finally, heartfelt thanks to all those who played a role, whether significant or minor, in my PhD journey. Their invaluable contributions and support are warmly acknowledged.

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## List of Acronyms

|                        |                                          |
|------------------------|------------------------------------------|
| <b>3PL</b>             | Third-Party Logistics                    |
| <b>ADP</b>             | Alternative Delivery Point               |
| <b>AI</b>              | Artificial Intelligence                  |
| <b>B2B</b>             | Business-To-Business                     |
| <b>B2C</b>             | Business-To-Customer                     |
| <b>C2B</b>             | Customer-To-Business                     |
| <b>C2C</b>             | Customer-To-Customer                     |
| <b>CO<sub>2</sub></b>  | Carbon Dioxide                           |
| <b>CBD</b>             | Central Business District                |
| <b>CDP</b>             | Collection And Delivery Point            |
| <b>COD</b>             | Company-Owned Driver                     |
| <b>CS</b>              | Crowd-Shipping                           |
| <b>CVRP</b>            | Capacitated Vehicle Routing Problem      |
| <b>CW</b>              | Clarke-Wright                            |
| <b>DC</b>              | Discrete Choice                          |
| <b>ETP</b>             | Expectation To Be Paid                   |
| <b>GHG</b>             | Greenhouse Gas                           |
| <b>GS</b>              | Greater Sydney                           |
| <b>ICT</b>             | Information And Communication Technology |
| <b>IQR</b>             | Interquartile Range                      |
| <b>ISD</b>             | Information-Sharing Driver               |
| <b>LC</b>              | Latent Class                             |
| <b>LMD</b>             | Last-Mile Delivery                       |
| <b>MNL</b>             | Multinomial Logit                        |
| <b>NAM</b>             | Norm Activation Model                    |
| <b>NO<sub>x</sub></b>  | Nitrogen Oxides                          |
| <b>NRC</b>             | Node Redundancy Coefficient              |
| <b>PL</b>              | Parcel Locker                            |
| <b>PM<sub>10</sub></b> | Particulate Matter                       |
| <b>PT</b>              | Public Transport                         |
| <b>RQ</b>              | Research Question                        |

|             |                                     |
|-------------|-------------------------------------|
| <b>SLR</b>  | Systematic Literature Review        |
| <b>TAM</b>  | Technology Acceptance Model         |
| <b>TBL</b>  | Triple Bottom Line                  |
| <b>TOE</b>  | Technology-Organisation-Environment |
| <b>TP</b>   | Transshipment Point                 |
| <b>UFDS</b> | Urban Freight Delivery System       |
| <b>VoT</b>  | Value Of Time                       |
| <b>VMT</b>  | Vehicle Miles Travelled             |
| <b>VRP</b>  | Vehicle Routing Problem             |
| <b>WTP</b>  | Willingness To Pay                  |
| <b>WTW</b>  | Willingness To Work                 |
| <b>YOY</b>  | Year-over-year                      |

## **CHAPTER 1**

# **INTRODUCTION**

# 1 Introduction

The unprecedented growth of e-commerce and the popularity of online shopping have increased direct Business-to-Customer (B2C) deliveries. Due to the lack of economy of scale in shipping parcels directly to customers' doorsteps, the last-mile segment of deliveries is the most expensive and least efficient part for carriers, accounting for nearly 28% of the total delivery cost (Goodman, 2005). Additionally, carriers face challenges in locating specific delivery addresses in urban and suburban areas, as well as finding parking spaces in Central Business District (CBD) areas. Carriers must also invest in expanding their vehicle fleets and personnel to maintain service efficiency, given the expected growth in the number of home deliveries in the future. Moreover, these direct deliveries increase the movement of delivery trucks and vans in the transport network, contributing to worsening air pollution, traffic congestion, and deterioration of roads and pavements, ultimately leading to an unsustainable freight distribution network.

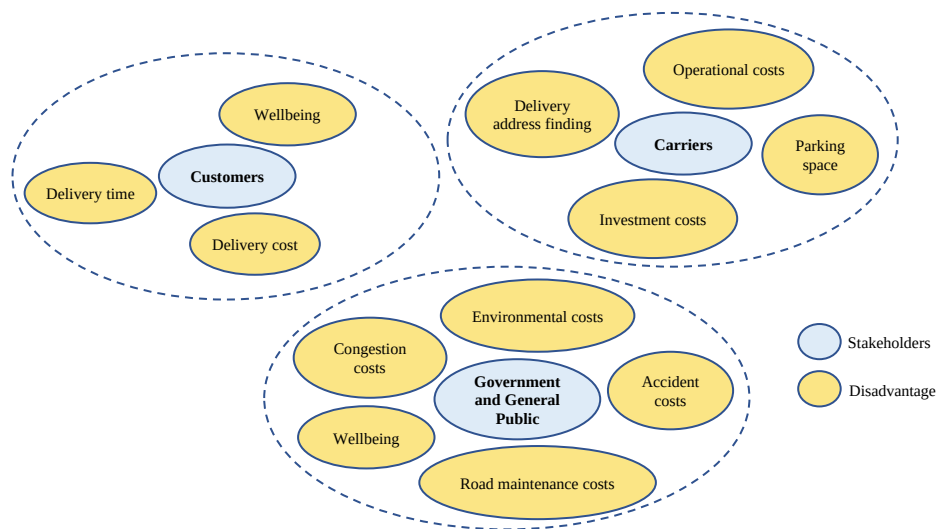


Figure 1.1 Disadvantages of home delivery with ordinary delivery vehicles

From the customers' standpoint, although home delivery using ordinary delivery vehicles (e.g., trucks and vans) can be convenient, customers should expect longer delivery times due to the significant increase in home delivery demand. Additionally, fulfilling the growing number of delivery tasks requires carriers to invest in expanding their personnel and vehicle fleets, which may result in higher delivery fees. The overall well-being of customers may also deteriorate due to the unsustainable issues associated with direct home deliveries, such as air pollution and road congestion. Figure 1.1 summarizes the disadvantages of the home delivery trend with ordinary delivery vehicles.

In recent years, several initiatives have been proposed that focus on "collaboration" in urban freight movement as a solution to the negative consequences of last-mile deliveries for all stakeholders in Urban Freight Delivery Systems (UFDSs), including customers, carriers, shippers, governments, and the general public. Urban freight collaboration can occur between freight carriers (Thompson and Hassall, 2012), between Public Transport (PT) or other modes of transport and freight carriers (Ghilas et al., 2016), or between customers and freight carriers (Deutsch and Golany, 2018).

Parcel Lockers (PLs), Collection and Delivery Points (CDPs), pick-up points, and self-collection points are some facilities that facilitate collaboration between the entities involved in urban freight initiatives. These facilities can serve as intermediaries between carriers and customers or between carriers themselves. The following subsections provide a brief overview of the application of PLs in facilitating collaboration between carriers and customers, as well as between carriers.

## 1.1 Research background

As shown in Figure 1.2, PLs can serve as substitutes for home delivery addresses, either for first deliveries—those dispatched from depots to customers on the initial attempt—or for failed deliveries. By sending first deliveries to PLs instead of home addresses, the routing and emission costs of delivery vehicles can be reduced. However, investment costs for installing these lockers are incurred by carriers, while customers may face additional trips (and the associated costs) to pick up their parcels from the PLs.

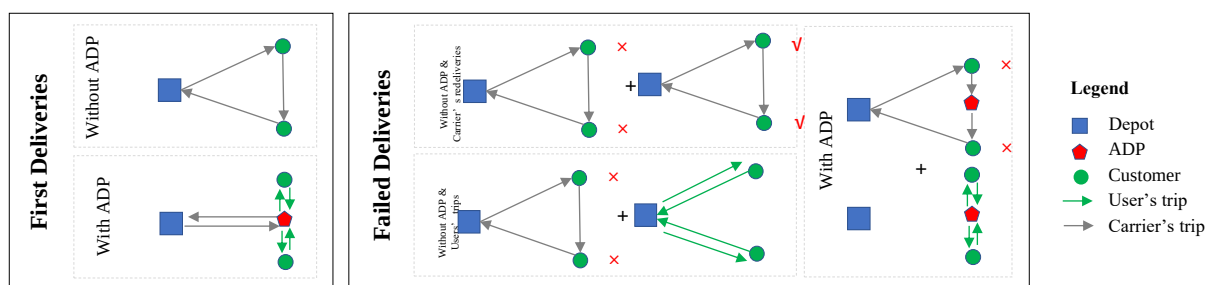


Figure 1.2 PLs applications in the processes of first and failed delivery

Failed deliveries can also be sent to parcel lockers (PLs), helping to address the challenges posed by failed deliveries for both carriers and customers. Quantifying the benefits of PLs for managing failed deliveries largely depends on the carrier's approach to handling

these deliveries, as shown in Figure 1.2. The carrier may choose to attempt re-delivery in the following days, requiring delivery vehicles to revisit customers with failed deliveries. This results in additional parcel volumes for the carrier and increased vehicle movements in urban transport networks. Alternatively, the carrier might opt not to attempt re-delivery, leaving the failed parcels at its depot for customers to pick up. This imposes extra trips for customers between their homes and the carrier's depot. If the depot is located far from residential areas, the economic and environmental costs of these additional trips for customers could be significant, greatly reducing customer satisfaction with the carrier's services.

As a solution to these negative consequences, failed deliveries can be left at local PLs near customers' homes. This approach eliminates the need for carriers to arrange repeated deliveries and for customers to make long trips to retrieve their parcels. However, installing PLs in UFDSs is costly, making it challenging to quantify the benefits of using PLs for failed deliveries. Researchers have defined various conditions, such as the rate of failed deliveries and the distance between the carrier's depot and residential areas, to determine under what circumstances this approach would be cost-effective.

There is extensive literature on quantifying the benefits of using lockers for first or failed deliveries (e.g., Wang et al., 2014; Carotenuto et al., 2018; Choi et al., 2021), exploring stakeholders' expectations of UFDSs with PLs (e.g., Weltevreden, 2008; Oliveira et al., 2019; Yuen et al., 2018), designing UFDSs with PLs (e.g., Janjevic et al., 2019; Yang et al., 2020; Janjevic et al., 2021), and evaluating existing UFDSs with PLs (e.g., Lachapelle et al., 2018; Xue et al., 2019; Vural and Aktepe, 2021).

PLs, Collection and Delivery Points (CDPs), pick-up points, and self-collection points can also facilitate collaboration between multiple carriers or Third-Party Logistics (3PL) companies. In this context, PLs are placed at facilities known as "transshipment points" (TPs). As shown in Figure 1.3, at a TP, a carrier can outsource the delivery of some of its parcels to another carrier, which could be a driver, a public transport user, a pedestrian, a cyclist, or a second ordinary freight carrier using vans or trucks. In this type of collaboration, customers are not directly involved and continue to receive their parcels at home. However, transferring part of the delivery process to sustainable transport modes or the existing delivery plans of other carriers can reduce the economic, social, and environmental costs associated with last-mile logistics.

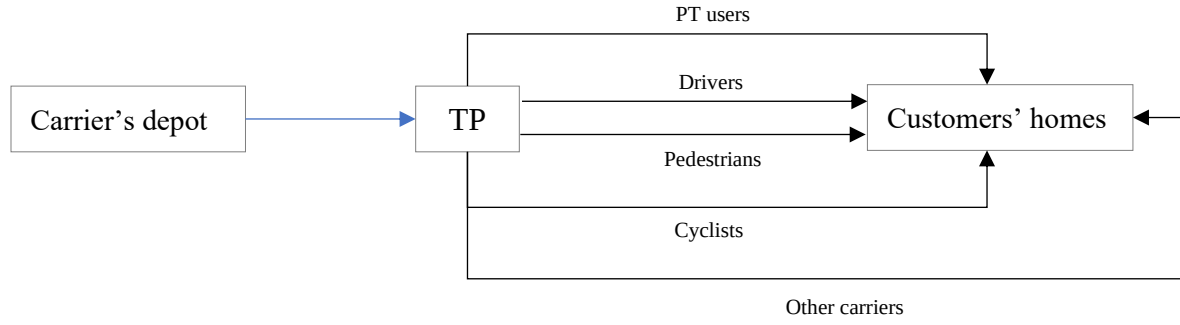


Figure 1.3 PLs applications in collaborations between carriers & carriers

In contrast to the first application of PLs in UFDSs, the second has received less attention so far. A related research stream, crowd-shipping (CS) using occasional drivers, has an extensive body of literature. However, most studies assume that occasional drivers provide delivery services in parallel with Company-Owned Drivers (CODs), with no collaboration between occasional drivers and CODs or among occasional drivers themselves. A recent publication by Yıldız (2021a) explored the impact of incorporating TP into UFDSs with occasional drivers and coordinating some delivery trips. The results demonstrated that TPs can play a critical role in enhancing the performance and robustness of CS delivery networks.

## 1.2 The research's motivations, scope and contribution

The focus of this research is on developing the second application of PLs (i.e., PLs for facilitating CS programs). This research is motivated to focus on the second application of the PLs for solving Last-Mile Delivery (LMD) problems because statistics show that even by the huge investment has been done major carriers in Australia such as Australia Post (i.e., more than 1000 locations for PL facilities), no significant rise in utilization of these facilities has been observed (Australia Post, 2021a; Australia Post, 2021b). Online shopping growth in Australia was 57% YOY in 2020 from which 87.7% of all deliveries is the share of home delivery. However, in 2019, the share of home delivery was 82%. It shows that this considerable increase in volume of deliveries in 2020 could not lead to a higher or even an equal increase in the share of other alternative delivery ways such as PL or PO boxes deliveries. In fact, the share of PLs went from 14% in 2019 to 8.5% in 2020. To increase the utilization of the lockers and raising profit for the investment on providing these lockers, Australia post is going to increase the degree of decentralization in PL distribution networks by placing small lockers on many retail stores such as 7-Eleven stores. However, there would not be any guarantee that parcel receivers show a great tendency to use PLs in this decentralized network

because these facilities are still a substitution for home delivery with a high popularity. Hence, this research decides to evaluate the performance of using PL facilities with a different role in LMD networks. The new role of the PL facilities is proving a connection between carriers and crowds to facilitate the CS delivery. Because CS delivery still provide home delivery for parcel receivers, it is expected that parcel receivers do not strongly oppose to receive their parcel through this delivery way.

Everyday thousands of people travel on PT networks. These networks are designed to provide mobility, capacity, and reasonable accessibility to all parts of the urban and even regional roadway networks. Urban freight shipping companies (i.e., carriers) can benefit from the immense existing mobility on PT systems for moving their parcels over urban areas within a day. Therefore, the research is motivated to consider PT users travelling daily in existing PT as the crowd-shippers in this application.

The benefits of this PT-based CS initiative are not limited to carriers. PT users and agencies, general public, and government can also benefit from it and would be encouraged to collaborate on as follows :

**PT users:** To encourage PT users to collaborate on this initiative, the carrier can offer some incentives such as free or discounted PT pass for those users delivering parcels along their daily trips. Hence, PT users, especially PT-dependent individuals, can address their mobility needs with reduced transport expenses .

**PT agencies:** The incentive plan offered by the carrier to PT users might also attract new users to the PT system; hence, it could increase the revenue of PT agencies in long term. Therefore, PT agencies would be willing to support this CS initiative.

There are several are in way of implementing CS programs using PT users which are left unaddressed in the literature. To outsource the deliveries to PT users, the primary question is “can parcel CS by PT users be a viable option?” If the answer is yes, then the pursuant question is “what would be the performance and characteristics of the optimal designed CS system?” To determine the performance and characteristics of an optimal design, this study provides responses for the following secondary questions? (1) which PT stations should be equipped by PL facilities?, (2) what would be the capacity of PLs?, (3) how existing parcels should be distributed between the selected lockers?, (4) how much incentive should be offered to PT users for delivering parcels?, (5) with what probability PT users accept to deliver parcels?, and finally (6) what would be the performance of the CS system in terms of decreasing parcel delivery costs of the delivery company?.

This Research aims to comprehensively study the concept of implementation of PLs for facilitating CS programs using unused capacity of PT vehicles and immense existing mobility of PT users. Therefore, as shown in Figure 1.4 a monolithic mathematical model is proposed that integrate a network design model, a behaviour choice model, an assignment model, a route choice model, and a mechanism design model to provide responses for the entire questions. In the following, a brief explanation of the application of each of the modelling components is provided. Also, Figure 1.5, a customized version of Figure 1.3 for our study, shows the position of each of the modelling components in our work. As illustrated in the figure, the carrier initially assigns a portion of the parcels to direct home delivery, while others are allocated to CS. After this initial allocation, another assignment model is applied to the parcels designated for CS, determining how they should be distributed to PLs. Decisions regarding the locations and capacities of PLs are also considered, and a model must identify the optimal choices for both. In subsequent steps, behavioural models will assist in understanding the probability of successfully outsourcing CS-allocated parcels to PT passengers. At this stage, a mechanism design model is required to determine the optimal compensation for PT passengers. Additionally, if no passengers agree to take the parcels at the PL facilities, they will be returned to the carrier depot and prepared for direct home delivery the following day. In the following, a detailed explanation of the models are provided.

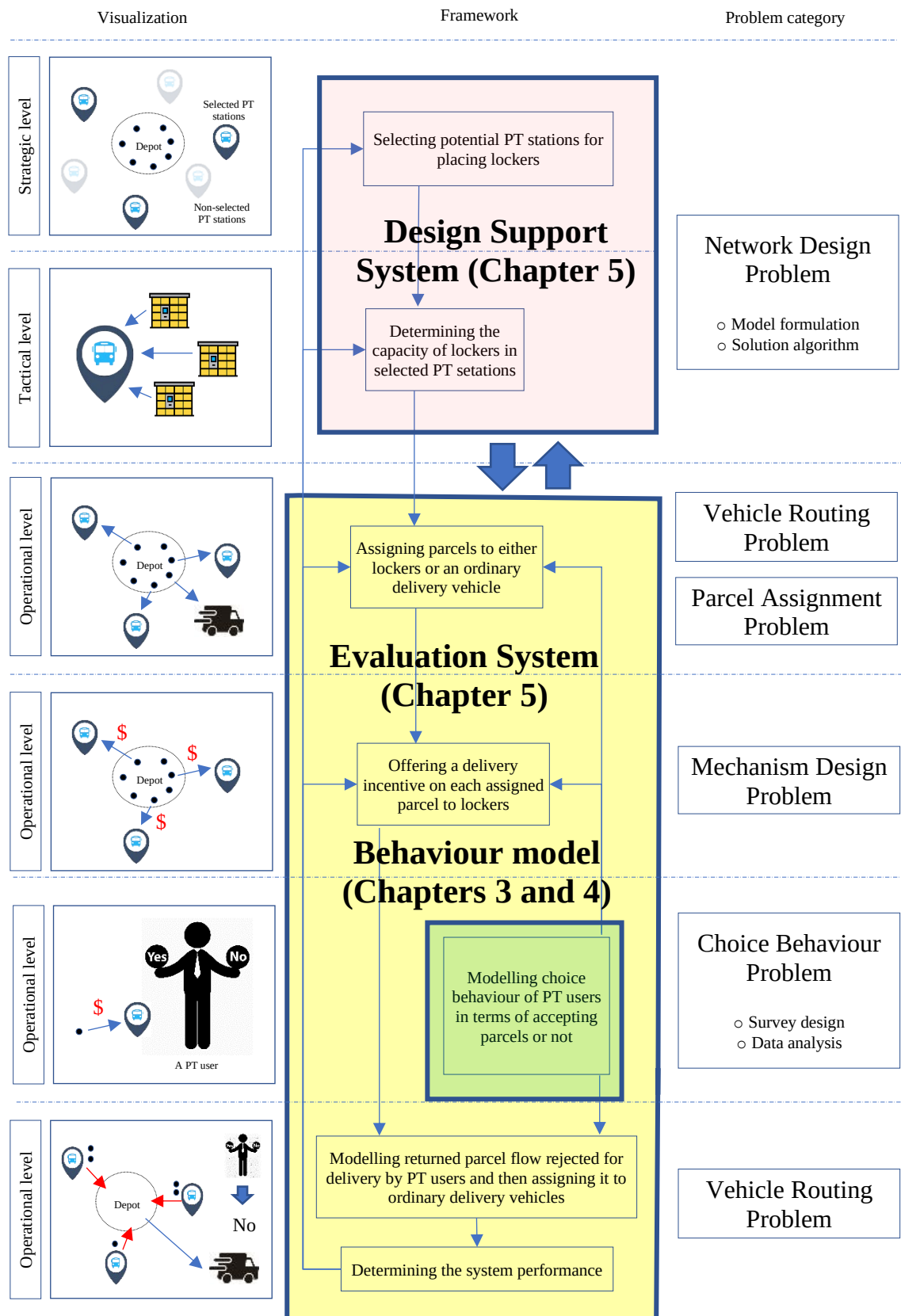


Figure 1.4 Framework

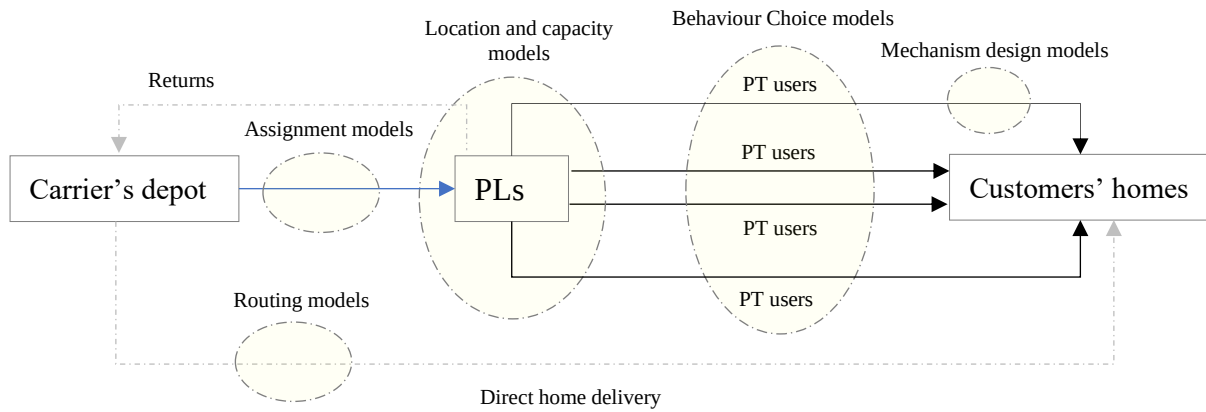


Figure 1.5 Modelling components in the application of PLs in CS

- **The network design model:** It is used to make some strategic and tactical decisions to identify the best location and capacity of lockers, respectively, placed on a subset of PT stations.
- **The behaviour choice model:** it is used to model the behaviour of PT users, as the crowd-shippers, in terms of accepting parcels, having characteristics such as their delivery incentives and weights. The required materials for calibrating the choice model are provided by surveying nearly 2000 PT passengers.
- **The assignment model:** It is used to make an operational decision, a daily decision, to determine which parcels are considered for the CS delivery plan and how they are assigned to existing lockers.
- **The routing model:** It is used to make an operational decision to find the best routes from a carrier's depot for charging lockers and visiting parcels not included in the CS plan.
- **The mechanism design model:** The participation rate of PT users in the CS plan and consequently parcel shipping acceptance probability can be increased by offering more incentives on parcels. However, offering more incentives will increase the delivery costs for the carrier. Hence, a mechanism design model is used to find the optimal incentive offered for delivering parcels in lockers ensuring a suitable participation rate, successful parcel outsourcing rate, and a reduced delivery cost for the carrier.

### 1.3 Research aims and objectives

The thesis aims to design, develop, and evaluate the PT-based CS system in urban areas from the lens of sustainability. A more detailed explanation of this aim is provided in Figure 1.6, which addresses the common "why," "what," and "how" questions typically involved in formulating research plans. In the following, the objectives are listed to describe concisely what the research is trying to achieve.

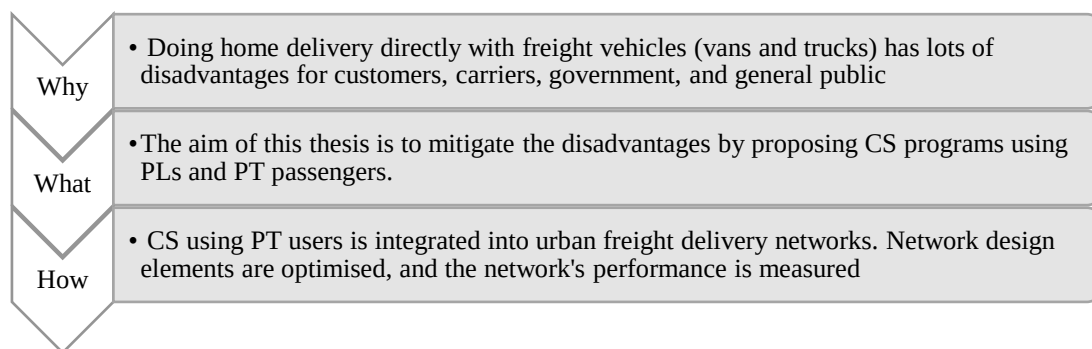


Figure 1.6 Research aims

#### ▪ Main Objective:

The first objective is to provide a crowd-shipper model (i.e., a behaviour model) focused on understanding and modelling the behaviour of PT users in collection station (CS) tasks. This includes two key aspects: (1) modelling the participation rate of PT users in the CS initiative, and (2) developing a behavioural choice model (i.e., a binary logit model) to reflect the behaviour of PT users in terms of accepting to deliver a parcel with given characteristics (e.g., weight, incentive, and address distance from PT stations). To achieve this, a comprehensive questionnaire will be designed to gather relevant data. This questionnaire will be distributed among a sufficient number of PT users to collect the necessary responses. The collected survey data will then be thoroughly analysed, and the resulting insights will inform the design of the user behaviour model. This behaviour model will be integrated into the overall evaluation system to assess the functionality of the proposed CS system.

The second objective is to develop a comprehensive evaluation system that measures the performance of the designed CS system. This system will utilize both the designed CS system and the behaviour model of PT users as inputs. By incorporating various operational and tactical decisions—such as vehicle routing, parcel assignment, and pricing strategies—the evaluation system will calculate the performance of the overall CS system across economic

and environmental criteria. To achieve this, the evaluation system will be carefully designed with a focus on high output accuracy and operational efficiency. The evaluation system will then be tested to ensure it runs with both high accuracy and fast processing speeds, ensuring reliable performance assessments.

The third objective is to develop a decision support system that aids in strategic decision-making by integrating the evaluation model with sensitivity analysis. This system helps determine the optimal locations and capacities of PLs by allowing decision-makers to explore and assess various scenarios. By conducting sensitivity analysis within the evaluation model, the system can address key strategic decisions, providing insights into how different factors influence the deployment plan for these facilities. This approach ensures that both operational and strategic considerations are evaluated in tandem, offering a comprehensive tool for optimising the CS system.

## **1.4 Thesis structure**

This thesis is organized into six chapters. Figure 1.4 illustrates the connection between the chapters and the research objectives, which are further elaborated upon in the following. The first chapter, Introduction, elucidates the motivation behind this PhD research, delineates the research problem and objective, and introduces the Research Questions (RQs). Chapter 2, *A Systematic Literature Review*, assesses the literature on CS utilizing a content-based framework grounded in the Triple Bottom Line (TBL) approach. This chapter involves the review, classification, synthesis, and analysis of papers to uncover prevailing research trends, challenges, potential areas, and gaps. Chapter 3, *CS Participation*, delves into the behavioural insights regarding the involvement of PT passengers in PT-based CS systems. This chapter focuses on one aspect of the first research objective outlined in the thesis. In Chapter 4, *CS Task Acceptance*, the focus shifts to another behavioural aspect, specifically measuring the likelihood of PT passengers accepting various CS tasks within the CS system. Chapter 4 concludes the exploration of the first research objective of the thesis. Operational and Strategic Planning, covered in Chapter 5, integrates the behavioural models developed in Chapters 3 and 4 into an optimization model. This model is designed to formulate a PT-based CS system at both operational and strategic decision-making levels. As a result, this chapter encompasses the investigation of both the second and third objectives of the research. Finally, Chapter 6, *Conclusions and Future Directions*, offers responses to the research problem, aim, objectives,

and questions. It outlines the contributions made by this research to the existing body of knowledge and suggests new avenues for future studies

## **CHAPTER 2**

# **Crowdshipping for Sustainable City Logistics: A Systematic Review of the Literature**

## 2 Crowdshipping for Sustainable City Logistics: A Systematic Review of the Literature

### Preface

In Chapter 2, an in-depth examination of CS is presented through the lens of sustainability. This review employs a content-based framework rooted in the TBL approach. Within this framework, papers undergo thorough review, classification, synthesis, and analysis to unveil prevailing research trends, challenges, potential areas, and gaps. The presented materials are based on an original journal paper published in *Transportation Research Part E: Logistics and Transportation Review* as follows:

Mohri, S.S., Ghaderi, H., Nassir, N. and Thompson, R.G., 2023. Crowdshipping for sustainable urban logistics: A systematic review of the literature. *Transportation Research Part E: Logistics and Transportation Review*, 178, p.103289. <https://doi.org/10.1016/j.tre.2023.103289>

This chapter is presented as a standalone research study in a journal publication format. There have been only minor changes to conform to the thesis style and section numbering.

## Abstract

CS solutions have been gaining popularity in industry and academia. Despite numerous CS platforms having been introduced in the real world, only a limited number of them have managed to remain viable. Academics have explored many challenges facing CS platforms and recommended appropriate solution measures. While the growing literature sporadically indicates “*economic*”, “*environmental*” or even “*societal*” benefits of CS initiatives, there is a lack of systematic and conclusive understanding of CS initiatives from these essential “*sustainability perspectives*”. Considering that sustainability and societal impacts of such new and emerging initiatives are key factors in gaining public policy support and potential government investments and involvements, as critical success factors for the uptake, growth and continuity of these initiatives, this paper aims to present a review of this topic in light of sustainability considerations. A content-based framework grounded on the TBL approach is adopted in this review and papers are reviewed, classified, synthesised, and analysed to reveal dominant research trends, challenges, potential and gaps. Furthermore, our analysis of the economic and behavioural considerations of CS actors reveals important insights into how various pricing strategies can be adopted to regulate supply and demand for operational continuity. Finally, using an intersectional sustainability approach, future research directions are also recommended to fill the gaps and improve the practical relevance of CS.

## 2.1 Introduction

As the result of increasing LMD activity and changing customers’ expectations for quick, free and flexible delivery services, cities are experiencing worsening levels of traffic congestion, air pollution, road accidents, and exacerbating challenges associated with couriers’ operations in urban transport systems (Simoni et al., 2020; Pratap et al., 2023). Given infrastructure bottlenecks, several innovative initiatives have been proposed in recent years to foster further collaboration among stakeholders and improve the utilisation of existing resources to address the growing challenges of urban freight. A niche, yet emerging number of such efforts fall under the umbrella of “Crowd Logistics”, which is defined by Frehe et al. (2017) as, “the outsourcing of logistics services to a mass of (not necessarily business) actors, whereby the coordination is supported by a technical platform, which is hosted and managed by a crowd logistics provider”. While crowd logistics can comprise a wide range of logistics

services (i.e., transport and warehousing), the dominant model is known as CS, also known as crowdsourced delivery. CS is a broad term with many definitions proposed in the literature (Gläser et al., 2021). In this paper, we reiterate the definition by Buldeo Rai et al. (2017): “CS is an information connectivity enabled marketplace concept that matches supply and demand for any kind of transportation of goods with an undefined and external crowd that has free capacity with regards to time and/or space, participates on a voluntary basis, and is compensated accordingly”.

CS has become an integral part of city logistics research with many well-recognised challenges, including dynamic delivery routing as well as pricing problems (Savelsbergh and van Woensel, 2016). Given the interest in CS among both researchers and practitioners and considering the environmental and societal implications of such emerging initiatives, this paper aims to present a comprehensive and timely review of this topic in light of growing city logistics challenges. By utilising a systematic literature review (SLR) approach, this paper provides an analytical review of the recent CS literature published in top-ranked operations management, operations research and transport journals and peer-reviewed conferences. Our SLR also incorporates a content-based framework grounded in the TBL concept, through which we study the extant research efforts in relation to the topic of sustainability. Specifically, we intend to answer the following RQ:

*How does CS contribute to city logistics sustainability?*

The remainder of this paper is organised as follows. In Section 2.2, we describe the SLR protocol, along with a descriptive bibliographic analysis. In Section 2.3, we focus on studies pertaining to the operational and economic aspects of CS, followed by environmental and social aspects in Sections 2.4 and 2.5, respectively. Finally, concluding remarks and future research directions are provided in Section 6.

## **2.2 Review Methodology**

Extracting relevant scholarly works

The aim of this research is to survey the extant literature pertaining to the intersection of CS and sustainability, and subsequently, to determine topics of interest among researchers, research gaps and opportunities for future research. To achieve this objective, we conduct a systematic literature review (SLR), which is known to be an appropriate and unbiased approach to conceptualise the literature and provide direction for theory building (Ambikar et al., 2022). In contrast to narrative reviews that are less structured, SLRs employ rigorous methodologies

to objectively observe research developments, particularly when studying emerging field such as CS (Kitchenham et al., 2010). To conduct the SLR, a protocol is needed to serve as our guiding framework for identifying, selecting, and analysing relevant studies (Dohale et al., 2022), as shown in Table 2.1. Our review protocol included articles published in English until 21 April 2023. We prepared a keyword string, based on the most prevalent terms used in CS research, particularly those pertaining to the applications of crowdsourcing for LMD. Scopus was considered as our main database, owing to its versatile search engine functionality and source coverage (Pournader et al., 2021). Furthermore, as CS is an emerging multidisciplinary field, we included Q2 journals and peer-reviewed conference papers to incorporate state-of-the-art topics.

*Table 2.1 Literature review protocol*

| <b>Protocol</b>   | <b>Description</b>                                                                                                                                                     |
|-------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Database          | Scopus                                                                                                                                                                 |
| Publication type  | Journal and conference papers                                                                                                                                          |
| Article language  | English                                                                                                                                                                |
| Timeline          | Until 21st April 2023                                                                                                                                                  |
| Search fields     | Title, keywords, and abstract                                                                                                                                          |
| Utilised keywords | crowd logistics” OR “crowd-shipping” OR (“crowdsourcing” AND “delivery”) OR “crowdsource delivery” OR “crowdsource-enabled delivery system” OR “crowdsourced shipping” |
| Data analysis     | Content-based analysis grounded on the TBL approach                                                                                                                    |

Our review methodology is inspired by a five-step approach developed by Dohale et al. (2022) to justify, extract, analyse and report on the extant studies relevant to the domain of interest (Figure 2.1). In Step 1, based on the SLR protocol, the initial pool of studies was established, resulting in 665 articles. In Step 2, we first conducted title and abstract screening, which reduced our pool to 196 articles. Subsequently, we performed full-text screening according to our inclusion criteria. This process resulted in 96 articles, of which 76 were published in Q1 journals and 20 associated with Q2 journals and high-quality conference proceedings. In Step 3. In Step 3, a full-text review of the papers was completed, followed by their analysis according to our TBL framework in Step 4. Finally, research gaps and future research opportunities were identified in Step 5.

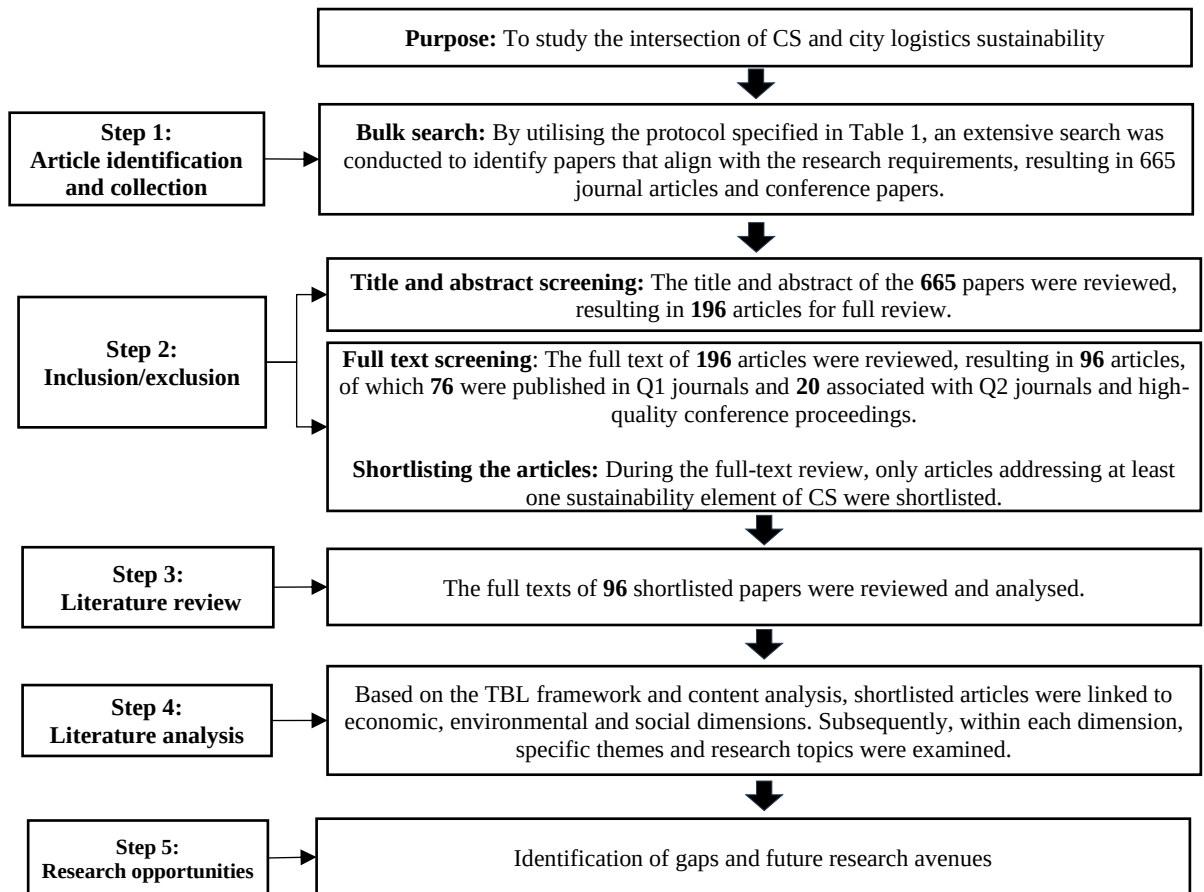


Figure 2.1 Literature review methodology

Figure 2.2 shows the distribution of journals and conferences, where Transportation Research Part E and European Journal of Operational Research are the leading outlets. Our pool also comprises 11 articles from INFORMS journals. This suggests CS is an emerging and scientifically relevant topic in the field of transport, logistics and operations research. Figure 2.3 illustrates the count of journal papers in each year based on a three-year moving average, where an ascending trend is evident.

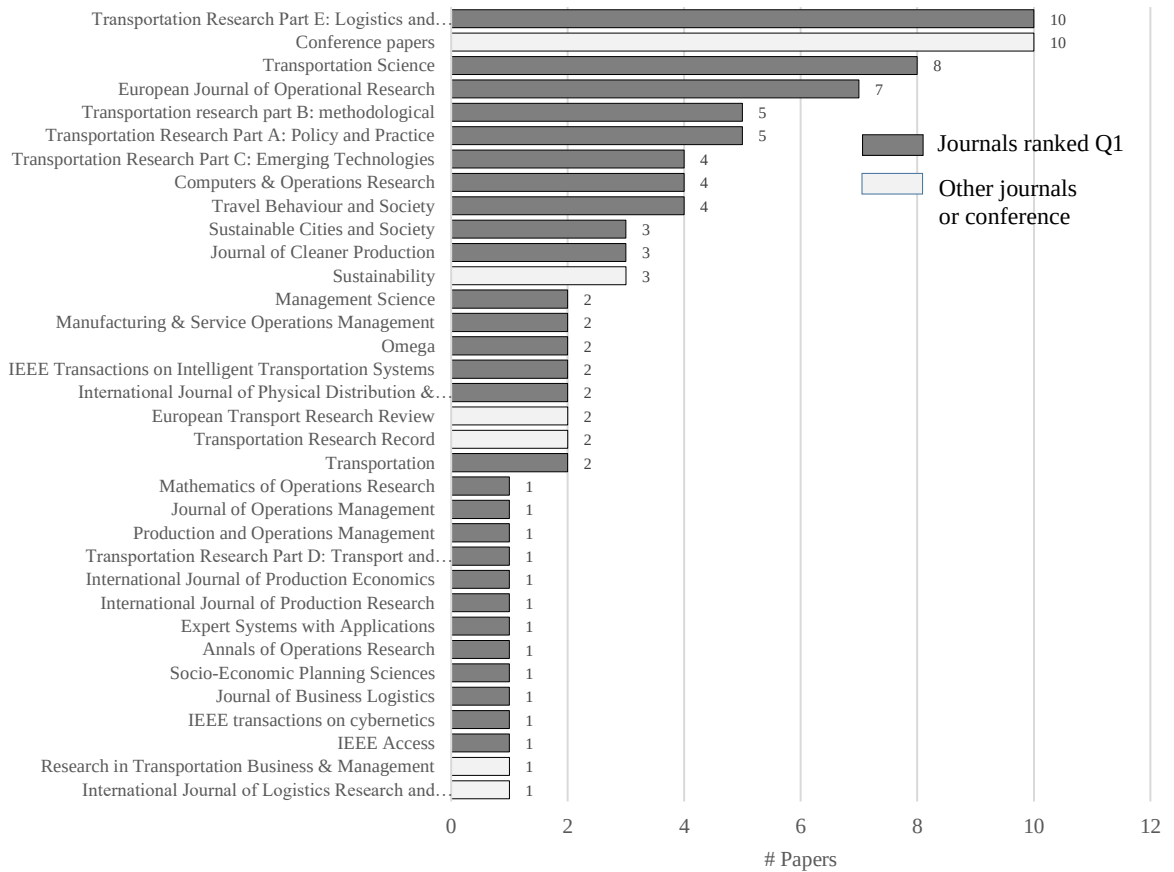


Figure 2.2 Outlets with the frequency of published CS papers.

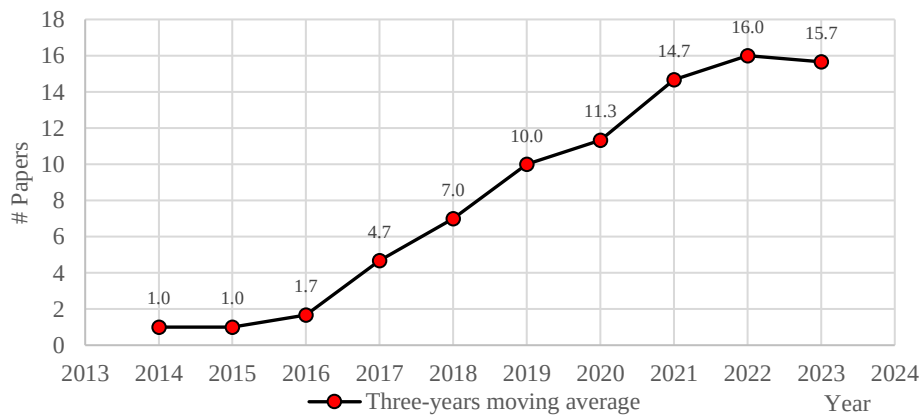


Figure 2.3 Count of CS papers in selected journals.

### 2.2.1 Existing surveys and paper contributions

At the broadest level, two categories of review papers study the topic of CS. First, studies such as Carbone et al. (2017), Ciobotaru and Chankov (2021), and Pourrahmani and Jaller (2021) conceptualise the concept of CS within logistics value chain and investigate real-world platform characteristics, and business models. This category of studies, published in earlier

years, predominantly relies on industry-based content and publicly available sources to achieve their respective research objectives. While providing useful directions for other research disciplines to further expand CS research, they are also informative for practitioners to better understand the business value of crowdsourcing in providing logistics services.

The latter category includes papers presenting more specific and technical content compared to the first group. For example, Le et al. (2019) studied CS based on three aspects of supply (crowdshippers), demand (receivers and senders), and operations and management models (CS platform). More recently, Alnaggar et al. (2021) adopted an operations research perspective to distinguish existing work in terms of their modelling techniques, decisions, assumptions, and objectives. Nevertheless, the study of Alnaggar et al. (2021) is relatively dedicated to elucidating the convergence between CS and ridesharing and ride-hailing systems. The study by Gläser et al. (2021) is a specific review paper that primarily examines academic research concerning the application of CS initiatives in last-mile logistics. Additionally, the paper delves into the challenges of CS in comparison to traditional delivery systems. Table 2.2 presents a summary of existing CS review papers.

We also acknowledge that the study of CS is evolving quickly. For example, since January 2019, nearly 55 high-quality papers have been published on various aspects of CS. This has necessitated the need for a recent and comprehensive review to provide state-of-the-art developments and findings on CS. Furthermore, recent studies emphasise the sustainability benefits of CS, specifically by proposing models that could lead to environmental and social outcomes (Ghaderi et al., 2022a;2022b). The review conducted by Le et al. (2019) analysed CS from the standpoint of its players, while Alnaggar et al. (2021) approached it from an operations research perspective, with a focus on modelling. However, the absence of a sustainability-cantered review is noticeable in the literature, particularly considering the net zero targets adopted by transport and logistics organisations, as well as retailers. Hence, given this research gap and evolving field, this study presents a unique taxonomical review of the CS literature based on a sustainability perspective, particularly to understand the working mechanisms and complexities associated with people (society), profit (economy), and the planet (environment) of this new business paradigm.

*Table 2.2 Summary of existing review papers on CS.*

| <b>Article</b> | <b>Review timeline</b> | <b># Reviewed materials</b> | <b>Research method</b> | <b>Sustainability focus</b> | <b>Areas of study</b> |
|----------------|------------------------|-----------------------------|------------------------|-----------------------------|-----------------------|
|----------------|------------------------|-----------------------------|------------------------|-----------------------------|-----------------------|

|                        |               |               |            |     |                                                       |
|------------------------|---------------|---------------|------------|-----|-------------------------------------------------------|
| Le et al (2019)        | 2012-2018     | 58 Papers     | Systematic | No  | CS Supply, demand and operations models               |
| Alnaggar et al. (2021) | Not specified | Not specified | Narrative  | No  | Assumptions, decisions, modelling types and platforms |
| Gläser et al. (2021)   | 2006-2020     | 61 Papers     | Systematic | No  | Not specified                                         |
| Current paper          | 2023          | 96 Papers     | Systematic | Yes | TBL                                                   |

## 2.3 Economic Aspects

CS is an emerging logistics service provision paradigm that is associated with new and less studied forms of business models and market dynamics, wherein players interact with each other by exchanging parcels, information, and financial transactions (Chen et al., 2022). Senders request the delivery service for an item, who can range from being a business providing a service or merchandise such as e-commerce companies, restaurants, and grocery stores, to non-profit organisations such as libraries and individuals. Similarly, receivers can be individuals or businesses. Given the characteristics of senders and receivers, four different CS business models can be identified: Business-to-Business (B2B), Business-to-Customer (B2C), Customer-to-Business (C2B), and Customer-to-Customer (C2C), also known as peer-to-peer (Rougès and Montreuil, 2014). On the other hand, crowdshippers are occasional couriers who conduct the whole or a part of the delivery. Finally, the CS platform is responsible for coordinating both sides of the market in which crowdshippers (supply side) and senders/receivers (demand side) can interact efficiently. The CS platform's role involves four types of decisions: matching the task to crowdshippers, pricing the service, routing, and scheduling that involves determining the time for picking-up and dropping-off (Alnaggar et al., 2021). Depending on the level of involvement in the coordination process, CS platforms can vary. For example, a platform may (or may not) make any pricing recommendation or simply facilitate a bidding/negotiation mechanism to allow demand and supply negotiation for delivery fees (Ermagun and Stathopoulos, 2018). In the following section, we examine the state-of-the-art developments related to pricing strategies and financial transactions in CS systems.

### 2.3.1 Demand and supply interactions

Pricing and compensation decisions are at the core of any CS system and critical to manage supply and demand dynamics. For example, rising delivery prices encourage more crowdshippers to participate in CS work, increasing the supply base, while lower prices can lead to reduced participation (Kung and Zhong, 2017). Similar to any other market, CS demand and supply market are governed through pricing mechanisms (Yan et al., 2021; Triki, 2021).

Eventually, platform's profitability is determined, on one hand by the volume of transactions, and on the other hand, by the difference between delivery fees charged to customers and the compensation offered to crowdshippers plus management and operational costs associated with running the platform. The literature has explored different pricing decisions, their relative demand and supply interactions and how they impact on players' behaviour and decisions to engage in CS which are contextualised in Figure 2.4.

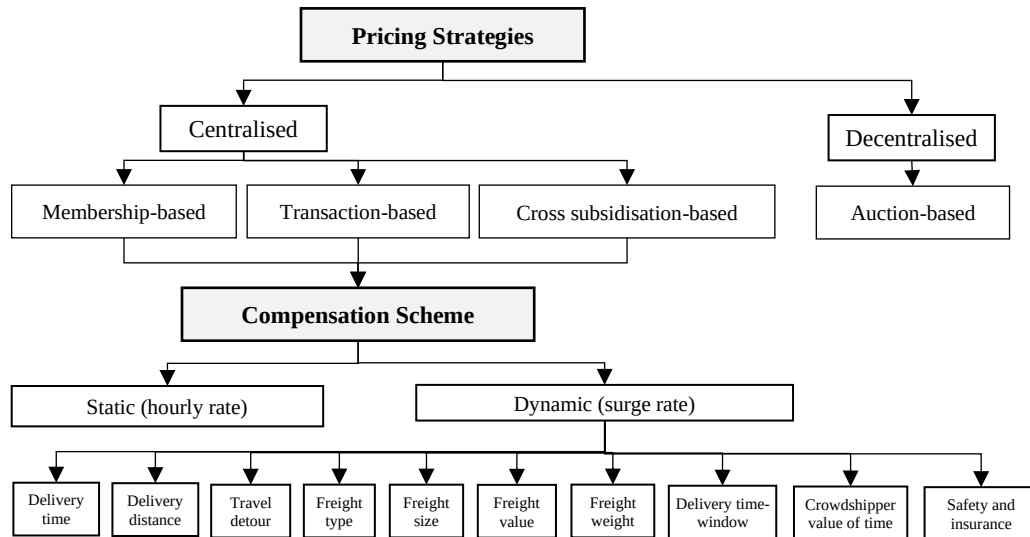


Figure 2.4 Pricing strategies and compensation schemes.

At the broadest level, pricing strategies can be categorised into centralised and decentralised models. In a centralised model, the platform has direct influence on pricing and costing decisions (Ghaderi et al., 2022a). However, in the decentralised model, the role of the platform is mainly associated with the governance of supply and demand. In such models, crowdshippers have a choice of timing and pricing, and may participate in auction and bidding processes facilitated by the platform (Ermagun et al., 2018). Platforms could also provide additional support mechanisms such as optimal routing, monitoring of traffic conditions and schedule planning. The following subsections provide a more detailed analysis of the CS pricing literature.

### 2.3.2 Centralised pricing strategies

According to Kung and Zhong (2017), centralised pricing can be classified into three pricing strategies of membership-based, transaction-based, and cross-subsidisation method. Membership-based pricing entails charging every consumer a fixed fee at the beginning of each membership period and providing free delivery for the entire service usage during that time

(Le et al., 2019). However, there can be some conditions on the maximum number of deliveries or their spatial scope. In transaction-based pricing, senders or receivers are charged per transaction, where the fee can be either fixed or variable depending on the delivery task characteristics. In the cross-subsidisation strategy, platforms receive both membership and transaction fees from senders or receivers and may keep the collected membership fees as their revenue and pay the transaction fees (total or partial) to the crowdshippers.

In a centralised model, platforms design and implement various compensation schemes to reimburse crowdshippers. Reimbursing crowdshippers can be made in static or dynamic approaches. In the static approach, the platform compensates a crowdshipper based on the total hours of being active/available, regardless of the number of completed deliveries. Some platforms guarantee a minimum hourly rate when the crowdshipper is active to improve and maintain their pool of available crowdshippers (e.g., Grubhub, 2022). In the dynamic approach, also known as surge compensation scheme, the platform offers a compensation figure for each task, which can vary based on multiple factors, as depicted in Figure 2.4. This study identifies two prominent research streams pertaining to centralised pricing strategies. The first stream involves comparing various centralised strategies to discern their respective strengths and weaknesses (Kung and Zhong, 2017; Dahle et al., 2019; Le et al., 2021; Yan et al., 2021; Wicaksono et al., 2021; Castillo et al., 2022). The second stream focuses on contrasting centralised pricing strategies in CS systems with pricing systems utilised in traditional delivery systems, aiming to underscore the advantages of CS centralised pricing strategies (Shen and Lin, 2020; Cao et al., 2020; Fatehi et al., 2022).

Kung and Zhong (2017) conducted a study to compare the performance of different centralised pricing strategies. They developed a two-sided pricing strategy for CS in grocery markets using a game-theoretic optimisation model to maximise profit under each pricing strategy. Findings show that when consumer order frequency is price-insensitive, all strategies perform equally. However, if order frequency depends on the per-transaction fee and the platform is impatient for revenues, membership-based pricing is the most profitable. Dahle et al. (2019) incorporated personal threshold constraints in a pickup and delivery problem to examine the acceptance behaviour of crowdshippers to design optimal compensation schemes. Three compensation schemes of fixed, dependent on travel distance and dependent on detour were tested. Findings show the schemes save 10-15% in total delivery costs of CS platforms; increased compensation complexity may lead to higher cost savings. Le et al. (2021) incorporated senders' willingness to pay (WTP) and crowdshippers' expectation to be paid

(ETP) to identify the best pricing and compensation schemes for profit maximisation. Considering different demand and supply scenarios, the authors show that the platform's profit is more sensitive to increasing WTP than ETP.

The literature acknowledges the availability of crowdshippers in the market as a major constraint, particularly when they can freely choose to work for multiple platforms (Peng et al., 2016). On one side, platforms compete to attract adequate crowdshippers for their services. On another side, crowdshippers compete over the limited monetary rewards provided by the platforms. In this regard, Yan et al. (2021) studied a two-sided competition market between platforms and crowdshippers. Using a game theoretic approach, the behaviour of platforms and crowdshippers was modelled based on non-cooperative and evolutionary games using an agent-based simulation model. Their results show increasing delivery fees and compensations can boost the platform's profit to a certain point, but the profit can decrease beyond that point. By utilising choice modelling, Wicaksono et al. (2021) investigated the demand and supply interactions for bike-based CS services to estimate the acceptance of customers for using CS services and the willingness of cyclists to work as crowdshippers. Based on a case study from the Netherlands, this study shows that although delivery fees appear to be the most important factor, flexible delivery time windows and reduced emissions were also highly influential factors. Moreover, compensation, travel time, and package weight were factors that significantly influenced the decision of crowdshippers to participate. Furthermore, it was observed that customers are more sensitive to service fees compared to crowdshippers in relation to compensation. Castillo et al. (2022) explored the implications of customer tipping for CS delivery performance. Using a multi-agent hybrid simulation, this study concluded that tipping could minimise the uncertainty in CS supply size and reduce delivery costs and time.

For CS systems employing non-professional and part-time crowdshippers, significant uncertainties exist related to the availability and mobility patterns. Such uncertainties bring along challenges for platforms in developing a reliable workforce supply. In this regard, Shen and Lin (2020) utilised data from a CS platform in the City of Atlanta (USA) to predict short-term CS delivery trips and compare the effectiveness of the CS pricing scheme with the compensation provided by FedEx. Results show that CS service has a clear price advantage over FedEx, particularly in same-day and express delivery services, as well as oversized package delivery. Cao et al. (2020) developed a CS model with the objective to minimise the expected delivery cost using dedicated drivers and crowdshippers, while maintaining optimal incentives for crowdshippers. Authors assumed that crowdshippers operate within a specified

time interval (a day) and unserved parcels would be delivered by professional drivers at the end of the time interval. The problem was formulated as a discrete sequential packing problem. Results demonstrate that CS systems utilising both crowdshippers and dedicated drivers can achieve up to 33% savings in total delivery costs compared to van-only delivery systems. Similarly, Fatehi et al. (2022) proposed a robust optimisation model for CS labour planning and pricing, as well as optimal assignment of delivery tasks. The model was designed for the case of Seattle as an on-demand delivery model with guaranteed delivery time window and experiments considered uncertainty in demand, crowd availability and traffic patterns. The findings indicate that, in comparison to a FedEx baseline scenario, CS can significantly reduce delivery costs.

### **2.3.3 Decentralised pricing strategies**

In a decentralised strategy, the platform plays an indirect governing role (He et al., 2020). Accordingly, the majority of decentralised models rely on auction-based systems, in which crowdshippers and sender/receivers interact directly (Ermagun and Stathopoulos, 2018). Various types of auction-based systems have been employed in the freight transport literature, where bidding systems are the most recognised model (Lafkihi et al., 2019). In the CS domain, reverse auction-based systems have received popularity, in which crowdshippers compete to win delivery work with the lowest bid (Hong et al., 2019). Triki (2021) studied the impact of bidding systems on total CS delivery costs by combining a winner determination problem and Vehicle Routing Problem (VRP) that involves dedicated vehicles and occasional drivers. Using data from an online bookstore with home delivery in Oman, authors reveal that delivery costs could be reduced by 30% when using occasional drivers participating in an auction-based system.

In a similar context, Ermagun and Stathopoulos (2018) explored factors influencing CS supply size in the bidding system using large historical data from different cities across the USA. They considered package characteristics, built environment and socio-economic factors as the determinants of crowdshippers supply. By developing a two-part supply model based on the probability of receiving a bid from a crowdshipper (a binary logit) and the total number of bids (a negative binomial regression), results show strict delivery deadline could drop the number of bids. Ermagun et al. (2020a) formulated a nested logit model to measure the probabilities of bidding, acceptance, and delivery of CS tasks. Findings show larger shipment sizes increase the likelihood of bid placement, while strict deadlines have the opposite effect.

However, this trend reverses during the delivery phase. Using a random forest machine-learning algorithm, Ermagun et al. (2020b) show that in addition to larger shipments, out-of-state destinations and C2C delivery have a lower chance of receiving a bid, which likely reflects the perceived risks of such transactions.

In summary, CS pricing and compensation schemes, along with their impacts on the supply and demand dynamics, are summarised in Table 2.3. About two-thirds of studies incorporate a centralised pricing approach, within them transaction-based models appear to be the most dominant mechanism. In terms of compensation schemes, static approaches have received significantly more attention compared to dynamic ones. This preference may stem from the simplicity of such payment systems and ease of understanding by crowdshippers. Advancements in computer science and artificial intelligence (AI) present opportunities for implementing behavioural and dynamic compensation schemes. Furthermore, the literature pertaining to decentralised systems is limited to negotiation and bidding processes. An opportunity for future research is to further model and understand other interaction mechanisms among crowdshippers, senders, and receivers. In terms of model development and pricing system design, the majority of research involves optimisation techniques using game theory. However, the inclusion of behavioural aspects, such as willingness to participate in CS systems and acceptance of CS tasks, has received less emphasis in the design models of CS pricing (Ermagun et al., 2020a; Wicaksono et al., 2021).

*Table 2.3 Summary of studies exploring CS supply and demand interactions.*

| Reference               | Pricing strategy                                                          | Compensation scheme | Research focus                      | Method                                    | Observations                                    |
|-------------------------|---------------------------------------------------------------------------|---------------------|-------------------------------------|-------------------------------------------|-------------------------------------------------|
| Kung and Zhong (2017)   | Centralised: Membership-based, Transaction-based, and Cross subsidisation | Static              | Comparing pricing strategies        | Optimisation (game modelling)             | Senders and crowdshippers are the same.         |
| Le et al. (2021)        | Centralised: Transaction-based                                            | Static and dynamic  | Pricing and compensation design     | optimisation with behavioural constraints | Considering senders' ETP and crowdshippers' WTP |
| Dahle et al. (2019)     | Centralised: Transaction-based                                            | Static and dynamic  | Pricing and compensation design     | optimisation with behavioural constraints | -                                               |
| Yan et al. (2021)       | Centralised: Transaction-based                                            | Static              | Pricing and compensation evaluation | Game theory & simulation                  | Competition between CS platforms                |
| Wicaksono et al. (2021) | Centralised: Transaction-based                                            | Static              | Pricing and compensation evaluation | Game theory & Choice modelling            | -                                               |
| Shen and Lin (2020)     | Centralised: Transaction-based                                            | Dynamic             | CS trip generation                  | Deep learning                             | -                                               |
| Cao et al. (2020)       | Centralised: Transaction-based                                            | Static              | Pricing and compensation design     | Discrete sequential packing problem       | Real-time CS matching                           |
| Fatehi et al. (2022)    | Centralised: Transaction-based                                            | Static              | Pricing and compensation design     | Robust optimisation                       |                                                 |
| Castillo et al. (2022)  | Centralised: Transaction-based                                            | Dynamic             | Evaluation of tipping               | Simulation & netnography                  | Use of empirical data                           |

|                                 |               |     |                                  |                                  |                           |
|---------------------------------|---------------|-----|----------------------------------|----------------------------------|---------------------------|
| Triki (2021)                    | Decentralised | N/a | Evaluating auction-based systems | Optimisation                     | -                         |
| Ermagun and Stathopoulos (2018) | Decentralised | N/a | Evaluating auction-based systems | Regression and choice modelling  | Use of historical CS data |
| Ermagun et al. (2020a)          | Decentralised | N/a | Evaluating auction-based systems | Choice modelling (nested-logit)  | Use of historical CS data |
| Ermagun et al. (2020b)          | Decentralised | N/a | Evaluating auction-based systems | Machine learning (random forest) | Use of historical CS data |

## 2.4 Operational considerations

Advancements in information and communication technology (ICT) and the widespread use of smartphone applications present opportunities to improve the efficiency and use of crowdsourced logistics (Mladenow et al., 2016). The availability of a large pool of crowdshippers connected via mobile phone devices allows for real-time and optimal matching and job assignment and systems efficiency. This section reviews important aspects relating to methodologies for enabling and maximising CS operational efficiency.

### 2.4.1 Time-space flexibilities

Point-to-point delivery employing crowdshippers presents several spatial and temporal constraints. These constraints are predominantly driven by the dynamic and stochastic natures of the crowdshippers' mobility patterns and potential mismatch between demand (i.e., parcel delivery requirements) and supply (i.e., crowdshippers). When a CS system service commits to special offerings such as fast or same-day delivery, such constraints become more pressing (Dayarian and Savelsbergh, 2020). To address these challenges, some studies propose advanced matching, routing and scheduling algorithms where the spatial-temporal constraints are explicitly formulated (Feng et al., 2019; Archetti et al., 2021). In this review, these studies are grouped under the category of 'Base Approach'. Studies pertaining to Base Approach contribute to the development of operational and tactical models to support task assignment and routing. However, due to their point-to-point structure, their performance is limited by time-space constraints. To gain further efficiency, four alternate approaches have been proposed in CS studies (see Figure 2.5) that relax some of the time-space constraints, which are summarised here:

- **Approach 1:** Offering a menu of CS delivery task options for each crowdshipper;

- **Approach 2:** Identifying and utilising crowdshippers with similar mobility patterns as the delivery job, resulting in quicker and more efficient matching and delivery (e.g., delivery along commute trip, or by in-store customers);
- **Approach 3:** Employing Alternative Delivery Points (ADPs) as pick-up and drop-off locations;
- **Approach 4:** Introducing temporary and permanent TPs into the delivery network structure.

Furthermore, hybrid approaches exist that incorporate more than one of the abovementioned models. For instance, placing ADPs in PT stations and employing PT users for moving parcels between ADPs (Fessler et al., 2022; Mohri et al., 2023b).

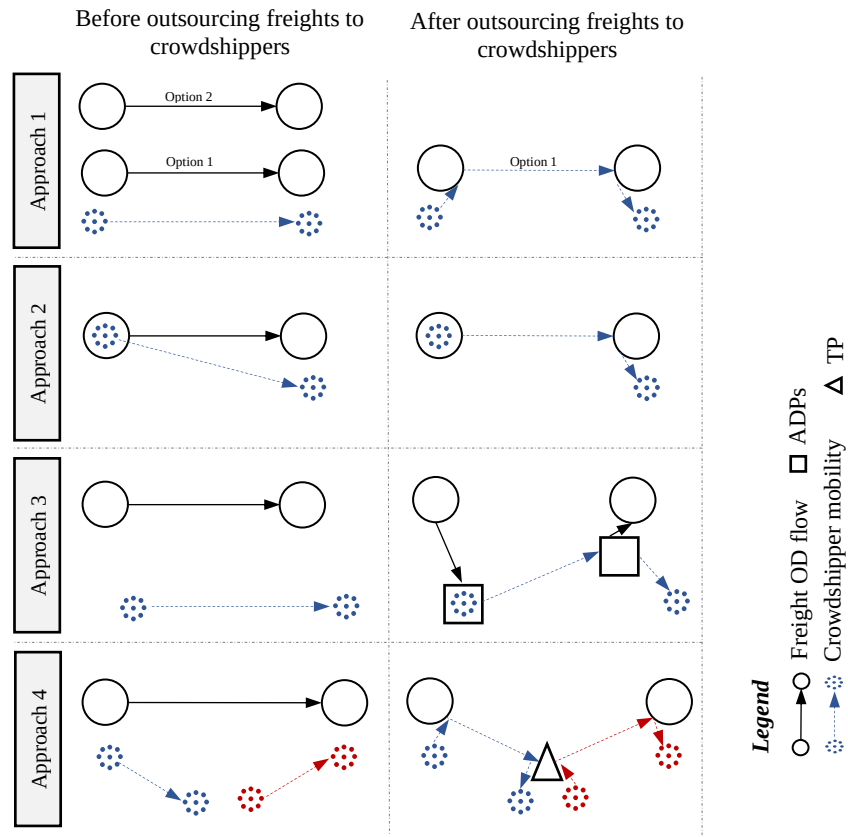


Figure 2.5 Approaches for providing time-space flexibility.

## 2.4.2 Base Approach: strict time-space constraints

As the Base Approach, certain CS studies incorporate time-space restrictions associated with crowdshippers' mobility patterns and delivery demands into the CS operational models.

For instance, Feng et al. (2019) proposed a generalised variant of the VRP with dedicated vehicles and occasional drivers that represent heterogeneous costs, time windows, and vehicle capacities. With the objective of minimising total fixed and variable costs, results show that employing occasional drivers could significantly reduce costs due to their low fixed costs. Similarly, Archetti et al. (2021) studied an online VRP with a company's owned fleet supported by occasional drivers available in specific time windows. With the objective of minimising total distribution costs, authors considered a penalty function when time windows were violated. Assuming that customer requests were either known before distribution planning or placed during the distribution process, experiments indicate that finding high-quality solutions challenging when both customer requests and occasional drivers' availability are subject to change. Pugliese et al. (2023) examined a CS system similar to Archetti et al. (2021) with a focus on the uncertainty in occasional drivers' travel time. To model this uncertainty, authors formulated a robust optimisation model and solved it using both Benders' decomposition and column-and-row generation algorithms. Considering time-space and capacity restrictions, Ahamed et al. (2022) proposed a deep reinforcement algorithm for the CS task assignment problem. Results show that the model is superior to the previous techniques in terms of solution quality, computational time, and scalability.

### **2.4.3 Approach 1: Menu offering**

Some CS platforms such as DoorDash and Roadie provide a full list of tasks to crowdshippers, allowing them to select their preferred tasks. Although this approach can reduce the spatial-temporal mismatch between demand and supply, studies such as Einav et al. (2015) and Newton (2014) demonstrate that such matching strategy results in a lower number of fulfilled deliveries. In this context, Horner et al. (2021) explored the possibility of offering a personalised menu rather than a full menu using a leader (platform)-follower (crowdshipper) game, where the platform optimises the menu with limited knowledge of crowdshippers' preferences. In the personalised menus, task duplications might occur. To tackle the challenge of eliminating duplicate CS tasks from multiple crowdshipper menus, Ausseil et al. (2022) proposed a two-stage stochastic model for optimising menu design, where the overlap between menus is bounded. The efficacy of the model was evaluated using data from the city of Chicago, and the results indicate that optimised menus not only enhanced the revenue of the platform but also led to an increased number of successful matches and a reduced waiting time for crowdshippers and deliveries.

#### **2.4.4 Approach 2: In-service crowd**

Traditional retailers with physical stores across urban areas could offer fast deliveries when utilising in-store customers as crowdshippers in return for compensation. Archetti et al. (2016) is one of the first studies suggesting the use of in-store customers as crowdshippers. In this study, the problem is formulated as a VRP, in which deliveries are performed using dedicated drivers/vehicles (i.e., dedicated company-owned or outsourced drivers/vehicles) and occasional drivers from in-store customers. In-store customers declare their willingness to deliver parcels ordered by online customers after arriving at the store, , therefore, the origin of all occasional drivers is the store, compared to the Base Approach with varying origin point.

Ni et al. (2019) measured the performance of a CS system for same-day delivery utilising in-store customers, dedicated drivers and information-sharing drivers (ISDs). ISDs are occasional drivers who share their forthcoming trips with retailers. A multi-period mathematical model was proposed, in which the orders are received periodically within a time horizon. The decision variables determine the appropriate depot for dispatching a parcel and selecting the best courier. The model minimises the total system costs, including delivery by different methods and a penalty cost for unfulfilled same-day delivery orders. The model constraints included the maximum number of available occasional drivers, store inventory, the delivery processing capacity of stores and the detour tolerance of ISDs. Dayarian and Savelsbergh (2020) studied the potential of employing in-store customers for same-day delivery, with online orders and in-store customer arrivals to the shop as stochastic inputs. The authors evaluated the overall performance of the system in terms of cost and service quality. Results show that a larger set of participating in-store customers could significantly improve service quality and reduce system costs. Another observation revealed that employing in-store customers is most beneficial when the delivery system is under stress (i.e., when there is limited information on future demand and short delivery requirements). Hou and Wang (2021) considered in-store customers' willingness to accept a delivery job. They proposed a two-stage stochastic model to match the online orders to in-store customers with an optimal compensation scheme that minimises total systems costs. Results show that the average delivery cost can be reduced by 7.30%, compared to delivery by dedicated vehicles when incorporating a compensation scheme based on crowdshippers acceptance behaviour. Similarly, Barbosa et al. (2023) modelled the probability of delivery acceptance by in-store customers with a logit model

based on questionnaire data, with incentive as the only explanatory variable. The logit model was integrated into a direct search algorithm to optimise CS routing, matching, and pricing decisions.

### **2.4.5 Approach 3: ADPs**

CDPs, pick-up points, self-collection points, collection terminals or mobile PLs are terms that are used interchangeably in the literature for ADPs (Pan et al., 2021). Incorporating ADPs in CS systems is known to be a successful mechanism to introduce spatial-temporal synergy among senders, receivers and crowdshippers (Vincent et al., 2022). Despite its theoretical advantages, there are operational and behavioural challenges that prevent the effective implementation of ADPS into CS systems. (Gatta et al., 2019a).

Chen et al. (2016) contend that large-scale fast delivery would not be feasible without restructuring the delivery network and incorporating ADPs. Using a case study from Hangzhou, China, experimental results show that over 85% of packages can be delivered within 8 hours when utilising ADPs, which is considerably faster than the conventional courier network model. Similarly, Gatta et al. (2019a), Fessler et al. (2022), Vincent et al. (2022), and Kızıl and Yıldız (2023) have also investigated CS networks involving ADPs. Gatta et al. (2019a) and Fessler et al. (2022) studied the application of ADPs in PT-based CS systems, in which PT passengers were the crowdshippers. Authors indicate that utilising the existing mobility patterns of PT passengers in CS without employing lockers as parcel pick-up and drop-off points in stations would not be practical. Kızıl and Yıldız (2023) suggest introducing a transfer facility (i.e., ADP) as a backup mechanism inside PT stations, by which passengers move parcels between the transfer facilities and lockers, while locker-to-locker movement is conducted by PT vehicles. Mohri et al. (2023a) investigated a locker-to-home CS system in which lockers are used as the only parcel pick-up points. Using survey data collected from Sydney metropolitan residents, the authors observed that removing lockers as drop-off points can raise safety and security concerns for both crowdshippers and receivers due to their direct contact for fulfilling a parcel delivery. Vincent et al. (2022) evaluated the performance of ADP supported CS systems in which receivers can select their preferred delivery option. While only dedicated drivers could deliver parcels to ADPs, results show that incorporating such facilities could reduce costs by around 28%.

#### 2.4.6 Approach 4: Employing TPs

The idea of using TPs, also called mini depots or micro hubs, in CS systems was initially introduced by Kafle et al. (2017). There is a consensus in the literature that TPs could significantly improve the overall performance of CS systems in terms of cost and service quality (Nieto-Isaza et al., 2022; Vincent et al., 2022). TPs can be categorised into two groups: stationary and mobile. Contrary to stationary TPs, mobile TPs can have flexible locations and capacities, hence providing a more flexible option for markets with dynamic demand and supply (Faugère et al., 2020).

**Stationary TPs:** Ballare and Lin (2020) compared the performance of TP-integrated CS systems involving occasional drivers and cyclists as crowdshippers with a traditional hub and spoke system in terms of reduction in truck movements, fuel consumption and operational costs. The study indicated that the hub and spoke system outperforms the CS in small instances (less than 18000 customers) in terms of daily operational costs, while CS performs better in larger cases located in high-density and metropolitan environments. Similarly, using an experimental study conducted in the Hague, Netherlands, Lin et al. (2020) showed that delivering every package using multiple cyclists, as crowdshippers, without employing TPs will increase the level of intrusiveness to cyclists' daily trips. In the same vein, Yıldız (2021a) proposed a two-echelon CS system with occasional drivers and dedicated vehicles to identify an optimal package routing policy for minimising total delivery costs. In the first echelon of the CS system, the movement of parcels from depots to lockers or from lockers to customer homes was optimised, while transfers between TPs were addressed in the second echelon.

Ghaderi et al. (2022b) explored the utilisation of green CS with PLs, in which a delivery task could be performed by one or multiple crowdshippers using PLs as exchange points. A two-phase algorithm was proposed to rate and select lockers from candidate locations. The algorithm initially classifies jobs into single and joint delivery and then scores PLs by their utilisation in joint delivery. Numerical results of this study performed on large instances demonstrate that joint CS delivery enhances delivery success by up to 5%. From the findings of Ghaderi et al. (2022b), it can be concluded that collaborative or joint CS has the potential for parcel delivery in low-density-long-distance settings.

In another study, Nieto-Isaza et al. (2022) identified the optimal location and number of TPs in CS systems. A two-stage stochastic model was formulated with time-dependent delivery capacity and volume. based on Munich's PT network, authors showed that employing crowdshippers could decrease the total cost between 2.1% to 7.6%, depending on the number

of TPs. Moreover, it was observed that in large cases, 23% to 60% of the shipments allocated to crowdshippers were routed through TPs. Wang et al. (2023a) investigated the optimisation of parcel allocation to TPs and crowd routing. This study considers a cost minimisation problem with the possibility of multiple deliveries by crowdshippers, provided that delivery time windows, vehicle capacity, and route maximum duration constraints are met. Authors reveal that stationary TPs should be located between the boundary and the centre of a delivery region to improve delivery performance.

**Mobile TPs:** While stationary TPs provide several benefits to both couriers and customers, they come with inherent limitations. Mobile TPs or relay points, present spatial flexibility by utilising dormant assets such as in-operation trucks, vehicle trunks or any other assets with available storage capacity. In this context, Kafle et al. (2017) proposed a CS system for urban deliveries involving pedestrians and cyclists to perform the first and final segments of trips in cooperation with a truck. In this study, it was assumed that crowdshippers submit their bids and then the courier coordinates the crowdshippers with their truck operations by offering alternative relay points. A mathematical model was formulated in which the selection of crowdshippers, relay points and truck routing and scheduling are optimised, with the objective of minimising the total cost of truck operation, crowdshippers' compensation and penalty associated with delivering parcels outside customers' desired time windows. The experimental results show that compared to the traditional truck-only delivery model, CS can reduce the total costs and vehicle miles travelled (VMT) by 9.25% and 24%, respectively. However, the reductions are sensitive to factors such as crowdshippers transport mode and Value of Time (VoT). Lan et al. (2022) proposed a two-echelon CS system with mobile TPs. In the first echelon, trucks move parcels from a depot to TPs, while in the second echelon, occasional drivers move parcels from TPs to customers' homes. A multi-objective model was formulated to minimise total delivery costs while maximising customer and crowdshipper satisfaction. Customer satisfaction was measured by the difference in actual vs. ideal delivery time and crowdshipper satisfaction was estimated by the ratio of the total deviated distance from their original itineraries. Results show that employing CS in conjunction with mobile TPs can reduce the average delivery cost by 3% and increase delivery speed by up to 42%. Similar to Lan et al. (2022), Mousavi et al. (2022) proposed a two-stage stochastic model with mobile TPs, in which crowdshippers' availability was subject to uncertainty.

In summary, studies related to time-space flexibilities reveal that effective matching is a challenging task due to the dynamic and stochastic nature of crowdshippers' mobility and

demand patterns. In the literature, several solutions have been proposed to address this issue, which were reviewed in Subsection 2.3.2. Some studies suggest incorporating spatiotemporal constraints into matching algorithms or offering a menu of CS tasks to each crowdshipper. However, such approaches have shortcomings, leaving delivery tasks unfulfilled (Feng et al., 2019; Archetti et al., 2021; Horner et al., 2021). To address this challenge, others suggest involving different types of crowdshippers such as in-store customers, which again comes with challenges for online retailers that have no physical stores (Archetti et al., 2016; Savelsbergh, 2020). More recent studies aim to improve systems flexibility by introducing ADPs, allowing for improved assignment of deliveries to crowdshippers (Ghaderi et al., 2022b; Vincent et al., 2022; Chen et al., 2016). While ADPs can improve matching, challenges remain in the first and last legs of deliveries (between sender location and ADP, and between ADP and customer location). Accordingly, a new line of research proposes the inclusion of TPs, enabling joint deliveries (Macrina et al., 2020; Mousavi et al., 2022). However, incorporating TPs and joint delivery also comes with challenges related to fairness of compensation. Furthermore, the decision of whether TPs should be stationary or mobile remains open in the literature.

#### **2.4.7 Spatiotemporal uncertainties**

In CS systems, the availability of receivers and crowdshippers as well as the arrival of delivery tasks is subject to uncertainty. To address the uncertainties associated with the availability of crowdshippers, Ulmer and Savelsbergh (2020) proposed a model to evaluate a combination of scheduled and unscheduled crowdshippers. Scheduled crowdshippers are those who are rewarded by the platform to be available for certain periods. Their results reveal that the value of unscheduled crowdshippers is significantly less than scheduled crowdshippers, and if unscheduled crowdshippers announce their start time in advance, the service level could be largely improved. Similarly, Behrendt et al. (2022) proposed a machine-learning approach to improve shift settings for scheduled crowdshippers. The methodology leveraged simulation-based optimisation for offline training and employed a neural network for online solution prescription. The machine learning method resulted in solution quality comparable to that of a bespoke sample average approximation method while exhibiting superior performance for online solution generation. Inspired by the results of Ulmer and Savelsbergh (2020), studies of Yildiz (2021a) and Yildiz (2021b) proposed CS systems with registered occasional drivers declaring in advance their planned trips, preferred pick-up and drop-off points and preferred

participation times. The results show that CS systems using TPs and occasional drivers (with advanced information) have significant advantages in terms of total operational costs under short delivery lead time. Zehtabian et al. (2022) estimated occasional drivers' arrival time, where both daily demand and supply for a CS platform are subject to uncertainty. Using a Markov decision process, two look-ahead policies were assessed. The first policy considered a constant look-ahead horizon and the other with a dynamically adjusted look-ahead horizon that outperforms the former by up to 19% in term of accuracy. Mousavi et al. (2022) modelled the availability of crowdshippers as the function of their observed commuting patterns. They proposed a matching algorithm with mobile TPs, in a two-stage stochastic integer program setting. The objective function was to minimise the operational costs of mobile TPs, plus the cost of failed deliveries due to the unavailability of crowdshippers. Based on a case study from Toronto, results indicate a 3.35% to 6.08% improvement in the solution quality in the presence of uncertainty. Also, improvements are more significant when uncertainty in crowdshipper availability is higher. Ghaderi et al. (2022a) proposed employing clustering techniques to understand crowdshippers mobility patterns before assigning tasks to them. Using a two-step methodology, first, trajectory analytics are performed to profile the pool of crowd and identify the list of suitable/available crowdshippers, while task assignment is conducted in the second step to maximise profit. Silva et al. (2023) considered occasional drivers performing multiple deliveries with uncertain demand and crowdshippers availability, where the uncertain variables were assumed to be dependent. Using a worst-case probability paradigm, the marginal distribution of every uncertain variable is calculated from historical data, while their joint distribution is considered unknown.

Unattended deliveries are a major source of complexity in urban freight systems. This issue is further exacerbated in CS systems compared with conventional courier models since crowdshippers holding or re-delivery of parcels can be challenging. In this regard, Akeb et al. (2018) proposed a CS system in which neighbours of parcel receivers could collect and pass parcels to the final customer. The performance of this neighbour-based CS system was measured by running a simulation technique using a case study from Paris with a high population density. Results show that the proposed model is economically effective and can solve the issue of unattended deliveries. Torres et al. (2021) proposed hiring occasional drivers with uncertain availability who agree to start and end their trips at a parcel distribution centre. In this work, a routing problem was formulated using two-stage stochastic programming in which both occasional drivers and dedicated vehicles can fulfil deliveries. In the first stage,

occasional drivers supply is estimated probabilistically based on historical participation records. A branch-and-cut solution algorithm was utilised to solve the model for modified Solomon instances, involving a pool of 100 crowd vehicles. Results showed that the improvements resulting from the stochastic solution are as high as 18% in comparison to solutions obtained from a deterministic simplification. Furthermore, expecting crowdshippers to make round trips to a parcel distribution centre could deteriorate participation level, leading to a smaller pool of available crowdshippers. To address this issue, Torres et al. (2022) proposed a new model in which the maximum duration of CS routes was restricted. The authors also strengthened the upper bounds of the proposed branch-and-cut solution algorithm by Torres et al. (2021).

In summary, this section examined mechanisms related to managing uncertainty in CS systems. Notably, the literature has primarily focused on mitigating uncertainty in crowdshippers availability, compared to receivers' availability. However, receivers' unavailability could also result in several operational issues such as failed or missing deliveries. It is important to note that CS platforms do not have a formal distribution network of conventional couriers such as consolidation points and full-time drivers with dedicated vehicles. Hence, management of failed deliveries could be more challenging. This introduces an important gap in research and potential shortcoming in CS business model. To manage uncertainties associated with crowdshippers availability, trip declaration (stated observation) and utilisation of historical commuting patterns (revealed observation) have been recently investigated in the literature (Yildiz, 2021a; Ghaderi et al., 2022a). These methods show promising results in managing supply uncertainty. However, with recent advances in mobility sensing technologies such as PT fare validation systems, mobile phone locational information and navigation apps, supported by advanced trajectory prediction methodologies, several future research directions emerge for managing CS spatiotemporal uncertainties. Table 2.4 provides a summary of strategies to manage uncertainties associated with crowdshippers and receivers.

*Table 2.4 Solutions for addressing uncertainties in the availability of crowdshippers and receivers.*

| Player       | Strategies                                              | Reference                                                                                                                                                                               |
|--------------|---------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Crowdshipper | Declaration of trip preferences by occasional drivers   | Declaring preferred start time (Ulmer and Savelsbergh, 2020)<br>Declaring preferred trip's start time, start point and end point (Yildiz, 2021a; Yildiz, 2021b).                        |
|              | Modelling trip uncertainty                              | Markov chain with look-ahead policy to model uncertainty (Zehtabian et al., 2022).<br>occasional drivers' Availability is modelled based on a worst-case scenario (Silva et al., 2023). |
|              | Using occasional drivers' historical commuting patterns | Mousavi et al. (2022), Ghaderi et al. (2022a), Torres et al. (2021), and Torres et al. (2022)                                                                                           |

|                 |                                                       |                                                                                               |
|-----------------|-------------------------------------------------------|-----------------------------------------------------------------------------------------------|
| <b>Receiver</b> | Trusted ADP                                           | Involving neighbours Akeb et al. (2018)                                                       |
|                 | Employing occasional drivers accepting round CS trips | Set start and end points at a distribution centre (Torres et al., 2021; Torres et al., 2022). |

### 2.4.8 Multiple and split delivery policies

Initially, CS was introduced as a community-based approach for delivering parcels, mainly by involving friends or neighbours (Paloheimo et al., 2016). Such models predominantly represent a single delivery approach. As technology becomes more accessible to coordinate CS activities, assigning multiple delivery tasks with the same and/or different pick-up or drop-off locations to crowdshippers has received increased attention (Behrend et al., 2019). As such, crowdshippers have the option to accept multiple deliveries collectively or individually while on their way to agreed locations. Figure 2.6 visualises three delivery policies with single, multiple and split delivery approaches. The newly offered tasks might alter existing delivery sequences and routing. Therefore, path finding and routing decisions become the core of any CD system (Arslan et al., 2019).

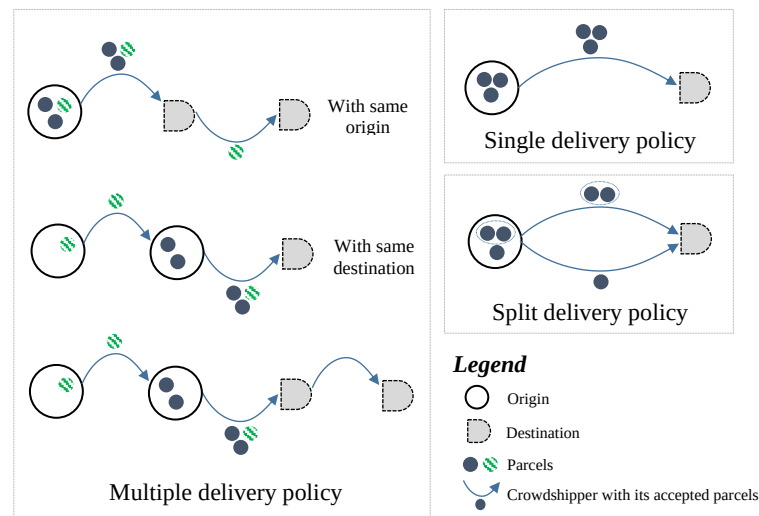


Figure 2.6 Delivery assignment policies.

In this context, Macrina et al. (2017) studied a VRP variant with time-window constraints for both dedicated drivers and occasional drivers. In this study, the possibility of delivering parcels by occasional drivers was evaluated under two policies. First, occasional drivers can accept multiple deliveries with different origins and destinations, known as “multiple delivery policy”. Second, more than one OD can visit an origin point and receive a fraction of the delivery demand, which is defined as “split delivery policy”. Results show that performing

multiple and split delivery policies would significantly decrease total delivery costs. Yildiz and Savelsbergh (2019) tested the impact of bundling deliveries at pick-up points as a multiple delivery policy in a food-based CS system. They observed that when courier availability is not a limiting factor, limited service quality improvement can be achieved (e.g., click-to-door time or ready-to-door time). The reason is that bundling of orders at restaurants adds waiting time and circuitry to delivery routes.

Arslan et al. (2019) highlight the difficulties in performing multiple delivery policies because of time window constraints. Hence, they proposed a dynamic pickup and delivery problem with occasional drivers and dedicated drivers for on-demand deliveries. A same-day delivery setting was considered in which both delivery tasks and occasional drivers dynamically arrive over time. A matching-routing problem was formulated in which the total routing costs of dedicated drivers and occasional drivers are minimised. Results show that including occasional drivers and performing multiple delivery policies can save delivery costs up to 37%, where large savings occur when crowdshippers have high flexibility in time and willingness to stop more. Simoni and Winkenbach (2023) explored the order batching and assignment problem in a CS-based meal delivery system with the aim to consolidate orders with distinct pick-up and drop-off locations into batches. This study revealed that increasing the batch size to more than three orders would provide little benefit, mainly due to time and capacity constraints. In summary, the literature shows equal popularity for both single and multiple delivery policies, while split delivery receiving less attention. Theoretically, implementing multiple delivery policies via bundling of orders could reduce the number of required crowdshippers and total delivery distances, plus minimising environmental impacts (Pugliese et al., 2023; Wang et al., 2023a; Fessler et al., 2022). However, this approach may lead to an inequitable distribution of delivery tasks among crowdshippers and restrict opportunities for new crowdshippers to participate in the system, resulting in lower participation in future (Triki, 2021). Due to the low spatiotemporal flexibility of PT users, it appears the single delivery policy is more appropriate for such crowdshippers, while those with dedicated vehicles could perform multiple deliveries (Fessler et al., 2022). On the other hand, while split deliveries could significantly improve geographical coverage and successful delivery rates (Ghaderi et al., 2022b), their uptake by crowdshippers could be low due to less financial incentives.

## **2.4.9 Potential markets**

Since CS services vary in their nature of offering and characteristics, it is essential to understand their unique value proposition for different markets; where and how each CS model is best positioned. The early implementation of CS in real-world cases (e.g., UberEATS, Postmates, Amazon Prime, Deliveroo, and PiggyBaggy) was proposed to address the LMD problem for food, grocery and e-commerce in B2C markets. However, the literature demonstrates a growing number of applications relevant to library services (Paloheimo et al., 2016), healthcare and humanitarian logistics (Le and Ukkusuri, 2019b), food rescue and charity (Mittal et al. (2021), item sharing (Behrend and Meisel, 2018) and reverse logistics for e-commerce (Pan et al., 2015; Upadhyay et al., (2020). In this section, we provide a summary of markets that can benefit from CS services. Since the majority of existing CS literature focuses on food, grocery, and e-commerce markets, we only focus on emerging and potential markets that are less known.

### **2.4.10 Item sharing**

Item sharing is an emerging collaborative consumption concept in which community members can temporarily lease their items to others (e.g., party equipment and gardening tools). With item sharing, multiple members can sequentially use a specific item by renting it instead of purchasing. However, the physical transfer of items between a lessee and a lesser using traditional couriers is challenging because it can cause increasing rental costs and environmental impacts, and consequently, deteriorate the attractiveness of item sharing (Behrend, 2020). Hence, Behrend and Meisel (2018) suggest that CS could be a suitable solution for the exchange of goods in item sharing with three proposed models: (i) self-sourcing in which the lessee conducts the delivery, (ii) delivery with an independent crowdshipper to the lessee's location and, (iii) a model in which crowdshipper performs the delivery to a neighbouring location where it is picked by the lessee. In Behrend and Meisel (2018), it is assumed that each crowdshipper can accept at most one item. To relax this assumption, Behrend et al. (2019) allowed private drivers to perform multiple deliveries at the same time if they had adequate vehicle capacity. This approach could lead to reduced delivery costs when several deliveries are combined in one route. Furthermore, such models could enhance drivers' interest to participate in CS as the result of improved reimbursement.

Later, Behrend et al. (2021) proposed a ‘request-changing’ extension to the item-sharing problem, in which items can be used by multiple customers before returning to their original locations. It is expected that request-changing could minimise total transport costs and improve item availability as a result of eliminating return trips. From a modelling perspective, this extension can be classified as a many-to-many pickup and delivery problem with dynamic characteristics due to new incoming announcements. To address the planning dynamics associated with the deterministic and stochastic nature of requests, the problem was formulated as a mathematical model with a rolling horizon approach. To predict future requests, this study relied on the concept of ‘word-of-mouth’ as a mechanism driven by interpersonal communications around the experience of previous consumers. Results show that when simultaneous effects of requests are considered in multi-period planning, the system’s profit is improved compared to the period-by-period approach.

#### **2.4.11 Food rescue and healthcare**

Food insecurity is a serious humanitarian concern. According to the U.S. Department of Agriculture (USDA), 10.5 million (13.8 million persons) U.S. households were food insecure at some time during 2020 (USDA, 2020), with many not qualifying for federal food assistance due to income ineligibility. At the same time, USDA estimates that 31% of the available food supply at the retail and consumer levels goes to waste each year (Buzby et al., 2014). The logistics of delivering excess food to demand locations presents major challenges, particularly considering the relatively small volumes and perishable nature of food items. Recently non-profit organisations and start-up companies in the US such as Food Rescue US and Goodr are recruiting volunteer drivers to pick up surplus food from restaurants and deliver it to soup kitchens and shelters (Food Rescue US, 2022). Applications of CS to address food insecurity have also received attention in academia. For example, Mittal et al. (2021) assessed the viability of a volunteer-based CS food rescue program from restaurants in Arlington, Texas using agent-based simulation models. This study considered couriers and senders to be represented as autonomous, heterogeneous and adaptive agents with their decision to participate in CS having interactive effects on others. While demonstrating the social benefits of CS for urban food rescue, Mittal et al. (2021) concluded that establishing an appropriate balance between the number of crowdshippers and restaurant donations is essential for the success of volunteer-based CS. In a similar context, Manshadi and Rodilitz (2022) studied how to maximise the engagement of volunteer crowdshippers to perform time-sensitive tasks, suggesting nudging

mechanisms to notify a subset of volunteers. Since excessive notifications might hurt engagement, an online volunteer notification problem (i.e., online policy) was proposed in which the trade-offs between notifying more volunteers and saving them for future tasks were examined. In crowd logistics systems, senders show heterogeneous behaviour; some are willing to pay more for quicker delivery and some only want the lowest delivery cost. Le and Ukkusuri (2019b) explored how senders choose shipping services for different products, given the availability of both CS and traditional delivery in a logistics market. Using survey data collected from the U.S. and applying Discrete Choice (DC) models, it was observed that personal health and medicine products appear to be a potential market segment for CS.

#### **2.4.12 Reverse logistics**

CS also presents opportunities for sustainable supply chains, including reverse and return logistics (Pan et al., 2015). More specifically, studies such as Le et al. (2019) have highlighted the potential of CS as a solution for product returns in e-commerce intensive markets. Collecting returned products is considered one of the most expensive activities in city logistics, mainly because of the lack of economies of scale and challenges with packaging. Chen et al. (2017) introduced CS to e-commerce reverse logistics, as an alternative solution to return goods from customers to retailers. Using a dataset consisting of shop locations, road networks and large-scale trajectory data generated by over 7000 taxis in China, various collection strategies based on passengers' destinations, collection points and online and offline taxi scheduling were proposed. The results of this study demonstrate that CS solutions were superior compared with other strategies in terms of reducing economic and environmental costs. Moreover, the CS solution provides extra income for taxi drivers and offers more convenience to customers for returning their parcels. From a modelling point of view, in a CS system, reverse logistics could be incorporated as a pick-up problem.

#### **2.4.13 Library services**

Paloheimo et al. (2016) presented a study of CS for library services in the city of Jyväskylä in Finland. Due to long travel distances, competition with e-book solutions, and cost complications, many libraries are not able to maintain their service levels and struggle to remain commercially viable. As a remedy for this problem, a pilot research project was conducted in which the distribution of books from libraries to customers, and vice versa, was performed via the CS service of PiggyBaggy. Real-world observations showed that the trial

attracted a large number of crowdshippers, mainly using bicycles, despite a low compensation rate (i.e., 2–5 euros per delivery). In contrast, the trial failed to quickly attract library customers even by offering a free service delivery. The analysis further showed that although nearly 80% of deliveries were within a 5 km radius, each CS delivery can reduce 1.6 km of travel, on average. More recently, Triki (2021) studied the application of CS services for delivering online orders from a bookstore in Oman by employing occasional drivers in addition to the company's available fleet. This study reveals that bookstores can minimise their fleet of dedicated couriers by 30% when relying on the CS service.

#### **2.4.14 Environmental Aspects**

Delivering parcels by crowdshippers is expected to contribute to enhancing the environmental performance of the urban freight ecosystem. Such initiatives can reduce delivery truck circulation, especially in local and residential areas, and reduce emissions, traffic congestion and safety risks, which benefits the general public significantly. Despite such importance, the topic of environmental assessment of CS systems or designing eco-friendly systems has received limited attention. The literature acknowledges that if CS requires dedicated trip generation by casual couriers travelling with unsustainable transport modes, it could result in unfavourable environmental outcomes (Rai et al., 2018). The remainder of this section summarises the relevant CS research related to environmental implications.

**CS with occasional drivers:** CS initiatives involving occasional drivers could impact drivers' mobility patterns or even induce new trips into transport systems. Although at first glance replacing dedicated freight movements with existing passengers appears to be an eco-friendly option, such solutions could have adverse effects if they become a major source of trip generation (The New York Times, 2020). Currently, there is limited empirical and academic evidence addressing the negative side of utilising CS for parcel delivery (Rai et al., 2018; Allahviranloo and Baghestani, 2019). In this context, Qi et al. (2018) examined the operational and environmental benefits of CS systems compared to truck-only delivery systems using a case study in San Francisco. They revealed that CS is not as scalable as conventional truck-only systems in terms of operating costs. However, a transition to CS could reduce fleet size and improve operational flexibility via better access to high-demand areas and peak hours. Furthermore, the authors conclude that emissions may increase in CS systems due to the prolonged trip distances of crowdshippers.

Rai et al. (2018) explored the environmental impacts of CS utilising occasional drivers based on historical data from the operations of a crowd logistics company in Belgium. This study formulated and evaluated the external costs of CS on society against a conventional parcel delivery system. By applying a multi-actor multi-criteria analysis, results indicate that the CS platform results in larger environmental impacts, as the result of the high number of dedicated trips, instead of capitalising on the existing mobility of individuals. Also, Rai et al. (2018) suggested that CS could provide higher synergy in B2B markets, because of higher economies of scale. In line with this argument, Allahviranloo and Baghestani (2019) study this phenomenon using an auction-based CS platform, in which senders submit pickup/delivery tasks and crowdshippers select the most compatible and desirable tasks. Benefiting from information on activity patterns from the California Household Travel Survey data (2001) to identify potential senders and crowdshippers, they indicate that the activity and travel patterns of both senders and crowdshippers could be impacted as a result of participating in CS. It was observed that CS can impact shifting travel demand from morning to evening hours. Ballare and Lin (2020) suggest a CS system with TPs involving drivers or cyclists. They compared the CS system with a hub and spoke delivery system in terms of sustainability objectives based on reductions in truck movements and fuel consumption. Results show that CS can reduce VMT and fuel consumption by up to 60% and 50%, respectively.

***CS with Eco-friendly transport modes:*** A growing number of researchers have investigated initiatives that utilise eco-friendly transport modes such as PT, cycling and active transport (Marcucci et al., 2017; Kafle et al., 2017; Serafini et al., 2018; Gatta et al., 2019a; Gatta et al., 2019b; Binetti et al., 2019; Simoni et al., 2020; Lin et al., 2020; Wicaksono et al., 2021; Fessler et al., 2022; Mohri et al., 2023a; Mohri et al., 2023b). Kafle et al. (2017) presented one of the first studies to quantify the environmental benefits of employing cyclists and pedestrians as crowdshippers for the first and last legs of parcel delivery in urban freight systems, where TPs are used to connect crowdshippers with delivery trucks. This study shows that total delivery costs and truck travel distance could be reduced on average by 9.25% and 24%, respectively, compared with truck-only delivery systems. Simoni et al. (2020) performed a dynamic traffic simulation-based analysis to estimate how air pollution, Greenhouse Gas (GHG) emissions, and traffic delay change after operating CS involving occasional drivers and PT users. It was observed that operating a CS system with occasional drivers will result in a slightly higher increase in air pollution, GHG emissions, and traffic delay (approx. 2%), while, running a PT-based CS system would reduce these factors by up to 35%. In a similar study

from Rome, Gatta et al., (2019b) showed that implementing PT-based CS can reduce 239 kg of particulates per year. Kızıl and Yıldız (2023) proposed an eco-friendly delivery system with ADPs and TPs, involving PT users as crowdshippers for short trips and PT vehicles for long-distance movements. The delivery system was designed as a two-stage stochastic problem considering demand and CS capacity uncertainties. Using a case from Istanbul, results reveal that a CS-based approach can deliver up to 97% of the daily demand on the same day and reduce emissions such as Nitrogen oxides (NO<sub>x</sub>), Carbon dioxide (CO<sub>2</sub>), and Particulate matter (PM<sub>10</sub>). In the work of Binetti et al. (2019), a CS system was proposed in which delivery tasks were outsourced to bike users of free-floating bike-sharing systems. Authors, in contrast, highlight that the demand for CS delivery causes a shortage in the availability of bikes for other cyclists and reduces the accessibility and utility of the bike-sharing system for personal trips.

***Integration of passengers and freight:*** CS can be integrated into taxi, ridesharing, ride-pooling or carpooling systems to minimise environmental impacts. In this context, Chen et al. (2016) proposed a taxi-based CS system in which taxis move parcels between ADPs. By testing the system on a case study from China, authors claim environmental and economic benefits. Fehn et al. (2023) investigated the integration of parcel deliveries into ride-pooling services in Munich, Germany. Using an agent-based simulation approach that assigns parcels to existing ride trips, results indicate that total vehicle kilometres can be reduced by 48%, compared to a scenario when freight and passenger services are separate.

At the broadest level, compared to operational and economic aspects, research on environmental considerations of CS is limited, with conflicting views presented. Studies such as Kızıl and Yıldız (2023) report on reduced emissions and VMT, while others indicate higher impacts (Rai et al., 2018). Our review, however, concludes that several factors could determine the environmental performance of CS, including the type of vehicle used, transport mode, platform structure, service offering and most importantly, the nature of the participating crowd. CS systems that employ occasional drivers delivering parcels as part of daily trips without creating new trips are reported to be more environmentally friendly (Ghaderi et al., 2022a). However, such models are also characterised by shortcomings, such as lower service levels, crowdshipper unavailability and poor incentivisation (Peng et al., 2016). To address such challenges, the more recent literature suggests the incorporation of TPs and ADPs into distribution network (Vincent et al. 2022), multiple and joint delivery options (Ghaderi et al., 2022b), integration of freight and passenger transport (Cavallaro and Nocera, 2022). Furthermore, a growing interest is observed in the utilisation of PT-based systems, particularly

through the installation of PLs in transit stations to improve service flexibility (Fessler et al., 2022). The benefits of PT-based CS systems are numerous, including lower cost, enhanced geographical coverage and the potential involvement of crowdshippers who are unable to drive.

## 2.5 Social, Behavioural and Motives

### 2.5.1 Understanding players' characteristics

This section aims to summarise the literature characterising CS actors, with a focus on how they interact with each other.

**Crowdshippers:** One of the main challenges facing CS companies is to secure a reliable pipeline of individuals for delivery tasks. To achieve this, a platform needs to understand the characteristics of potential crowdshippers, their needs and behavioural considerations throughout the end-to-end CS process. Miller et al. (2017) studied the attributes of occasional drivers choosing to work as part-time crowdshippers, specifically examining the likelihood of accepting delivery considering variables such as willingness to work (WTW). In contrast to WTP, which measures the trade-off between money and time saving, WTW determines the trade-off between an individual's time contribution and profit expectations. In this work, the acceptance likelihood was estimated using a mixed logit model developed based on survey data from the U.S. Results show that people in the mid-income range with a graduate degree are more willing to accept CS tasks. Furthermore, the median WTW estimated by this research was around 19 USD per hour. Similarly, Devari et al. (2017) studied a system in which friends or acquaintances of a customer in social networks act as crowdshippers, showing that nearly 72% of respondents would agree to deliver a package to their friends, from which 60% are willing to deliver for free, and 85% accept spending up to 15 minutes detouring from their regular trip for delivery. Marcucci et al. (2017) investigated the conditions under which students in Rome would be willing to act as crowdshippers. By surveying nearly 190 students, authors state that most students are unfamiliar with CS, but 87% of them would be willing to act as crowdshipper. Participation of students as crowdshippers would decrease to 55% and 40%, if the parcel is large and the reward is less than 5 Euros, respectively. Also, the maximum acceptable detour distance was around 1.5 km for carless students and 3.1 km for students owning private vehicles. Moreover, 57% of students acting as crowdshippers were unwilling to be tracked.

Studies such as Punel et al. (2018) explore the profile, behavioural factors, attitudes and preferences of crowdshippers when engaging in such activities. Using a binary logit model with an online survey conducted in the United States, Punel et al. (2018) showed that CS is more common among younger individuals, men, and full-time employees. Moreover, CS is more dominant in urban areas, where the delivery task requires medium-distance travel. Le and Ukkusuri (2019a) further explored behavioural considerations for engaging in CS work. Based on US-based survey and using a binary logit model, they reveal that parcel delivery experience, socio-demographic characteristics, and social media usage are key factors that influence respondents' decision to participate in CS. Furthermore, this study shows that crowdshippers' reimbursement expectation is correlated with their VoT.

An emerging stream of CS research focuses on examining parcel delivery using PT users (Marcucci et al., 2017; Serafini et al., 2018; Gatta et al., 2019a; Gatta et al., 2019b; Fessler et al., 2022). Conceptually, such services do not generate new dedicated trips for parcel delivery/collection and could potentially minimise the movement of delivery vans (and cars) in congested city centres. These PT-based CS systems predominantly utilise intermediary points such as PLs to facilitate the process of picking up and dropping off parcels, which could have varying implications on the behaviour and preferences of PT users, receivers and CS platforms. Studies such as Serafini et al. (2018) and Gatta et al. (2019a) benefited from survey data to develop DC models to explore the conditions under which commuters of the metro network would accept locker-to-locker CS tasks as part of their daily travel. Results of both studies show that PT passengers favour CS with lockers inside metro stations. Furthermore, students show the largest marginal utility, while older and high-income passengers are reluctant to accept CS tasks. Fessler et al., (2022) used survey data of 524 respondents in the Greater Copenhagen Area with a mixed logit model to explore PT users' willingness to carry parcels on their trips. Results reveal that younger individuals, students, and employed and self-employed individuals, in that order, show the highest willingness to participate. Findings also show that the marginal disutility of time spent retrieving and dropping off parcels at lockers was higher for older (aged +60) and higher income participants (i.e., earning more than 50,000 DKK/month), while this figure was lower for people with lower educational levels (i.e., below 2 years education after high school). Fessler et al., (2022) also concluded that higher compensation rates increase the willingness to participate in CS, while increasing the number, size, and weight of parcels have negative impacts. Mohri et al., (2023b) modelled task acceptance behaviour in PT-based CS systems using a LC choice model and survey data

collected from 2208 PT users in the Sydney metropolitan area. The LC choice model was utilised to identify heterogeneous preferences for accepting CS delivery tasks, under different levels of offered incentives, package weight, and required detour distance at the destination. The study revealed three distinct user classes: leisurely, avid, and sceptical, comprising 19%, 53%, and 28% of the sample, respectively.

**Receivers:** For CS platforms, a preliminary step is to understand receivers' needs, expectations, and associated interactions. Marcucci et al. (2017) studied the conditions under which students in Rome would be willing to receive CS services. The results show that nearly 93% of students would be willing to act as a receiver and more than 80% expect to be able to track their parcels in CS systems. Devari et al. (2017) also showed that more than 60% of their study population were willing to receive their parcels through a CS service when delivered by friends or acquaintances in their social networks. Similarly, Punel et al. (2018) studied the attitude, preferences, and characteristics of customers who agreed to use CS for parcel delivery using a binary choice model and stated preference data. The results revealed that individuals with a strong sense of community and environmental concerns were more likely to use CS by 86.4% and 83.9%, respectively. However, individuals who had reservations regarding affordability and trust were less likely to use CS by 68.3% and 64.9%, respectively. In a similar study, Rai et al. (2021) employed a two-step clustering technique to examine receivers' preferences towards the use of CS. While the results showed low general interest in CS services, customers were supportive of neighbourhood delivery services. More specifically, Rai et al. (2021) stated that people who support CS were interested in LMD innovations and sustainability initiatives. Wang et al. (2023b) modelled factors influencing customers' adoption of CS delivery services based on the technology acceptance model (TAM) and norm activation model (NAM) considering trust, social influence and loss of privacy as explanatory variables. Through a cross-sectional survey of 2,333 participants in China, this study reveals that social influence and trust are the most influential factors in customers' acceptance of CS. In the same vein, the study of Cebeci et al. (2023) aimed to quantify the impact of trust on the receivers' choice between CS and professional courier delivery. To achieve this objective, a hybrid choice model with trust as a latent variable was developed and measured by indirect variables such as CS provider reputation, delivery damage likelihood, and insurance policy. Using data from the Netherlands, the authors conclude that reputation and the likelihood of damage significantly influence trust.

**Senders:** CS platform success is driven by the number of delivery tasks completed. Delivery tasks are predominantly initiated by senders in a CS system; hence, it is of utmost importance for a platform to sustain and improve its sender base (Dablanc, 2016). Punel and Stathopoulos (2017) studied senders' preferences for CS services by utilising a survey in the US. Multiple CS alternatives were offered to respondents to select from. The alternatives had specific attributes related to delivery distances, costs, durations, pick-up dates and times, and crowdshippers' experience and ratings. Using a multinomial Logit (MNL) model, senders' utility function from each CS scenario was estimated. Results showed that for shorter delivery distances, senders highly regarded the transparency of the driver's performance along with delivery speed. However, for longer delivery distances, senders gave higher priority to delivery conditions and driver's training and experience.

**CS platforms:** Compared to other CS players, the academic literature on CS platforms is limited. According to Rai et al. (2018), CS is a new concept, hence platforms progressively alter their operations and strategies. The industry literature shows CS systems are either formal or informal. Formal CS systems are predominantly operationalised through digital systems. Ciobotaru and Chankov (2021) provided a comprehensive taxonomy of CS platforms operating across the world and reviewed their structures and business models. This study shows, existing CS platforms were mainly introduced by large international companies such as Amazon, Walmart, DHL, and Uber or smaller tech-based start-ups such as PiggyBee or Chronobee. Given its potential to create logistics value for different types of businesses, Bin et al. (2020) conducted a study of the factors influencing enterprises' willingness to implement crowd logistics systems. Using a technology-organisation-environment (TOE), authors concluded that a firm's absorptive capacity, relative advantage, market environment and external motivations are influential in the adoption of crowd logistics. CS could also take the form of informal models, for example, when players utilise social media platforms to connect, interact and execute delivery tasks (Guo et al., 2019). This form of CS could be popular for specialised and not-for-profit delivery services, including long-distance/overseas and healthcare deliveries (El Arifeen et al., 2013).

In summary, by examining the literature on players' characteristics, two behavioural instruments have received attention. First, one stream of research examines the intention of people to participate in CS work, and the other stream explores the willingness to accept CS service. The intention of participation approach provides insights into the characteristics and likelihood of engagement of potential users (Mohri et al., 2023a). On the other hand,

acceptance of CS delivery by crowdshippers who have participated may vary depending on changes in parcel delivery characteristics such as incentives, types, and weight (Mohri et al., 2023b). Table 2.5 summarises the literature pertaining to these considerations, based on the method utilised and the region of study.

*Table 2.5 Key aspects of behavioural studies on CS.*

| Reference                                                     | Player                             | Behavioural problem | Method                           | Case                 |
|---------------------------------------------------------------|------------------------------------|---------------------|----------------------------------|----------------------|
| Miller et al. (2017)                                          | Crowdshippers (occasional drivers) | Acceptance          | DC: Mixed logit model            | U.S.                 |
| Devari et al. (2017)                                          |                                    |                     | DC: Binary logit model           | U.S.                 |
| Marcucci et al. (2017)                                        |                                    | Participation       | Descriptive analysis             | Italy                |
| Punel et al. (2018)                                           |                                    |                     | DC: Binary logit model           | U.S.                 |
| Le and Ukkusuri (2019a)                                       |                                    |                     | DC: Binary logit model           | U.S.                 |
| Mohri et al. (2023a)                                          | Crowdshippers (PT passengers)      | Participation       | DC: MNL model                    | Australia            |
| Serafini et al. (2018)                                        |                                    | Acceptance          | DC: MNL model                    | Italy                |
| Gatta et al. (2019a)                                          |                                    |                     | DC: MNL model                    | Italy                |
| Fessler et al., (2022)                                        |                                    |                     | DC: Mixed logit model            | Denmark              |
| Mohri et al. (2023b)                                          |                                    |                     | DC: LC model                     | Australia            |
| Marcucci et al. (2017)                                        |                                    | Receiver            | Participation                    | Descriptive analysis |
| Punel et al. (2018)                                           | DC: Binary logit model             |                     |                                  | U.S.                 |
| Rai et al. (2021)                                             | two-step clustering model          |                     |                                  | Belgium              |
| Wang et al. (2023b)                                           | TAE and NAM                        |                     | China                            |                      |
| Cebeci et al. (2023)                                          | Acceptance                         |                     | DC: latent variable choice model | Netherlands          |
| Punel and Stathopoulos (2017)                                 | Sender                             | Acceptance          | DC: MNL model                    | U.S.                 |
| Bin et al. (2020)                                             | CS platform                        | Participation       | TOE Model                        | China                |
| DC: Discrete choice; MNL: Multinomial logit; LC: Latent class |                                    |                     |                                  |                      |

DC: Discrete choice; MNL: Multinomial logit; LC: Latent class

As shown in Table 2.5, in terms of methodologies utilised, basic DC modelling such as binary logit and MNL techniques emerge as the dominant approach (Miller et al., 2017; Devari et al., 2017). On the other hand, recent studies, aim for more complex choice modelling approaches such as mixed logit and latent-variable models (Cebeci et al., 2023; Fessler et al., 2022). Furthermore, studies that aim to model the behavioural considerations of CS have mainly focused on one country, with no cross-regional comparison currently presented in the literature to explore cultural and social differences governing CS decisions.

## 2.5.2 Trustworthiness

Trustworthiness is an important behavioural consideration in CS systems that encompasses issues related to reliability, privacy, safety, security, and accountability. Strulak-Wójcikiewicz and Wagner (2021) examined five different CS platforms operating in Poland in terms of their structures, business models, managers' priorities, and community feedback. Results showed while the popularity of CS platforms is growing, users have concerns about their service quality and business model. It was also found that the platforms' managers are

aware of trust-related concerns and associated impacts on their business (i.e., value creation and destruction). Studies such as Rougès and Montreuil (2014), Kafle et al. (2017), and Le et al. (2019) propose mechanisms to address the issue of trustworthiness in CS. In this section, we provide a summary of mainstream mechanisms reported in the literature that address trustworthiness. Platforms implement various strategies (e.g., removing information after order completion, concealing part of unnecessary information from crowdshippers) to protect sensitive and private information (Punel et al., 2018). The literature shows privacy protection remains a key decision-making factor for wider adoption of CS (Wang et al., 2023b). To improve confidence and engagement, many platforms utilise rating and feedback systems to understand the quality of the CS service provided by individuals. This feedback information can help senders and receivers in peer-to-peer systems to identify, rank and assign tasks to crowdshippers, appropriate to their performance and capabilities (Fessler et al., 2023). Insuring parcels is known as a mechanism to address concerns of CS users over problems related to the delivery of valuable and sensitive goods, damage, fraud, theft, and delayed deliveries. Crowdshippers also benefit from insurance provision that ease their concerns when moving expensive and/or hazardous parcels or unknown goods (He et al., 2023). Payments in C2C CS platforms can cause concerns for both receivers and crowdshippers. Hence, some platforms provide a secure online payment system, by receiving the shipping fee from receivers in advance and then transferring it to either senders or crowdshippers, once the job is completed (Le et al., 2019). Furthermore, platforms employ systems to improve privacy and security when players communicate with each other. For example, some platforms provide secure direct messaging systems that enable receivers and crowdshippers to communicate with each other, without sharing their personal information (Marcucci et al., 2017). To ensure registered crowdshippers meet the minimum quality criteria and avoid scammers registering on the platform, many platforms conduct background checks such as a police clearance, interview and driving license for registration (Le et al., 2019). This is also known as a mechanism to protect platforms from potential reputational damage (Moayedikia et al., 2020).

The academic literature addressing the trustworthiness aspects of CS mainly focuses on models that involve community-based and informal approaches (Devari et al., 2017; Akeb et al., 2018; Boysen et al., 2022). For example, Devari et al. (2017) considered a CS model with friends or acquaintances of a customer on social networks as crowdshippers, which generally leads to less privacy, safety and reliability complications. Recently, one of Germany's largest online retailers and Walmart in the US invited their employees to deliver shipments after work

to online customers living in their neighbourhoods (Bhattarai, A., 2017). Distribution centres and outlets could leverage their employees as a reliable and geographically diverse source of crowdshippers. Boysen et al. (2022) proposed the use of employees as crowdshippers with the objective to maximise the number of matched shipments, while satisfying the minimum expected earning of employees.

A handful of academic studies have looked at more formal mechanisms such as insurance. He et al. (2023) state that in China, CS platforms such as Dada Now and UU Runner have introduced value-insured services to enhance the trustworthiness of their systems and attract more users. In He et al. (2023), the authors examined the impact of three value-insured schemes of revenue-sharing, fixed-fee and reinsurance on the profitability of CS systems. Using a game-based approach model in which the CS platform is the leader, and the insurance company is the follower, the authors conclude that the reinsurance scheme is the preferred option when the average declared value is below a specific threshold. However, the fixed-fee scheme is more advantageous when the average declared value exceeds the said threshold.

## **2.6 Conclusion**

We provide a unique and timely conceptualisation of the topic CS in a time that the topic is receiving a great amount of attention from researchers and logistics companies as a solution for sustainable LMD. By synthesising the extant literature, it became evident that there was an absence of review unpacking the sustainability implications of CS. By acknowledging this gap, we explored several considerations of CS, including operational models, service offerings, and agents involved, under the lens of sustainability main pillars, namely, economic implications and considerations, environmental and societal outcomes. This conceptualisation allowed us to further inform the nexus between CS research and sustainable city logistics, the underlying methodologies, and particularly breaking the stereotypes around the promised benefits. Furthermore, through our extensive review, we have identified and evaluated the critical success factors and conditions in which CS could contribute to sustainable city logistics.

The primary objective of CS is to leverage on underutilised crowd and associated resources to facilitate the delivery of goods, while meeting economic, social and environmental objectives. CS has the potential to reduce the environmental impacts of urban delivery tasks while supporting low-income participants and developing community by creating social constructs in markets that are not traditionally studied in the literature. Moreover, by reviewing CS applications, we conclude that CS has been mainly proposed as an LMD solution for food

delivery and e-commerce, which explains why the majority of studies aim to address economic aspects such as profit maximisation through the development of task assignment tools and detour management. On the other hand, the application of CS in markets such as healthcare and reverse logistics, which are more aligned with environmental and humanitarian objectives, is very limited. Furthermore, we emphasise that changing economic conditions such as volatile job markets could have profound impacts on both supply and demand sides of CS. The literature, however, does not reveal any insights on how such macro-economic factors could impact the operational and financial viability of CS platforms. This is of particular importance for those start-up companies providing CS services. While this research aimed to investigate CS from a sustainability point of view, our observations indicate that the literature eliciting the interplay of economic, social and economic aspects of this topic is unusually scarce. For CS, as a human-centric business paradigm, the extant body of literature predominantly focuses on addressing the economic problems using mathematical approaches, although few studies such as Qi et al., (2018) and Tapia and colleagues (2023) follow a multi-objective approach (e.g., maximising profit, while minimising environmental impacts of CS) in their design. From this review, we recommend the following directions pertaining to the intersectional aspects of sustainability for future research:

***CS for social good and humanitarian markets:*** Several incentive-based models exist for CS. While financial reimbursement methods have been largely discussed using dynamic and fixed payment practices, CS has also been proposed as a platform for humanitarian logistics via the voluntary participation of crowdshippers or senders (Mittal et al., 2021; Manshadi and Rodilitz, 2022). Modelling the intention to participate in such activities is challenging due to the absence of non-monetary and social currency. Therefore, the socio-economic utility of CS for voluntary work presents a research gap, which could facilitate the uptake of CS for humanitarian purposes.

***Flexible workforce base:*** While the benefits of CS systems have been mainly studied from the perspective of technology-based platforms, logistics service providers such as traditional couriers could leverage on a large pool of dormant resources and people when coping with high demand. More specifically, CS can be seen as a solution to address the challenges of courier workforce shortage and over-supply when demand is volatile. For example, during the COVID-19 lockdowns, when demand for home delivery surged and delivery worker supply was limited, CS approaches could be utilised to improve access to essential goods in both B2C and B2B applications. However, we suggest future research be

undertaken to identify appropriate business models to protect workers' rights and avoid potential exploitations while addressing the resilience and responsiveness of such systems. While the early research in crowd logistics provides the taxonomical perspective of the nexus between crowdsourcing and logistics work (Mladenow et al., 2016; Carbone et al., 2017), we recommend future empirical research to demystify the concept of fairness in both centralised and decentralised CS models (Ermagun et al., 2020a;2020b).

***Behavioural consideration of crowdshippers:*** The literature of CS is mainly concentrated on optimisation studies, particularly the development of task assignment, supply and demand analytics, as well as pricing and compensation schemes to increase the operational and financial performance of platforms. In other words, the extant literature largely ignores the behavioural components of engaging and interacting with users. Recent studies such as Mohri et al. (2023a) highlight crowdshippers' concerns over security, availability, flexibility, safety, and responsibility besides monetary incentives are key prohibiting factors for participation in CS. Accordingly, qualitative and behavioural studies are suggested to further understand, model and simulate human agents, specifically, we recommend the application of choice modelling, agent-based systems and game-based optimisation. Furthermore, trustworthiness is an under-studied topic in CS literature, which could create significant value for users if managed appropriately. Given this research gap, we recommend qualitative studies followed by behavioural and system performance evaluation (i.e., measuring the trade-offs between trust and its impacts on supply, demand, and matching processes) to further measure the value of trustworthiness in CS systems.

***Regulations and the role of government:*** Despite its potential to create social value and sustainable outcomes, CS and other sharing economy models have been criticised for unfair compensation and poor working conditions (Schor and Attwood-Charles, 2017). Existing regulatory frameworks used for traditional markets do not necessarily support a balanced approach between economic outcomes and the risks associated with not addressing safety, privacy and social inclusion. It is expected that appropriate regulatory frameworks could act as an enabling mechanism for the uptake of CS-like solutions to effectively respond to the growing sustainability challenges of transport systems. Additionally, the intersection of technology and regulation is an unexplored area. For example, how could appropriate technological solutions such as location-based and context-aware mechanisms improve safety, security and establishment of the chain of custody?

**Collaborative consumption:** CS predominantly involves the provision of transport services. In a humanitarian context, delivery services could accompany other value-adding services. For example, similar to the work of Behrend et al. (2018; 2019) on item-sharing, delivery services could incorporate other collaborative consumption models with various sustainability benefits. In this context, CS could be utilised for second-hand markets, increasing the total economic utility for both sellers and buyers. As second-hand household items have lower prices, the use of commercial delivery services is not always viable. As a result, CS could create further utility in second-hand markets. In terms of new market creation, existing CS initiatives focus on short-distance lightweight delivery within urban environments. However, CS can be used for inter-city and inter-region services, similar to carpooling systems to minimise externalities. CS services can also be utilised for addressing the problem of reverse logistics, particularly the return of unwanted or defective products from consumers to distribution and/or disposal points (Upadhyay et al. (2020). Cost-efficient and accessible return services, through CS, would reduce the environmental effects of end-of-life or defective items.

**Technology to support Crowdshippers:** In essence, CS is facilitated via online platforms and mobile devices. Advanced geo-locational tools such as trajectory analytics could provide significant benefits to both crowdshippers and CS platforms. More specifically, in CS systems utilising occasional drivers, understanding the spatiotemporal patterns of crowdshipper is critical. Such mechanisms support efficient task assignment by identifying the right crowdshipper for a delivery task, leading to reduced trip detour and environmental footprint, convenience, optimised reimbursement and higher participation in CS. To date, limited number of studies have explored the use of such techniques, mainly due to a lack of real-world data, computational complexities and challenges in modelling crowd behaviour (Ghaderi et al., 2022a,2022b).

**Coopetition and resource sharing:** Coopetition refers to the act of collaboration among competing firms. Competing CS platforms could create win-win situations when resources are constrained. By considering ‘platform-to-platform’ interaction, one CS could trade a delivery request to another when there is no suitable crowdshipper available in their pool. Furthermore, when a delivery task is complex, appropriate systems could support task sharing and joint delivery. How such interactions could be managed on a large scale, either as one-to-one or many-to-many interactions, is an important area of research for future studies. Furthermore, facility and infrastructure sharing could be another subject of collaboration in which platforms share the capacity of their existing resources such as depots, TPs, and ADPs.

In the end, we acknowledge that our study has some limitations. First, this work mainly incorporates quantitative studies, thus, qualitative works such as exploratory and conceptual studies were excluded from our analysis. Since CS is an emerging field with an important human interface, we suggest future studies and reviews to further demystify the behavioural aspects of CS through qualitative and case study approaches. Second, the scope of work was limited to journals associated with transport, logistics, operations research and management. In recent years, CS is becoming a topic of interest among computer and data scientists, who employ a different set of methodologies. Hence, future review works could focus on such streams, and subsequently, compare methodological differences with what we have presented. Specifically, the applications of mobile computing and AI to support real-time CS task assignment and pricing optimisation is a potential avenue.

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## **CHAPTER 3**

# **PUBLIC TRANSPORTATION-BASED CROWD-SHIPPING INITIATIVES: ARE USERS WILLING TO PARTICIPATE? WHY NOT?**

### **3 Public Transportation-Based Crowd-Shipping Initiatives: Are Users Willing to Participate? Why Not?**

#### **Preface**

In Chapter 3, the outcomes of modelling the intention of PT passengers to participate in the CS system, as well as the barriers that hinder their involvement, are presented. Practically, understanding the intention to participate in the CS system offers insight into how PT passengers will register for the CS delivery system and nominate themselves as crowdshippers.. The CS participation model is crucial for CS managers, as it provides an estimate of the potential supply size and the characteristics of the crowdshippers. Increasing the supply size in the CS system enhances the likelihood of successfully matching delivery tasks with crowdshippers. Following participation, the probability of accepting CS delivery tasks, addressed by the CS task acceptance model, becomes a key consideration. This model is thoroughly explained in Chapter 4. This chapter offers valuable practical insights that can aid in effectively conceptualizing, introducing, and promoting a new CS initiative based on PT. The information presented is derived from an original journal paper published in *Transportation Research Part A: Policy and Practice* as indicated below:

Mohri, S.S., Nassir, N., Thompson, R.G., Lavieri, P.S., Public Transportation-Based Crowd-Shipping Initiatives: Are Users Willing to Participate? Why Not?, *Transportation Research Part A: Policy and Practice*. (Status: Under revision)

This chapter is presented as a standalone research study in a journal publication format. There have been only minor changes to conform to the thesis style and section numbering.

## **Abstract**

An emerging stream of CS solutions focuses on existing momentum in PT to ship viable delivery packages by PT passengers. Few studies have explored the package delivery acceptance behaviour of passengers engaged in PT-based CS initiatives while passengers' behavioural intention to participate (i.e., engage) is not studied. It is requisite that newly introduced CS platforms explore their potential crowdshippers' behaviour on intention to participate and set efficient marketing strategies. Given survey data collected from 2208 PT passengers in Sydney metropolitan area, this study explores the intention of PT passengers as crowd-shippers to participate in PT-based CS initiatives, as well as prohibiting factors in way of participation. Accordingly, a binominal logit model is developed whereby the variables impacting the intention to participate are identified. Then, using an inductive thematic analysis, 917 reasons (text responses) for not participating are scrutinized, and the prohibiting factors are identified and categorized. Considering demographic and socio-economic characteristics of the respondents, the study reveals to what degree passengers with different characteristics are sensitive to prohibiting factors. This research provides several practical insights that can assist in successfully defining, launching, and advertising a new PT-based CS initiative. As a key finding, it is observed that women, full-time employees, elderly, retirees, and low-income PT passengers hardly participate, while the youth, individuals with a positive attitude towards sustainable freight initiatives, and those who experienced working with PLs would participate with a higher probability. Moreover, it is observed that factors relating to time availability/flexibility and physical health condition/importance of passengers are much more important than the compensation level for passengers to accept to participate in PT-based CS initiatives.

## **3.1 Introduction**

The e-commerce industry has grown rapidly in recent years. Working-from-home is becoming a new norm and online shopping and home deliveries are dominating retail markets (Vonage, 2021; Beck and Hensher, 2022). Global e-commerce sale has soared from \$1.3 billion in 2014 to \$4.3 billion in 2020 and is estimated to grow to \$6.4 billion by 2024 (U.S. Department of Commerce, 2022). As part of this growth, customers' expectations for quick, free, and flexible delivery services are changing rapidly.

Given the emerging changes in retail markets, several innovative freight LMD initiatives have been launched in recent years, among which initiatives based on the concept of crowd logistics have gained great attention (Mohri et al., 2022; Carbone et al., 2017). Crowd logistics is a type of crowdsourcing in which outsourcing logistics services is the subject of debate. CS is a segment of crowd logistics in which only freight shipping services are outsourced to crowds, called crowdshippers. Crowdshippers are occasional carriers who conduct the whole or a part of a freight delivery task from its origin to its destination or between some intermediate points.

For many years, both industry and academia have mainly focused on CS by occasional drivers. In the industry, e-retailers and couriers have introduced many CS platforms such as Amazon Prime, Walmart Spark Delivery, DHL MyWays, Deliveroo, UberEATS, DoorDash, and PiggyBee (Alnaggar et al., 2021). In academia, many studies have been conducted to advance planning for CS by occasional drivers in terms of behavioural, design, and evaluation aspects (Le et al., 2019; Mohri et al., 2023a). From the sustainability perspective, although CS initiatives can reduce van or truck dedicated trips for package delivery, relying on occasional drivers as crowd-shippers in the CS initiatives may not be ideal as it induces additional car traffic. Evidence shows that these initiatives might induce traffic demand in transport systems since many drivers may adopt it as a secondary job, or new immigrants in developed countries find it a ready-to-hire job option (The New York Times, 2020). Considering this shortcoming, a new, yet emerging stream of CS research focuses on CS using PT passengers (Marcucci et al., 2017; Serafini et al., 2018; Gatta et al., 2019a; Gatta et al., 2019b; Fessler et al., 2022). Green CS is the terminology used for PT-based CS, as such services may not generate dedicated trips for package delivery (Gatta et al., 2019a) or even if they do, the capacity utilization and revenue in the PT systems will be improved.

As expected, initial research work in the scope of PT-based CS has concentrated on the behavioural reactions of PT passengers to these sustainable CS initiatives because such behavioural studies can justify conducting subsequent design and evaluation studies.

In ride-sharing, ride-sourcing, or CS systems, there are typically two consecutive behavioural stages that users (i.e., riders or crowdshippers) go through. As shown in Figure 3.1, the first stage involves users showing their intention or willingness to participate in the system by registering. This participation does not guarantee the acceptance of CS delivery tasks; it merely reflects users' initial willingness to encounter such tasks, which in turn contributes to increasing the supply of potential task performers in ride-sharing or CS initiatives. However, during this initial stage, users often do not have a clear understanding of

the tasks and their specific details. They possess a basic understanding of the system's workings and its benefits, which they acquire through diverse channels such as social media, word of mouth, outdoor ads, print media, and broadcast media. The second stage occurs after a user has successfully registered and is now considered a participant in the system. In this stage, users are presented with actual tasks and the associated details. Here, users face a crucial decision point: they must choose whether to accept or reject the tasks offered to them. This decision is based on a more concrete understanding of what the tasks entail and the potential benefits or drawbacks.

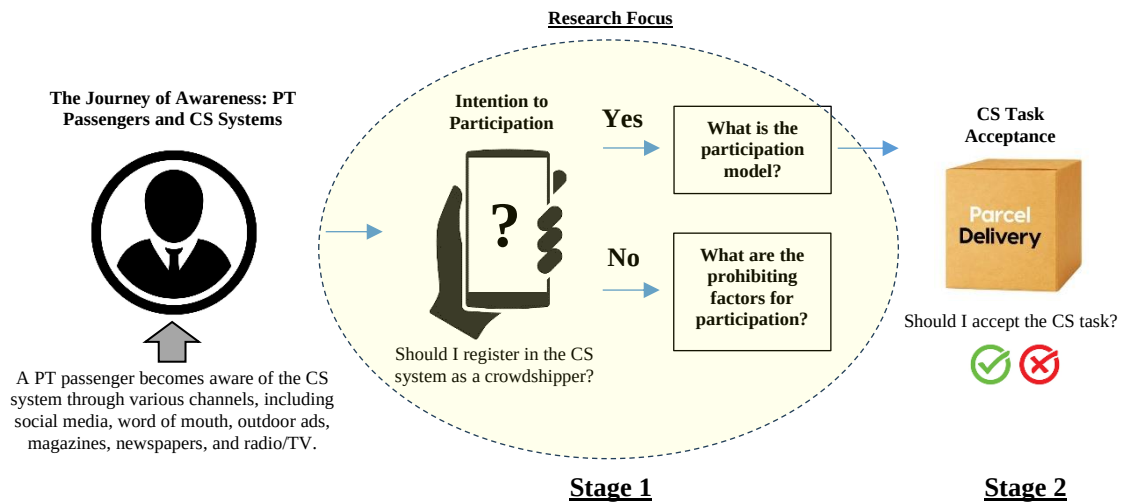


Figure 3.1 Research scope.

This study focuses primarily on the first stage, where users express their intention or willingness to participate in the system. We aim to shed light on two critical aspects:

**Probability of Participation:** One of the research objectives is to examine the probability of intention to participate in the system using a binomial logit model, developed based on survey data collected from the Sydney metropolitan area in 2022. Results of the model can estimate the initial attractiveness of the initiative for PT passengers and be used in approximating the expected number of registered crowd-shippers.

**Prohibiting Factors for Non-Participation:** Additionally, this research delves into the factors that may deter certain users from participating in the system. These factors could include concerns about safety, lack of trust, or perceptions of inconvenience. By pinpointing these barriers, we can provide insights into how to address them and encourage broader user engagement. The survey data includes the reasons for passengers rejecting the initiative, collected through an open-ended question in the survey. Using an inductive thematic analysis, nearly 917 text responses on the rejection reasons are investigated, coded, and categorized into

nine major categories of prohibiting factors. Moreover, assessing the demographic and socio-economic characteristics of the categories' members, the sensitivity degree of respondents with different characteristics to the prohibiting factors are revealed. Therefore, CS platform managers can design an optimal marketing strategy to maximize the expected participation rates by strengthening motivational factors for their platform that can be either common for all passengers or customized for different sociodemographic groups<sup>1</sup>.

## 3.2 Literature Review

In pursuit of the net-zero emission target for city logistics, as outlined in the Paris Agreement, researchers are actively investigating various sustainable urban freight systems. One of the promising systems is crowdsourced delivery involving PT passengers (CS by PT passengers). In this CS system, package movements are outsourced to PT passengers who are travelling in the PT system for their own purposes. In this section, the literature on CS and CS by PT passengers are reviewed and the contributions of the paper are highlighted.

It is worth noting that CS by PT passengers can also represent an innovative integration of passenger and freight solutions, sometimes referred to as cargo hitching or co-modality (Antoniou et al., 2023). While traditional cargo hitching solutions primarily concentrate on sharing spare capacity in PT vehicles for freight movement and utilizing PT infrastructure (including lines and stations) for freight operations (Machado et al., 2023; Zhu et al., 2023; Hatzenbühler et al., 2023), CS by PT passengers include a different approach. In CS by PT passengers, it is the “users” of PT services that are leveraged as contributors to the movement of goods. This solution proves particularly sustainable when incorporates PT links with high volumes of PT trips (Mohri et al., 2023a). This is in contrast with existing integration of passengers and freight which are typically more suitable for underutilized service with spare capacities inside PT vehicles or at stations. Accordingly, cargo hitching applications may be more suitable in suburban and rural areas in which PT system is in operation below capacity (Cavallaro and Nocera, 2023). Given these structural differences, this section focuses specifically on reviewing literature related to CS, aiming to position the contributions of the current paper within the broader CS literature. Interested readers to other solutions around integration of passengers and freight can refer to a special issue recently published in 2023 (Antoniou et al., 2023).

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<sup>1</sup> It is worth mentioning that advertising services through social media can be individually customized by exploring individual likes, dislikes, hobbies, and so on.

Early studies on CS date back to the period 2014 to 2016; hence, it is a newly emerging research subject in academic literature (Rougès and Montreuil, 2014; Archetti et al., 2016; Chen et al., 2016). However, the subject has been well appreciated by researchers and a remarkable uptake in the number of research and review papers on this subject has been observed in recent years (Carbone et al., 2017; Le et al., 2019; Alnaggar et al., 2021; Gläser et al., 2021; Mohri et al., 2023a). While early publications clearly highlighted the importance of bringing environmental benefits in CS initiatives (Rougès and Montreuil, 2014), this is mainly overshadowed by the monetary gains for stakeholders (retailers, CS platform, and crowd-shippers).

This section reviews the literature concerning eco-friendly CS systems. Consequently, the review encompasses papers that address not only the environmental dimension but also the economic aspects of sustainability. There are 17 papers focusing on achieving environmental gains in CS initiatives. Our observations show there are three different approaches for meeting eco-friendly goals in CS initiatives.

**Approach 1: Eco-friendly objectives:** A group of researchers consider environmental objectives such as minimizing total CO<sub>2</sub> emissions when designing a CS system (Rai et al., 2018; Gatta et al., 2019b; Ballare and Lin, 2020; Simoni et al., 2020).

**Approach 2: Eco-friendly transport modes:** Some studies suggest recruiting crowds traveling on eco-friendly modes such as bikes (Kafle et al., 2017; Binetti et al., 2019; Lin et al., 2020; Wicaksono et al., 2021) or PT (Marcucci et al., 2017; Serafini et al., 2018; Gatta et al., 2019a; Gatta et al., 2019b; Simoni et al., 2020; Giuffrida et al., 2021; Fessler et al., 2022).

**Approach 3: Detour minimization:** Some studies employ existing mobilities with a minimum detour for CS trips. Also, the issue that a CS system should not induce additional traffic (e.g., vehicle trips) is of concern (Chen et al., 2016; Allahviranloo and Baghestani, 2019; Yildiz and Savelsbergh, 2019).

Although adopting Approaches 1 or 3 can reduce the environmental impacts produced from CS initiatives by occasional drivers (i.e., crowd-shippers traveling by unsustainable modes); as long as the reliance is on occasional drivers, sustainability of the initiative may be compromised. Nevertheless, the industry seems to be reluctant to launch CS initiatives by eco-friendly transport modes (Approach 2) since there have been only a few real-world implementations, primarily in the food retail industry, that have been developed in comparison to CS by occasional drivers. Companies like UberEATs and DoorDash have successfully implemented CS systems by cyclists although the delivery cyclists are dedicated riders officially employed by the companies as casual workers. Therefore, they generate induced

cycling demand in the networks. These food delivery CS systems mainly operate well in dense population areas of mega cities, where a substantial amount of demand for delivery lies within a small spatial area (Dötterl et al., 2020). Chronobee is a PT-based CS platform, mainly designed for outsourcing interregional freight movements to passengers (Chronobee, 2022).

In terms of measuring the efficiency of PT-based CS systems, Simoni et al. (2020) performed a dynamic traffic simulation-based analysis to explore the effect of package delivery by occasional drivers and PT passengers on reducing air pollution, greenhouse emissions, and traffic delays. By considering the city centre of Rome, Italy, as the case study, their results show that CS by PT passengers is more beneficial than by occasional drivers from both an environmental and congestion perspective. Moreover, considering the level of matched demand of 50%, nearly 35% reduction is achieved in air pollution, greenhouse emissions, and traffic delays. Giuffrida et al. (2021) explored the spatial feasibility of outsourcing freight deliveries to university students who commute in the network with PT services and other active modes of transport. A case study from the city of Catania, Italy, is used where the university campuses are in different zones of the city. Some spatial considerations for matching deliveries with student movements are regarded including the origin-destination flows of students' movements, the proximity of delivery points to students' home addresses, and main transport modes for student trips to/from university campus. By assuming a maximum walking distance equal to 500 meters for package delivery by students, the authors found potential locations where their deliveries could be outsourced to the students.

Although CS by PT passengers can have significant environmental benefits, without a large volume of passengers as crowd-shippers, the benefits would not be attained. Hence, a group of studies focuses on the behavioural side of the initiative. Studies such as Serafini et al. (2018) and Gatta et al. (2019a) used survey data to develop DC models to explore the conditions under which commuters on the metro network would accept delivery CS tasks as part of their daily travel. Such PT-based CS systems predominantly utilize intermediary points such as PLs to facilitate the process of package pick up and drop off, which might have different inevitable implications on the behaviour and preferences of PT passengers. In this regard, by applying a MNL model to the survey data, these studies observed that PT passengers are more sensitive to the location of lockers (preference for lockers inside stations) as compared to compensation rates (1–3€/delivery). Also, contrary to students who display the largest marginal utility, older and high-income passengers are reluctant to accept CS tasks.

Marcucci et al. (2017) investigated the conditions under which students in Rome would be willing to act as crowd-shippers in CS systems. By surveying nearly 190 students, they

showed that most of the students are unfamiliar with CS, while 87% of them would be willing to act as a crowd-shipper. The participation of students as crowdshipper would be decreased to 55% and 40%, if the package is large and the reward is less than 5€, respectively. Also, the maximum acceptable detour distance was around 1.5 km for carless students. Moreover, 57% of students acting as crowd-shippers are unwilling to be tracked. Fessler et al., (2022) explored how PT passengers in the Greater Copenhagen Area accepted some CS tasks having different weights, sizes, incentives, and detours. A CS system in which passengers pick up and drop off packages only from lockers inside PT stations is proposed. Therefore, this CS plan can mitigate deliveries to city centres by vans with packages outsourced to PT passengers to move towards lockers in city centres. Using survey data and applying a mixed logit model, results show youth, students, and employed and self-employed individuals show the highest willingness to accept CS tasks. Findings also show the marginal disutility of time spent retrieving and dropping off packages at ADPs is higher for elderly (aged +60) and individuals with higher income (i.e., earning more than 50,000 DKK/month), while it is lower for individuals with short-term education (i.e., below 2 years education after high school). The authors also observed that increasing compensation increases the willingness to accept while increasing the number, size, and weight of packages decreases the willingness.

In addressing the challenges and barriers of implementing an initiative, researchers often employ a mixed-methods research approach, which combines quantitative and qualitative methodologies (Creswell, 1999). This multifaceted approach involves collecting responses from stakeholders through surveys and interviews, enabling a comprehensive exploration of the challenges at hand. Subsequently, qualitative analysis techniques, such as thematic analysis, are applied to the collected data to identify and categorize the main challenge themes. In the field of city logistics, some studies have employed this approach (Lindholm and Behrends, 2012; Anosike et al., 2013; Kassai et al., 2020; Sista and De Giovanni, 2021; Alharbi et al., 2022).

Lindholm and Behrends (2012) employed thematic analysis to explore the difficulties in making city freight transport more eco-friendly and to examine how cities around the Baltic Sea plan for it. They conducted detailed interviews with people from the government and businesses and studied documents to find important topics. Their findings showed that city freight transport is crucial for the competitiveness of the region, but it's also harming urban sustainability. The way cities are designed makes it hard for freight operations to run smoothly, and surprisingly, both city authorities and transport companies often overlook these problems. Anosike et al. (2013) investigated the challenges of introducing electric vehicles in last-mile

parcel delivery operations from both academic literature and the perspectives of parcel carriers. The research involved conducting semi-structured interviews with two prominent parcel carriers in the UK, followed by a thematic analysis to identify key challenges. These challenges revolved around aspects such as operations, infrastructure, battery technology, and the cost components associated with electric vehicles.

Kassai et al. (2020) examined the potential of autonomous self-driving trucks for delivery services, focusing on the courier, express, and parcel sectors. They conducted semi-structured interviews with industry experts and used thematic analysis. The findings reveal parcel delivery companies' interest in innovative solutions like autonomous vans for B2C deliveries, but they also highlight barriers to implementation, including legislative hurdles, technological challenges, workforce adjustments, and the management of evolving customer expectations. Sista and De Giovanni (2021) studied the common issue of smart city logistics projects failing to scale up and aim to identify key success factors related to their scalability. To achieve this, the researchers conducted a qualitative case study using the SMOOTh project in Gothenburg, Sweden, which involves multiple companies like Volvo Group and DHL. They conducted semi-structured interviews with seven project stakeholders and employed thematic analysis to identify four categories of success factors: business model, technical, stakeholder, and regulatory. Alharbi et al. (2022) investigated the use of CS to tackle LMD challenges in Saudi Arabia. The research involved semi-structured interviews with a range of stakeholders aimed at identifying the challenges associated with CS. Through doing thematic analysis, the study pinpointed four main obstacles impeding the effective implementation of CS: legislative constraints, availability of crowdshippers, trust issues, and cultural factors.

### **3.2.1 Contributions**

Previous behavioural studies in the field of CS have primarily concentrated on modelling the acceptance behaviour of crowdshippers regarding package delivery. Notable works by Marcucci et al. (2017), Punel et al. (2018), and Le and Ukkusuri (2019a) have delved into the participation issues associated with CS involving occasional drivers. In all three studies, the choice questions employed fixed and deterministic attribute levels. However, a crucial aspect is that, prior to engaging in CS systems, users often lack a clear understanding of the tasks and their specific details. Consequently, modelling willingness to participate based on choice questions with exact attribute levels may lead to estimation errors. In this study, a departure from this approach is taken, as attribute levels are presented in broad ranges rather than exact

values. These ranges encompass additional variations that may occur in the attribute levels defined for CS tasks.

Table 3.1 Review Table.

| Reference               | Crowdshipper         | CS Task          | Behavioural problem | DC method        | Attributes type |
|-------------------------|----------------------|------------------|---------------------|------------------|-----------------|
| Miller et al. (2017)    | OD                   | Without lockers  | Acceptance          | Mixed logit      | Deterministic   |
| Devari et al. (2017)    | OD <sup>a</sup>      | Without lockers  | Acceptance          | Binary logit     | Deterministic   |
| Marcucci et al. (2017)  | General <sup>b</sup> | Without lockers  | Participation       | No DC model      | Deterministic   |
| Punel et al. (2018)     | OD                   | Without lockers  | Participation       | Binary logit     | Deterministic   |
| Serafini et al. (2018)  | PT passenger         | Locker to locker | Acceptance          | MNL <sup>c</sup> | Deterministic   |
| Le and Ukkusuri (2019a) | OD                   | Without lockers  | Participation       | Binary logit     | Deterministic   |
| Gatta et al. (2019a)    | PT passenger         | Locker to locker | Acceptance          | MNL              | Deterministic   |
| Wicaksono et al. (2021) | Cyclist              | Without lockers  | Acceptance          | MNL              | Deterministic   |
| Fessler et al., (2022)  | PT passenger         | Locker to locker | Acceptance          | Mixed logit      | Deterministic   |
| Mohri et al., (2024)    | PT passenger         | Locker-to-home   | Acceptance          | LC model         | Deterministic   |
| Current study           | PT passenger         | Locker-to-home   | Participation       | Binary logit     | Stochastic      |

a: Friends of package receivers in social platforms; b: Students traveling by any mode; c: Multinomial Logit (MNL);

While the intention to participate problem has been investigated for CS involving occasional drivers, there has been a gap in exploring this aspect for PT-based CS initiatives. As depicted in Table 3.1, existing behavioural studies on PT-based CS have primarily focused on the acceptance problem related to CS tasks (Serafini et al., 2018; Fessler et al., 2022; Mohri et al., 2024). These studies in the PT-based CS literature typically involve PT passengers facilitating locker-to-locker deliveries, contrasting with the approach taken in this study, which considers PT passengers for locker-to-home (package receiver's location) deliveries, specifically addressing the last mile. As illustrated in Figure 3.2, the existing PT-based CS studies involve passengers transferring packages solely between two lockers, rather than delivering them to the actual destinations. The substitution of receivers' delivery addresses (such as homes) with locker facilities has the potential to influence the participation rate of PT passengers in the CS system. In locker-to-home CS systems, crowdshippers would encounter significant detours and interactions with package receivers. Therefore, this study aims to enhance the modelling of the intention to participate in PT-based CS systems by incorporating the substitution of receivers' homes with locker facilities.

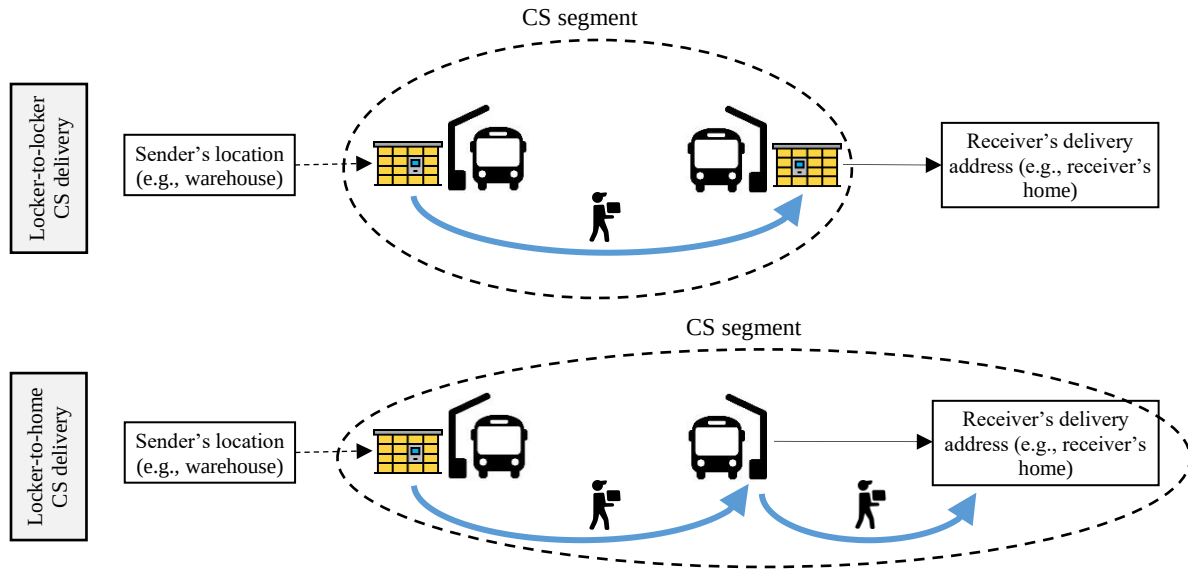


Figure 3.2 Delivery segments outsourced to crowd-shippers.

Regarding every new service, participants have implicit concerns that could be beyond the capability of service providers in advance to include them. Qualitative research techniques are an appropriate tool for recognizing their concerns. To the best of our knowledge, this study is the first to study the concerns of PT passengers refusing to participate in PT-based CS systems and identify the main prohibiting factors for participation. By conducting an inductive thematic analysis on the data collected, categories of prohibiting factors are identified which can significantly aid service providers in ways of successfully defining, launching, and advertising their services.

### 3.3 Survey Data

Sydney has an area of 12.4 thousand square meters and is home to nearly 5.4 million people, according to the estimated population in June 2021 (Australian Bureau of Statistics, 2022). The PT system in Sydney includes train, bus, metro, light rail, and ferry whereby nearly 30% of total passenger trips are made by PT modes. Train and bus are the dominant PT modes in Sydney, where on average 53% (420 million passenger trips) and 41% (324 million passenger trips) of annual PT passenger trips (before COVID-19) were made by train and bus, respectively (TfNSW, 2022). The train system consists of 8 lines and 170 stations, while the bus system has more than 600 routes and 4.2 thousand stops. Given the dense and attractive PT system, Sydney can be a viable option to launch PT-based CS initiatives.

To explore the intention of Sydney PT passengers to participate in the proposed PT-based CS initiative, an online survey was conducted in February 2022. The survey asked respondents to provide information of their preferences for city logistics initiatives including the PT-based CS initiative. Two pilot studies were also conducted to improve the research quality and make it realistic and workable. The first pilot targeted 12 professionals in areas of statistical analyses and freight last-mile logistics. The second pilot was conducted through Qualtrics and targeted 10% of the sample size for Sydney. After revising the survey based on the feedback received from both pilot studies, the survey was finalized and launched. Two specific questions were included to explore the intention to participate, as shown in Figure 3.3.

In the realm of experimental design for choice modelling, there is a prevalent emphasis on achieving a high level of resemblance between the experiment and the real-world context that unfolds after implementation. This alignment with the post-implementation scenario is sought to enhance the generalizability and practicality of the experiment's results (Haghani et al., 2021). As depicted in Figure 3.1, in crowd-based systems such as ride-sourcing or CS systems, occasional service providers (e.g., crowdshippers in CS systems) often lack a comprehensive understanding of the tasks and their precise details. They possess a rudimentary grasp of the system's operations, with information presented in broad ranges rather than exact values. Consequently, the first question (Q1) is formulated to present attribute quantities, like incentives or parcel delivery weights, in varying ranges that align with the fluctuations observed in CS delivery tasks. This approach fosters similarity between the experiment and the post-implementation scenario.

### Crowd-shipping by public transport passengers

**Note:** *Imagine, as part of a sustainable government-sponsored freight initiative program, you are offered a small parcel delivery task (i.e., 1 to 3kg) at your public transport station, near work or home location. You will be given a parcel, at your origin station locker, and you are asked to deliver it to an address close to your final destination within a short walking distance (i.e., 200 to 600 meters).*

**Q1:** Would you be interested to participate in the above program, and deliver parcels in return for a monetary incentive (e.g., 3-8 AUD per delivery)?

Yes ☐ No ☐

(If the answer is No:)

**Q2:** Please explain why you are **not** interested to participate in the above program?  
(You can select multiple reasons or write your own reason)

- ☐ I rarely use public transport services
- ☐ I do not need the incentive
- ☐ I cannot carry additional items/weight
- ☐ I do not have time
- ☐ Other reasons
- ☐
- ☐

*Please explain*

Figure 3.3 Questions for exploring the intention to participate.

The first question (Q1) was posed to all respondents who use PT at least once a month. It defines the key parameters for the CS tasks, including the range of incentive values, parcel weight, and delivery detour. These parameters were determined through a comprehensive review of prior research (Gatta et al., 2019a; Fessler et al., 2022), analysis of delivery costs in Australia (Fair Work Ombudsman, 2023; Sendle, 2022), and consultation with 12 industry experts specializing in statistics and last-mile logistics. Parcel weights in the CS initiative were suggested to fall between 1 kg and 3 kg, in consideration of the fact that over 90% of global package deliveries are under 3 kg (Statistica, 2022). For delivery detours, a range of 200 meters to 600 meters was proposed, based on a study of walking distances to PT stations in Sydney that shows walking distance to bus/train stations follows a triangular distribution with a mean of around 400/600 meters (Daniel and Mully, 2013). To make the CS initiative appealing to PT passengers, a minimum hourly pay rate higher than the national minimum wage of 23 AUD (Fair Work Ombudsman, 2023) was set. This ensures that even the least attractive CS task, involving a 3 kg parcel and a 600-meter detour, meets or exceeds the national hourly wage.

Given an average walking speed of 5 km/h, the minimum incentive was determined to be above 3 AUD. To make it attractive for carriers, the maximum incentive was set at 8 AUD, aligning with the average delivery fees charged by carriers in Australia for small packages (8-12 AUD) (Sendle, 2022). This balance aims to meet carrier expectations while keeping CS tasks economically attractive.

Once the response for Q1 was “No”, a follow-up question, Q2, was asked to determine the reason for rejecting the participation decision. This is an open-ended question in which respondents were allowed to either choose one (or more) reasons in a multiple-choice menu or write their own reasons.

The survey was distributed in March 2022 through the Qualtrics platform. The sample was aimed to be representative of Sydney’s population in terms of age, gender, and level of income, and only included respondents older than 18. Through this survey, 2208 valid responses were collected. The demographic details of the collected sample and Sydney’s population are summarized in Table 3.2, which shows that the collected sample is well representative of the population.

Data shows 1589 of 2208 respondents travel by PT services at least once a month, hence, 1589 responses were collected from Q1 where 952 responded “Yes”, as shown in Figure 3.4(a). It shows that 60% of the total population in Sydney traveling at least monthly by PT services intend to participate in the PT-based CS initiative which can lead to an appropriate participation rate. On another side, 637 respondents (40%) were unwilling to participate and provided their reasons by answering Q2. Figure 3.4(b) shows the frequency of the selected reasons by the respondents. Since Q2 was a multiple-response open-ended question, there are more than 637 reasons (917 reasons) for rejecting the participation decision.

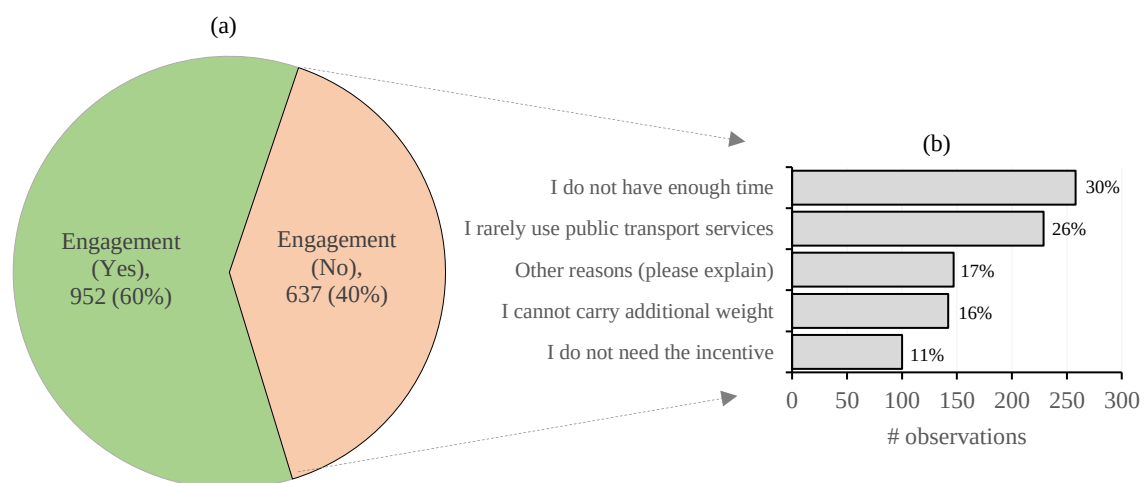


Figure 3.4 Questions for exploring reasons for rejecting the participation decisions.

Figure 3.4(b) shows that the most and least frequent reasons are “I do not have enough time” and “I do not need the incentive”, respectively. Also, the second most frequent reason (i.e., rarely using PT services) has a similar frequency to the first reason. It is interesting that 147 respondents (17%) provided other reasons, motivating the research to conduct qualitative analysis to extract prohibiting factors and categorize them.

In addition to Q2, respondents who agreed to participate are asked to declare on which trips they prefer to serve as a crowdshipper. The alternatives were (1) home to work, (2) work to home, (3) both, and (4) all trips. Figure 3.5 demonstrates which trips PT passengers prefer to carry packages on. Results show only 34% of passengers might accept carrying CS packages along all their trips. Accordingly, 29% and 10% of passengers would act as crowdshipper while travelling only from work to home and home to work, respectively. It can indicate a higher potential of outsourcing packages to passengers during afternoon and evening periods when passengers are returning from their workplaces to homes.

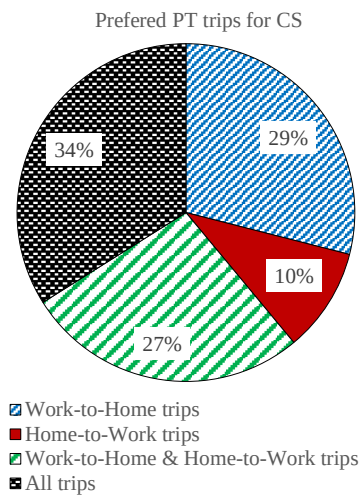


Figure 3.5 Preferred PT trips for participation in CS delivery.

### 3.4 Method

In order to model the intention of PT passengers to participate in the PT-based CS initiative, this research relies on DC models based on random utility maximization (Train, 2009). The participation question, Q1, has a “yes”/or “no” response; hence, there are two alternatives. The binominal logit model was selected to represent the probabilities of the alternatives. Accordingly,  $U_{n,i}$  is the utility of choosing alternative  $i$  for individual  $n$  which has

two parts: the representative (or systematic) utility ( $V_{n,i}$ ) and the random utility ( $\varepsilon_{n,i}$ ). The  $V_{n,i}$  includes the observed factors ( $\beta_{k,n}$ ,  $k$  is the index of factors) affecting the systematic utility, while  $\varepsilon_{n,i}$  represents the random part of the utility, including factors that cannot be captured in the model, or measurement errors. In binominal logit one utility function can represent the choice model ( $U_{n,i=yes} - U_{n,i=no}$ ), as shown by Equation (3.3). Assuming that the error term follows an independent and identically distributed (iid) extreme value distribution for all  $i$ , the probability of accepting the initiative can be calculated by Equation (3.4). Moreover, the probability of rejecting the initiative is  $1 - P_n(i = yes)$ .

$$U_{n,i} = V_{n,i} + \varepsilon_{n,i} \quad (3.1)$$

$$V_{n,i} = \alpha + \sum_{k \in K} \beta_{k,n} x_{k,n,i} \quad (3.2)$$

$$U_{n,i=yes} - U_{n,i=no} = \alpha' + \sum_{k \in K} \beta'_{k,n} x_{k,n} + \varepsilon'_{n,i} \quad (3.3)$$

$$P_n(i = yes) = \frac{1}{1 + e^{-(U_{n,i=yes} - U_{n,i=no})}} \quad (3.4)$$

$$P_n(i = no) = 1 - P_n(i = yes) \quad (3.5)$$

To build the binominal logit model on the 1589 collected responses for Q1, the software Stata version 15 was used (StataCorp, 2017). Several factors observed in the survey were grouped as follows: **Demographics** (age, gender, dwelling type, employment status, and household size), **socio-economic** (income and sustainability role<sup>2</sup>), **e-shopping activity-related** (delivery volume, PL experience<sup>3</sup> and acceptance<sup>4</sup>), and **PT mobility-related factors** (PT trip frequency per month). In table 3.2, different levels of the factors, as well as their frequencies in the sample, are presented.

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<sup>2</sup> Sustainability role: It is a binary variable indicating whether the respondent is willing to play a role in achieving sustainability in urban freight systems (e.g., accept higher delivery cost, accept longer delivery time, and accept PL or office post delivery if they contribute to reducing air pollution, congestion, and road accidents. Additional information on how the variable was constructed can be found in Appendix A

<sup>3</sup> PL experience: It is a binary variable indicating whether the respondent had any PL experience.

<sup>4</sup> PL acceptance: It is a binary variable indicating whether the respondent accepts using PLs.

Table 3.2 Observed factors.

| Attribute                  | Frequency | Breakdown | Census 2016 | Attribute                                            | Frequency          | Breakdown | Census 2016 |
|----------------------------|-----------|-----------|-------------|------------------------------------------------------|--------------------|-----------|-------------|
| <b>Demographic factors</b> |           |           |             | <b>Socio-economic factors</b>                        |                    |           |             |
| <b>Gender</b>              |           |           |             | <b>Sustainability role</b>                           |                    |           |             |
| Male                       | 1061      | 48.05%    | 51.1%       | Yes                                                  | 1688               | 76.45%    | -           |
| Female                     | 1147      | 51.95%    | 49.90%      | No                                                   | 520                | 23.55%    | -           |
| <b>Age</b>                 |           |           |             | <b>Annual income</b>                                 |                    |           |             |
| 18-30                      | 476       | 41.56%    | 42.61%      | Less than \$30,000                                   | 484                | 27.92%    | 29.50%      |
| 31-40                      | 464       | 30.01%    | 31.09%      | \$30,000 to \$60,000                                 | 526                | 21.82%    | 22.10%      |
| 41-50                      | 460       | 8.83%     | 10.00%      | \$60,000 to \$90,000                                 | 511                | 23.14%    | 22.60%      |
| 51-60                      | 369       | 8.71%     | 7.28%       | \$90,000 to \$120,000                                | 373                | 13.89%    | 23.50%      |
| 61-70                      | 253       | 6.46%     | 5.22%       | More than \$120,000                                  | 314                | 12.22%    |             |
| 71 and older               | 186       | 4.42%     | 3.80%       | <b>E-shopping activity-related factors</b>           |                    |           |             |
| <b>Employment status</b>   |           |           |             | <b>Delivery volume</b>                               |                    |           |             |
| Full time employee         | 1157      | 52.40%    | 51.20%      | Under 5 items/year                                   | 244                | 11.05%    | -           |
| Part time employee         | 396       | 17.93%    | 38.6%       | 5-10 items/year                                      | 456                | 20.65%    | -           |
| Retired                    | 348       | 15.76%    |             | 11-20 items/year                                     | 534                | 24.18%    | -           |
| Disabled                   | 39        | 1.77%     |             | More than 20 items/year                              | 974                | 44.11%    | -           |
| Student full time          | 89        | 4.03%     | -           | <b>PL experience</b>                                 |                    |           |             |
| Unemployed                 | 179       | 8.11%     | 5.90%       | Yes                                                  | 514                | 23.28%    | -           |
| <b>Dwelling type</b>       |           |           |             | No                                                   | 1694               | 76.72%    | -           |
| Stand-alone house          | 1341      | 60.73%    | 66.40%      | <b>PL preference</b>                                 |                    |           |             |
| Apartment                  | 727       | 32.93%    | 32.10%      | Yes                                                  | 1433               | 64.90%    | -           |
| Other                      | 140       | 6.34%     | 3.50%       | No                                                   | 775                | 35.10%    | -           |
| <b>Household size</b>      |           |           |             | <b>PT mobility-related factors</b>                   |                    |           |             |
| 1                          | 341       | 15.44%    | 16.00%      | PT trip frequency per month<br>(Continuous variable) | 2 trips (min)      |           |             |
| 2                          | 701       | 31.75%    | 36.60%      |                                                      | 34 trips (max)     |           | -           |
| 3 or 4                     | 934       | 42.30%    | 47.40%      |                                                      | 12 trips (average) |           |             |
| 5 or more                  | 232       | 10.51%    |             |                                                      |                    |           |             |

### **3.4.1 Inductive thematic analysis**

Survey-based quantitative research has emerged recently to investigate the participation and acceptance behaviour of crowdshippers in CS initiatives (Marcucci et al., 2017; Serafini et al., 2018; Gatta et al., 2019a; Gatta et al., 2019b; Fessler et al., 2022; Devari et al., 2017; Miller et al., 2017; Le and Ukkusuri, 2019a; Punel et al., 2018). However, there is no qualitative research of crowdshippers behaviour in the literature while conducting qualitative research in city logistics literature is essential (e.g., Kester et al., 2018; Vakulenko et al., 2018). Accordingly, a lack of in-depth understanding of the intention of potential crowdshippers to participate in CS initiatives motivates research in qualitative analyses.

The inductive qualitative data analyses (i.e., inductive thematic analyses) (Rahman et al., 2021) generate theories from the survey data by processing the text responses, coding text responses with inherent meanings, and categorizing the codes into meaningful units of information called categories or themes (Thomas, 2003; Nowell et al., 2017). The resulting themes built on the raw data can show the perspectives of different research participants and generate unanticipated insights (Braun and Clarke, 2006). This process begins with the extraction of text responses from the survey dataset. In our approach, we employed NVIVO 12 software, a widely used tool in qualitative research, to assist in this initial step. NVIVO 12 aids in extracting and organizing text responses efficiently. Once the text responses are extracted, the software facilitates the creation of preliminary categories or themes based on inherent meanings found within the text. However, it's important to note that this initial categorization is not the final step. To ensure the accuracy, coherence, and semantic relevance of the generated categories, the modeler carefully reviews and revises the segmentation and categorization produced by the software. This crucial phase involves a close examination of the extracted content to verify that it aligns with the research objectives and captures the nuances and subtleties in the responses.

## **3.5 Results**

This section is organized into three subsections as follows. In Subsection 3.5.1, the results of the intention of PT passengers to participate in the proposed CS initiative are shown. In Subsection 3.5.2, the results of conducting the inductive thematic analysis on reasons for rejecting the participation decision are presented and the main prohibiting factors are

recognized. The sensitivity of different sociodemographic groups to the prohibiting factors are identified and described in subsection 3.5.3.

### 3.5.1 Modelling the intention to participate

Using the observed factors, illustrated in Table 3.2, several explanatory variables are defined by which the binominal logit model is developed. To find the best representative model, various combinations of variables are used iteratively. The decision to include variables in the final model is made based on the sign and z-statistic of the variables as well as their impacts on the model's goodness-of-fit. Overall, the best model is shown in Table 3.3, where except for one variable ("Large household size"), all the variables are significant at the 95% confidence level. Moreover, the Pseudo  $R^2$  value is 0.234 which is indicative of a relatively good model fit.

Table 3.3 The binominal logit model representing the intention to participate.

| Variable name (units)                                                         | Units      | Parameters estimated | Z (P> Z )     | 95% confidence interval |
|-------------------------------------------------------------------------------|------------|----------------------|---------------|-------------------------|
| Female (yes:1, no:0)                                                          | 1,0        | -0.418**             | -4.28 (0.000) | -0.610 to -0.227        |
| Young adults (yes:1, no:0)                                                    | 1,0        | 0.268**              | 2.60 (0.027)  | 0.066 to 0.470          |
| Senior adults (yes:1, no:0)                                                   | 1,0        | -0.403**             | -2.27 (0.030) | -0.751 to -0.055        |
| High-income (yes:1, no:0)                                                     | 1,0        | -0.347**             | -2.62 (0.014) | -0.607 to -0.870        |
| Full-time employee (yes:1, no:0)                                              | 1,0        | -0.230**             | -1.89 (0.037) | -0.469 to 0.008         |
| Retired (yes:1, no:0)                                                         | 1,0        | -0.527**             | -2.71 (0.030) | -0.907 to -0.146        |
| Large household size (yes:1, no:0)                                            | 1,0        | 0.165                | 1.67 (0.137)  | -0.290 to 0.360         |
| PT trip frequency per month                                                   | Continuous | -0.012**             | -3.20 (0.000) | -0.201 to -0.004        |
| Sustainable role (yes:1, no:0)                                                | 1,0        | 0.537**              | 3.95 (0.000)  | 0.270 to 0.804          |
| Locker preference (yes:1, no:0)                                               | 1,0        | 0.793**              | 6.80 (0.000)  | 0.565 to 1.021          |
| Locker experience (yes:1, no:0)                                               | 1,0        | 0.514**              | 4.41 (0.000)  | 0.286 to 0.742          |
| Medium-volume delivery (yes:1, no:0)                                          | 1,0        | -0.990**             | -5.71 (0.000) | -1.328 to -0.650        |
| High-volume delivery (yes:1, no:0)                                            | 1,0        | -1.007**             | -5.55 (0.002) | -1.363 to -0.652        |
| Constant                                                                      |            | 0.486* <sup>0</sup>  | 2.03 (0.082)  | 0.016 to 0.956          |
| Model fit statistics                                                          |            |                      |               |                         |
| Number of observations                                                        | 1589       |                      |               |                         |
| Log-likelihood at zero betas                                                  | -1623.37   |                      |               |                         |
| Log-likelihood at convergence                                                 | -1283.91   |                      |               |                         |
| Pseudo R <sup>2</sup>                                                         | 0.234      |                      |               |                         |
| Variable definition:                                                          |            |                      |               |                         |
| Female: Women                                                                 |            |                      |               |                         |
| Young adults: Individuals aged less than 40                                   |            |                      |               |                         |
| Middle-aged adults: Individuals aged between 40 to 60                         |            |                      |               |                         |
| Senior adults: Individuals aged more than 60                                  |            |                      |               |                         |
| Low income: Individuals with an income less than 30k AUD per year             |            |                      |               |                         |
| Medium income: Individuals with an income between 30k AUD to 90k AUD per year |            |                      |               |                         |
| High income: Individuals with an income more than 90k AUD per year            |            |                      |               |                         |
| Full-time employee: Individuals working full time                             |            |                      |               |                         |
| Part-time employee: Individuals working part time                             |            |                      |               |                         |
| Unemployed: Unemployed individuals                                            |            |                      |               |                         |
| Retired: Individuals who are retired                                          |            |                      |               |                         |
| Disable: Individuals with disability                                          |            |                      |               |                         |

|                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                     |
|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| <p><b>Small household size:</b> Individuals living in households with maximum 2 members</p> <p><b>Medium household size:</b> Individuals living in households with 3 or 4 members</p> <p><b>Large household size:</b> Individuals living in households more than 4 members</p> <p><b>PT trip frequency per month:</b> An average number of PT trips per month</p> <p><b>Sustainable role:</b> Individuals supporting sustainable urban freight initiatives</p> <p><b>Locker preference:</b> Individuals not having an opposition to contact with PL facilities</p> <p><b>Locker experience:</b> Individuals having has working experience with PLs</p> <p><b>Low-volume delivery:</b> Individuals having less than 5 deliveries per year</p> <p><b>Medium-volume delivery:</b> Individuals having between 5 to 20 deliveries per year</p> <p><b>High-volume delivery:</b> Individuals having more than 20 deliveries per year</p> <p><b>Apartment dwellers:</b> Individuals living in an apartment</p> <p><b>House residents:</b> Individuals living in a house</p> |
|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|

The binomial logit model developed suggests the intention to participate in PT-based CS initiatives is affected by several factors. In particular, women, senior adults, low-income individuals, full-time employees, retired, and individuals with high PT trip frequency, and medium or high number of deliveries per month are less likely to participate in this initiative. Conversely, individuals who are young, living in large households, caring for sustainability in urban delivery systems, and have had experience with PLs (or preference) would be more likely to participate in this type of CS initiative.

The observation that women are more reluctant to participate in comparison to males can be attributed to their attitude towards risk, considering that women are statistically more likely to be risk averse (Jianakoplos and Bernasek, 1998), and carrying unknown packages and delivering to unknown receivers may be perceived as relatively risky task. Also, young adults as compared to seniors or retired individuals might be in better physical health and ability required for delivering packages, which may explain the signs of coefficients for young and senior adults. Full-time employees might not have enough time, or high-income individuals might not need the compensation. It is also interesting that the participation of individuals with frequent deliveries per month is less likely. This can be attributed to the fact that those on the receiving end of crowd-shipped packages may not feel comfortable receiving their packages from random individuals. While this observation may indicate the necessity for a separate line of research to uncover receiver behaviour, this is out of the scope of this paper.

Moreover, frequent PT passengers may be less likely to participate in CS, as the negative sign indicates the coefficient associated with PT trip frequency per month. This might indicate that regular PT passengers (most of which may have full-time jobs) may not like to (e.g., daily) be burdened with CS tasks. Utilizing PL services may pose a challenge for individuals who lack prior experience or are hesitant to give it a try; hence, it is observed that having experience or a positive attitude to contact the facilities can be associated with higher intention to participate. Since the initiative can contribute to achieving sustainability in urban freight

systems, individuals feeling a sense of responsibility in this regard would participate more than others.

Table 3.4 Direct elasticities of choice.

| Variable name (units)                | Variable type | Elasticity/Semi-elasticity* | Z (P> Z )     |
|--------------------------------------|---------------|-----------------------------|---------------|
| Female (yes:1, no:0)                 | Discrete      | -0.198                      | -4.28 (0.000) |
| Young adults (yes:1, no:0)           | Discrete      | 0.126                       | 2.63 (0.009)  |
| Senior adults Old (yes:1, no:0)      | Discrete      | -0.204                      | -2.14 (0.032) |
| High-income (yes:1, no:0)            | Discrete      | -0.165                      | -2.61 (0.009) |
| Employed full-time (yes:1, no:0)     | Discrete      | -0.110                      | -1.89 (0.059) |
| Retired (yes:1, no:0)                | Discrete      | -0.251                      | -2.70 (0.007) |
| Large household size (yes:1, no:0)   | Discrete      | 0.079                       | 1.66 (0.096)  |
| PT trip frequency                    | Continuous    | -0.104                      | -3.19 (0.001) |
| Sustainable role (yes:1, no:0)       | Discrete      | 0.265                       | 3.92 (0.000)  |
| Locker preference (yes:1, no:0)      | Discrete      | 0.378                       | 6.67 (0.000)  |
| Locker experience (yes:1, no:0)      | Discrete      | 0.245                       | 4.41 (0.000)  |
| Medium-volume delivery (yes:1, no:0) | Discrete      | -0.471                      | -5.63 (0.000) |
| High-volume delivery (yes:1, no:0)   | Discrete      | -0.480                      | -5.48 (0.000) |

\* For continuous variables elasticity and for dummy and integer variables semi-elasticity should be computed (Greene and Hensher, 2010).

Although the parameter estimates are statistically significant and meaningful, calculating their elasticities can demonstrate the magnitude of their influence on the dependent variable. Hence, Table 3.4 shows the elasticities of the explanatory variables in the model. Results show that elasticity estimates for medium- and high-volume delivery, which are two discrete variables, are substantially large and negative. The finding implies that as the delivery volume for an individual transitions from low to medium and subsequently from medium to high, there is a significant decline in the individual's willingness to participate in the CS initiative. Additional discrete variables, including being retired, female and senior adult, similarly exhibit notably substantial negative effects on the utility associated with the intention to participate. Consequently, being retired, female, or a senior adult is indicative of a greater reduction in participation in the CS initiative. Conversely, possessing prior experience with PLs, coupled with a strong inclination to contribute to sustainability efforts, yields the most significant positive effects on utility. Thus, having hands-on experience with PLs or holding a favourable attitude towards sustainability and a willingness to actively contribute to its realization enhances individuals' intentions to participate in the CS system. At the next level, being young or living in a large household can also improve the chances of participation.

While the binomial logit model serves as an intention-to-participate model and lacks alternative-specific attributes, it is still feasible to provide a rough estimate of the WTW)

among PT passengers by considering the expected values of weight and detour attributes related to CS tasks. According to our findings in Q1 (Figure 3.3), PT passengers tend to expect an incentive of approximately 5.5 AUD for a parcel delivery with a weight of 2 kilograms, and an additional detour of about 400 meters. Given the observed 60% participation rate (Figure 3.4), we can estimate the WTW with respect to weight and detour attributes to be roughly 1.65 AUD per kilogram and 0.825 AUD per 100 meters, respectively. These estimates closely align with the WTW values reported in Mohri et al. (2024), who utilized a MNL model to address the CS task acceptance problem using the same dataset. In their study, Mohri et al. (2024) reported WTW values associated with weight and detour as 1.15 AUD per kilogram and 1.09 AUD per 100 meters, respectively.

In the following sections, respondents' reasons for rejecting the participation decision are investigated, to discover the underlying prohibiting factors for not participating in the initiative.

### **3.5.2 Results of the inductive thematic analysis**

The main prohibiting factors for participation in the CS initiative are discussed in this section. A total of 917 text segments were extracted from the 637 reasons for rejection declared by respondents. As illustrated in Figure 3.4(b), 17% of the provided reasons fall into the "other reasons" category, where respondents have articulated specific reasons. Conversely, the remaining text segments are aligned with the top four choices indicated in Q2 (Figure 3.3), corresponding to the selections made by respondents. Given that Q2 allowed for multiple answers, respondents had the flexibility to choose multiple reasons and also provide additional, context-specific explanations. Through the analysis of reasons for rejecting participation, it has been noticed that some PT passengers specifically cited some aspects of convenience as a factor influencing their rejection of participation. The term "convenience" pertains to the quality of being user-friendly, efficient, and aligned with one's preferences and needs and it encompasses various aspects, including accessibility, simplicity, comfort, safety, security, time-saving, and reliability. Among these convenience-related aspects, those with higher frequencies of observation were classified into distinct prohibiting categories. These categories include "time," "social/labour aspects," "safety and security," "responsibility," and "physical/mental ability"

However, some responses didn't specify the particular aspects of inconvenience and simply mentioned "convenience" in a general sense as the reason for declining participation. Additionally, few responses highlighted other inconvenience factors, like congestion within

the PT system. Therefore, reasons related to inconvenience that had a low probability or were mentioned in a general manner are grouped under "additional convenience aspects." Ultimately, the inductive thematic analysis resulted in categorizing reasons for declining participation into nine primary categories: (1) Time, (2) physical/mental ability, (3) compensation, (4) responsibility, (5) safety and security, (6) social/labour aspects, (7) additional convenience aspects, (8) infrequent PT passengers, and (9) lack of interest. Figure 3.6 shows the share of each of the categories from total text segments.

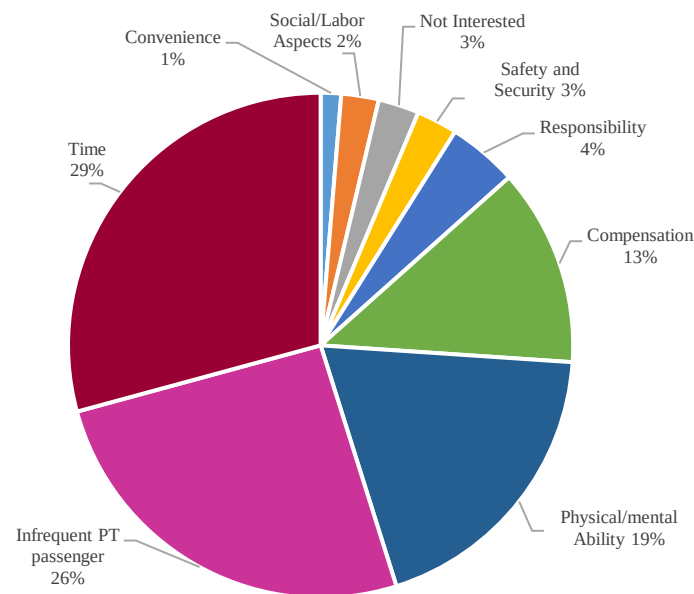


Figure 3.6 Prohibiting factors and their shares.

### 3.5.3 Time

As shown in Figure 3.6, time-related factors are the most frequent reasons hindering passengers' intention to participate in the initiative with a 29% contribution. The respondents brought up multiple time-related prohibiting factors relating to lack of time, uncertainty in time schedule, and concerns over spending too much time dealing with the package's receiver. Some examples are presented: Lack of time: "It's a great idea in theory, I'm just too time poor to do something like this - maybe if it was for a neighbour but wouldn't have time to go out of my way", "At the moment my work and personal life are full! I am not 100% sure I could commit to this properly at the moment. Sorry!", or "If I am on public transport it is usually to get somewhere at a set time, and I am likely to be in a rush". Uncertainty in time schedule: "My schedule can change" or "Can't commit on a regular basis". Concerns over spending too much

time dealing with package receiver: “Concern that I may have to deal with recipients. And I didn’t have time”.

### **3.5.4 Infrequent PT passenger**

Infrequent travel by PT services may be less motivated to participate in the initiative. Although, the respondents were those travelling at least monthly, the frequency of their trips within a month can affect their participation decision. As shown in Figure 3.7, 91% of those refused to participate had less than 3 PT trips per month while based on total survey data only 47% of respondents making PT trips less than 3 times per month. Moreover, a further 5% has 4 to 7 PT trips per month.

It's reasonable to posit that PT passengers with low PT trip frequency may not perceive CS initiatives as financially rewarding, leading them to decline participation. Interestingly, the binary logit model's results indicate a negative relation between PT trip frequency and participation in CS initiatives. This suggests that individuals with medium PT travel frequency (neither too high nor too low) constitute the most promising demographic for participation. This aligns with the corresponding pie chart in Figure 3.7, which illustrates the frequency of PT trips among engaged respondents. This observation bears significance for companies seeking to establish PT-based CS systems. They should take into account that passengers taking fewer than three, or even seven, PT trips per month, as well as those with high trip frequencies (over 15 trips per month), are less likely to participate compared to PT passengers who usually travel two to three times per week.

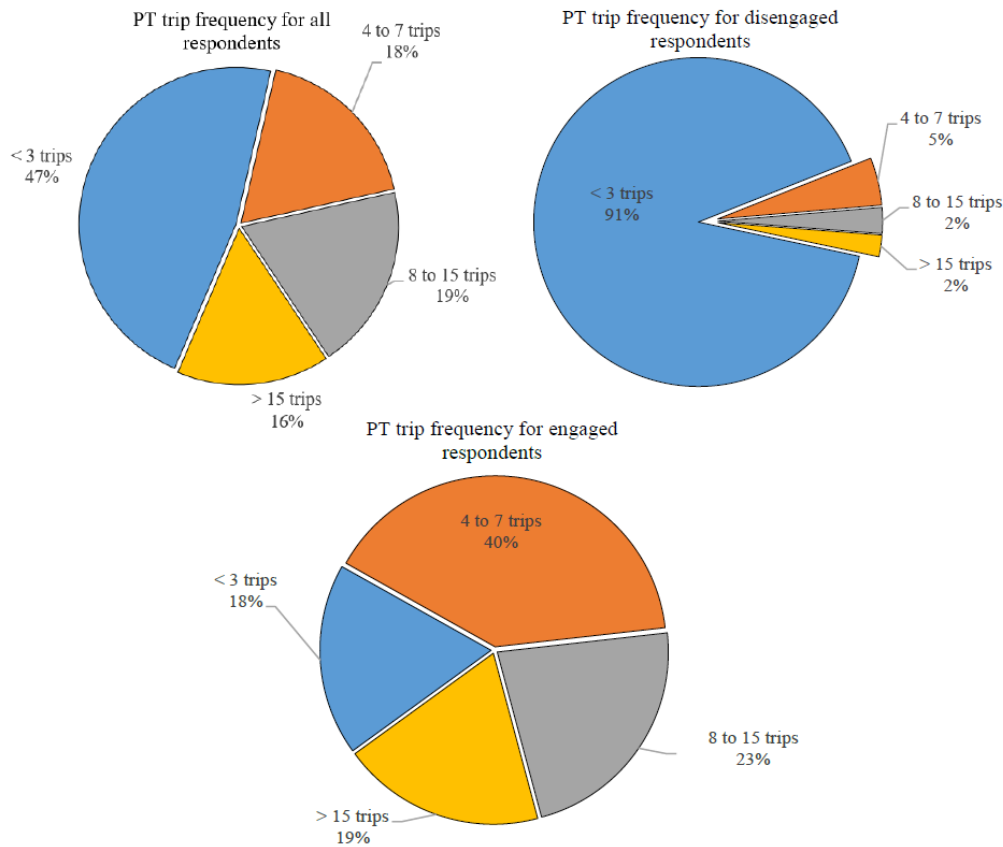


Figure 3.7 PT trip frequency among respondents.

### 3.5.5 Physical/mental ability

Nearly 19% of the prohibiting factors were around physical and mental health problems of respondents, where physical problems are more frequent than mental health problems. Physical health problems are mainly related to mobility restrictions of respondents; however, some might avoid participating just because of high importance of maintaining their physical health. Some examples are as follows: Mobility restrictions: “I have a walking disability”, “I travel by public transport and use a walker so I can't carry much weight with me”, “I have joint issues”, “My disability prevents me”, or “probably difficult in a wheelchair”. Physical health importance: “My health is very important. I cannot carry any package”, “It is too heavy and may endanger my health”. Mental health problems: “I might not be able to find the delivery address, I have terrible sense of direction” or “People are annoying”.

### 3.5.6 Compensation

With 13%, compensation-related reasons are the fourth most important prohibiting factors. Some respondents highlighted that the suggested compensations for the tasks are not enough and less than their time value. Hence, their participation is conditional on the offered compensations over CS tasks. Here are some relevant responses to the prohibiting factor: *“Not enough money offered”, “It isn't worth the time”, “Because it's incentive is under minimum wage”, “Not enough pay. That's slave wages”, “the incentive is not worth it if I deliver by public transportation”, or “The incentive does not justify the costs of transport”.*

### 3.5.7 Responsibility

Responsibility is one of the major concerns of passengers when considering participation in this initiative, with 118 text segments indicating responsibility issues. Respondents believe the initiative might entail three types of responsibility. The first type is when the package receiver is not at home. Some respondents pointed out their concern about leaving the package at the door; *“I envisage the possibility that I would be responsible should the parcel go missing if the recipient isn't at home when I leave it”, “I would be concerned delivering to someone's home if it went missing I would be responsible”, or “What happens if someone steals the parcel after delivery or there is no one to accept delivery....Can you leave it on the doorstep or do you have to keep coming back to get the delivery signed off”.*

The second type is when package receivers are not happy with the delivery services or don't receive the package, etc. Respondents show concern about cases when the product in the package is damaged before being pick-up. Here are some examples: *“What if the parcel is damaged prior to pick up and I am not aware, who is responsible”, “I wouldn't want the responsibility of caring for the parcel. What if there is damage?”, “Would not want to be responsible if recipients of parcels had an issue with the delivery. There are too many ways consumers could dispute method of delivery”, “What if you made the delivery and the other person denied receiving the delivery, too risky”, “Liability for false claim of failed delivery”, “All I can see are difficulties involving claims of the parcel not being delivered”, or “I am concerned about the responsibility of carrying the parcel and being blamed or accused of losing it/not delivering it”.*

The third type is when the crowdshipper may be responsible for receiver identification, information and privacy. Some respondents mentioned, *“I do not want to be responsible for someone else’s package. That is a privacy issue, and I might be liable”* or *“Responsibility of recipient identification”*.

### **3.5.8 Safety and security**

Nearly 3% of the text segments refer to some potential safety and security risk for crowdshippers. They have elaborated on details of the risk from four different perspectives: (1) receiver anonymity: they believe it is risky to interact with unknown individuals; (2) product anonymity: it might be an unsafe or illegal product that they are carrying; (3) dogs: the risk of dog attacks when they enter a property or the back garden. Some examples for the perspectives are as follows: Receiver anonymity: *“I don’t know what type of person I am delivering to. Safety comes first”* or *“I’m female and delivering to a private address may be unsafe”*; Product anonymity: *“I’m not comfortable delivering parcels that contain unknown items”*; Dogs: *“scared of dogs; looks suspicious if I enter properties”* or *“I wouldn’t feel safe dropping off items in case there were dogs”*

### **3.5.9 Social/labour aspects**

It is very interesting that some respondents refuse to participate because of social/labour aspects of the business. Some believe CS initiatives threaten jobs since some drivers in freight delivery sector might lose their jobs with the emergence and expansion of CS systems. Here are some examples: *“It’s not my job. This takes jobs away from people who are delivery workers. A lot of which actually enjoy their jobs. I’m sick of this obsession of taking away unskilled jobs. Some people and families depend on these jobs”*, *“Sounds too much like Amazon Flex (dodgy casualisation in lieu of supporting workers)”*, or *“It will put delivery drivers out of a job”*.

Although respondents were only asked to declare why they reject participating in the CS initiative as a crowdshipper, some responded that they would not like to be package receivers in a CS system, if/once this system becomes popular. This observation emphasizes the importance of exploring the intention of package receivers to participate in CS initiatives as well, which is left unaddressed in the literature (Marcucci et al., 2017; Devari et al., 2017). Some of the relevant text segments to this concern are as follows: *“I wouldn’t want to do it*

*because I would not want to have some random member of the public delivering a parcel to me” or “I wouldn't want to participate because if that was my parcel, I wouldn't want the risk of the parcel being stolen by another civilian. I trust myself to deliver someone else's parcels, but I guess the program would go both ways and I value the security I have through the standard postal delivery services”.*

### **3.5.10 Additional convenience aspects**

Some respondents believe inconveniences arise from participating in the initiative. The represented inconvenience can occur either at the pick-up point to the PT destination stop or from the PT destination stop to the package receiver's destination. Regarding the former, respondents highlighted that they want to relax during their PT trips or sometimes PT is so crowded; hence, carrying a package makes it difficult to ride. When walking from a PT destination stop to the package receiver's destination, the detour as well as approaching buildings with centralized security systems can cause additional inconvenience for crowdshippers. Some relevant examples are: *“Usually use public transport if I'm going out on occasion. “I don't want to be delivering a package when I'm relaxing”, “I would not want to carry anything extra on public transport”, “Too crowded on public transport”, “I couldn't be bothered to go out of my way”, or “Difficulty in delivering to secure apartments or office buildings”.*

### **3.5.11 Not interesting**

Only 1% of those rejecting participation in the CS initiative highlighted that the idea is not interesting or naive (e.g., *“Not interested in this proposal” or “I think it is a silly idea”*). Some respondents compared this initiative with other city logistics initiatives such as PL delivery (e.g., *“I believe we have enough options for parcel delivery collections. Quite happy with the local PO lockers”*).

### **3.5.12 Prohibiting factors at a micro level**

In this section, the contribution of different prohibiting factors is investigated for different sociodemographic groups. Respondents are grouped based on demographic and

socio-economic factors (gender, age, income and household size). Sociodemographic factors have different attribute levels as shown in Table 3.3 (comment box). For example, gender has two attributes (male and female) and income has three attributes (low, medium, and high). To identify the contribution of prohibiting factors ( $a$ ) for every attribute ( $s$ ), the probability of observing the attribute in total responses ( $P(s)$ ) is compared with the probability of observing the attribute in the total responses given rejecting the participation choice by prohibiting factor  $a$  ( $P(s|a)$ ). Accordingly,  $P(s|a) - P(s)$  shows the deviation between the probabilities. In cases where the deviation is a large positive/negative percentage, it is concluded that people with attribute  $s$  are high-sensitive/low-sensitive to prohibiting factor  $a$ . Figure 3.8 shows the deviations for different attributes and the prohibiting factors with the highest observed frequency as depicted in 4. Recognizing the importance of robustness in our analysis, we have taken into account the limitations posed by small sample sizes, particularly in cases where prohibiting factors exhibited low observed percentages. Consequently, through the application of the sample size formula, we have retained only those categories of prohibiting factors for which the observed frequency exceeded the ideal sample size, as determined by the formula, at a 90% confidence level and with a 5% margin of error. These selected categories will undergo further analysis. This decision ensures that our analysis maintains its robustness by focusing on factors with more substantial representation within the dataset, thereby enhancing the reliability and validity of our findings.

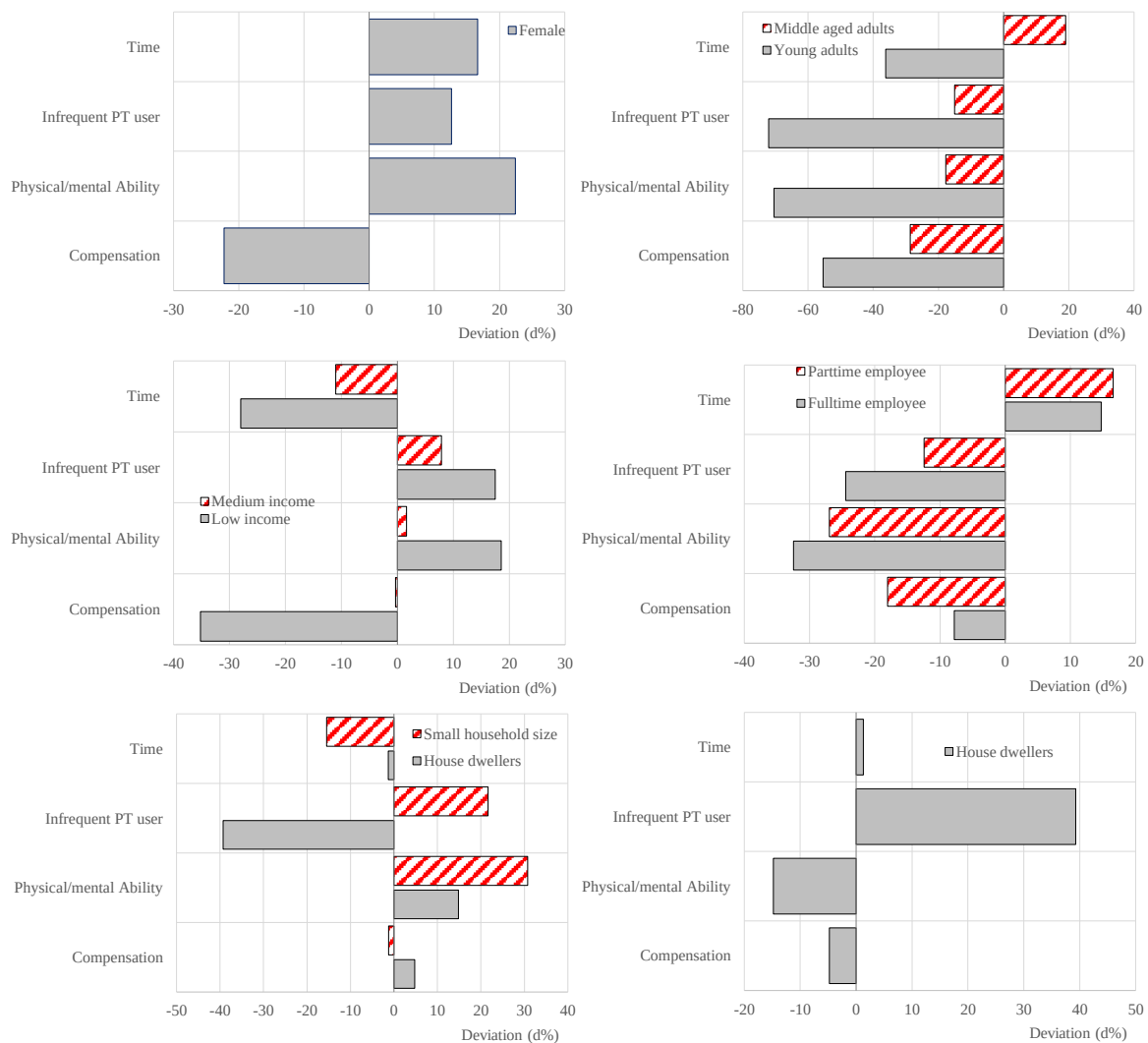


Figure 3.8 Degree of sensitivity to prohibiting factors from survey respondents with different attributes.

As shown in Figure 3.8, the investigated attributes belong to six sociodemographic factors (gender, age, income, employment status, household size, and dwelling type). The most and least significant prohibiting factors for people with specific demographic and socio-economic profiles are identified and discussed below.

- Female:** The primary considerations for female respondents when declining participation in the proposed PT-based CS initiative revolve around their physical health and time availability. Curiously, compensation appears to be of lesser concern to them. Consequently, it is advisable for CS managers to emphasize the non-demanding nature of CS tasks, assuring passengers that they are lightweight and manageable in size, which should alleviate concerns related to physical health. Furthermore, by ensuring that CS tasks can be accommodated at various times

throughout the day, CS managers can help alleviate worries regarding time availability, especially for those with busy schedules. These two factors hold greater significance for female respondents than compensation and should be prioritized to enhance the platform's supply of female participants (crowdshippers).

- **Young adults:** Younger respondents are less sensitive to all the prohibiting factors particularly the impact of CS tasks on their physical health. Hence, it is not recommended that CS managers advertise their initiative differently for them.
- **Middle-aged adults:** Except for “time”, middle-aged respondents are less sensitive to other prohibiting factors. Hence, CS managers should take into consideration the time-related factors of their CS initiatives if they plan to effectively absorb middle-aged adults as crowdshippers in their systems.
- **Low-income vs. medium-income individuals:** Medium-income individuals are neutral to the entire set of prohibiting factors. In contrast, low-income individuals are less sensitive to compensation and time. However, physical health aspects are fairly important for them. Therefore, addressing and promoting the alleviation of concerns about potential threats to physical health should be a key focus when reaching out to low-income individuals regarding the initiative.
- **Full-time vs. part-time employee:** Results show full-time employees are actually interested in the initiative; however, they are more sensitive to physical health aspects. However, part-time employees are less sensitive to many of the prohibiting factors except for time, which still has neutral sensitivity (less than +20%).
- **Small vs. medium household size:** Individuals living in small and medium households have opposite sensitivity to the prohibiting factors. For instance, contrary to individuals within medium sized households, those living in small households are mainly not interested to participate and have serious health concerns.
- **House dwellers:** Individuals living in a house mainly rejected the participation decision because of the reason that they infrequently travel by PT services. Hence, if the CS platform decides to improve its supply using house dwellers, they should inform them that it is not a requirement for them to be a frequent PT passenger to participate unless they have some other reasons rejecting the participation choice decision.

### 3.5.13 Anticipated Sustainability Gains from the CS System

In this study, we address the issue of participation intention in the CS system by developing a model. To assess sustainability benefits, additional factors should be incorporated such as the CS task acceptance model for PT passengers and the strategic and operational design of PT-based CS systems. However, in this section, we offer a preliminary estimate of the potential maximum sustainability gains (savings in external costs) achievable through this PT-based CS system.

This PT-based CS system is designed for transporting light and small to medium-sized parcels. Therefore, van deliveries will still be necessary for heavy and large parcels. We denote  $\rho$  as the percentage of heavy and large parcels requiring van delivery. Within our model,  $\widetilde{FA}$ ,  $\widetilde{PA}$ , and  $\widetilde{AC}$  represent three probabilistic parameters with expected values of  $\overline{FA}$ ,  $\overline{PA}$ , and  $\overline{AC}$ , reflecting the probabilities of PT passengers being familiar with the CS system, participating in it, and accepting CS tasks, respectively. Additionally,  $\widetilde{e}_1$  and  $\widetilde{e}_2$  are two other probabilistic parameters with expected values of  $\overline{e}_1$  and  $\overline{e}_2$ , indicating the external costs associated with one parcel delivery in the van-only and CS delivery systems, respectively. Given the specific inputs for a case study and considering a total daily delivery volume of  $N$ , we calculate the daily external costs before and after implementing the CS delivery system ( $EC_{before}$  and  $EC_{after}$ ) using Equations (3.6) and (3.7), respectively

$$EC_{before} = \sum_{i=1}^N \widetilde{e}_1 \approx N\overline{e}_1 \quad (3.6)$$

$$EC_{after} = \rho \sum_{i=1}^N \widetilde{e}_1 + (1 - \rho) \sum_{i=1}^N \widetilde{FA}\widetilde{PA}\widetilde{AC} \widetilde{e}_2 + (1 - \rho) \sum_{i=1}^N (1 - \widetilde{FA}\widetilde{PA}\widetilde{AC}) \widetilde{e}_1 \approx \quad (3.7)$$

$$N\rho\overline{e}_1 + N(1 - \rho)\overline{FA}\overline{PA}\overline{AC}\overline{e}_2 + N(1 - \rho)(1 - \overline{FA}\overline{PA}\overline{AC})\overline{e}_1$$

In Equation (3.6),  $N\overline{e}_1$  represents the total expected external delivery costs incurred when exclusively using van delivery. The expected external costs within the CS delivery system, in conjunction with van delivery, can be broken down into three distinct cost components. The first component,  $N\rho\overline{e}_1$ , calculates the external costs associated with delivering large and heavy parcels, which must be exclusively handled by vans. The second component estimates the expected external costs for delivering small and light parcels via the CS system. Within this term,  $\overline{FA}\overline{PA}\overline{AC}$  denotes the overall expected probability of successfully delivering a parcel through the CS system. This probability encompasses the PT passenger's familiarity with the

CS system, their participation in it, and their acceptance of a CS delivery task. The final component estimates the external costs resulting from unsuccessful attempts to outsource small and light parcels to PT passengers, necessitating a return to the van delivery system. In this term,  $(1 - \overline{FAPAAC})$  reflects the probability that CS delivery could not be executed successfully.

Mohri et al. (2024) have previously calculated the anticipated probability of accepting CS tasks for the same PT-based CS system and case study examined in this research. Their findings indicated an expected acceptance probability of approximately 86% among passengers willing to participate in the CS initiative. Given the 60% expected participation rate observed in our study, and assuming a 100% familiarity rate with the CS initiative, the combined probability  $\overline{FAPAAC}$  would amount to 0.516 (or 51.6%). Furthermore, roughly 21% of parcel deliveries in Australia consist of large and heavy parcels (Mohri et al., 2023b). Thus,  $\rho \approx 0.21$ . Parcel delivery by PT passengers through the CS system incurs no external costs, whereas transporting parcels to lockers in PT stations via vans does entail some external costs. Since the van delivery system primarily serves large and heavy parcels, and some of these parcels would typically be destined around PT stations with lockers, it is reasonable to assume that, in the best-case scenario, there would be minimal detouring of delivery vans when loading small and light parcels into lockers at select PT stations. Consequently,  $\bar{e}_2$  is significantly smaller than  $\bar{e}_1$ , approaching zero. With the defined parameter values used in Equation (3.7),  $EC_{after}$  can be calculated as  $0.59N\bar{e}_1$ . As a result, it can be deduced that the utilization of the CS system can yield savings in external costs of up to 41%.

### 3.6 Conclusion and managerial implications

This study explores the intention of PT passengers to participate in PT-based CS initiatives. Given a survey data from 2208 PT passengers in the Sydney metropolitan area and using two quantitative and qualitative techniques, the intention to participate is studied. As the quantitative technique, a binominal logit model is developed whereby the characteristics of passengers showing a willingness to participate are identified. Next, an inductive thematic analysis is employed to recognize the main factors prohibiting passengers to participate.

The results of the binomial logit model show that being female, senior adult, low-income person, full-time employee, retired, and having high PT trip frequency, and medium or high number of deliveries per month are associated with a decreasing likelihood of CS participation. In contrast, being young, living in large households, caring to achieve sustainability in freight

delivery systems, and having had prior experience with PLs or preference to use them is associated with increasing the utility of intention to participate in the CS initiative. By computing the elasticities of variables in the model, it is observed that elasticity estimates for medium- and high-volume delivery are the largest, but negative. In contrast, the largest positive elasticity estimates belong to having had prior experience with PLs or preference to use them in addition to caring to achieve improved sustainability in freight delivery systems.

The results of the inductive thematic analysis show there are nine major categories of factors prohibiting PT passengers to participate: (1) time, (2) physical/mental ability, (3) compensation, (4) responsibility, (5) safety and security, (6) social/labour aspects, (7) convenience, (8) infrequent PT passenger, and (9) not interested. Lack of time and a regular time schedule, infrequent use of PT services, having physical and mobility restrictions, and expecting higher compensation are the main reasons that participation in the CS initiative is rejected by respondents. Fear of responsibility, safety, taking jobs of traditional labourers in delivery markets, and potential concerns regarding becoming package receiver of CS systems in the future are the other interesting reasons of rejecting the participation choice decision by respondents.

Within the categories of the prohibiting factors, characteristics of respondents were explored to show the degree of sensitivity individuals with different demographic and socio-economic profiles are to the prohibiting factors. Several observations are provided in Subsection 3.5.3. For instance, it is observed that physical health concerns can prevent women, low-income persons, and those living in small households to participate in the CS initiative.

Providing a large and balanced supply (i.e., crowdshippers) with demand (i.e., delivery tasks) in CS systems is of utmost importance, particularly in the initial phases of launching CS initiatives. If an oversupply or overdemand situation exists, a deadweight loss will occur which leads to market inefficiency. This study can help CS managers keep the demand and supply balanced. For example, once a surge demand situation is present, CS managers can focus on attracting PT passengers who participate with a higher probability by taking an optimal advertising strategy. For instance, young male passengers with high PT trip frequency and having experience in contacting PLs can be prioritized for labour absorption. Once, CS managers decide to expand their market share and the rate of labour observation is declining, they can shift from generalized to personalized marketing strategies. This study has some recommendations for taking personalized marketing strategies as well. For example, women might have a higher intention to participate if their own safety and the jobs of existing

employees in delivery markets are not threatened. Moreover, a larger labour absorption rate from full-time employees would be achieved if they could find it convenient.

We recommend future studies extend this research by exploring the intention of other potential crowds to participate in CS initiatives in different scopes such as occasional drivers, cyclists, and passengers of ride-sourcing or ride-sharing systems. Specifically for launching PT-based CS initiatives, PT passengers' intention to participate can be modelled by advanced DC models such as mixed or latent-class DC methods. Moreover, exploring prohibiting factors for participation in the initiative can be collected through interview-based surveys rather than online surveys with open-ended questions. Therefore, the possibility of building richer models based on grounded theory would be attainable. Furthermore, due to the fixed nature of the case study, we were unable to assess the influence of PT network characteristics, such as its level of accessibility, on the participation rate. Future studies could investigate these impacts by gathering data from diverse cases worldwide and examining whether PT system characteristics can indeed affect participation rates. Introducing compensation enhancements to PT-based CS systems can potentially boost participation in the PT system. Consequently, exploring the substitution effect on trips from other modes to PT, in response to modifications in the compensation scheme, presents an intriguing avenue for future research. Another future research stream would be more in-depth investigations into the factors that influence the participation rate in CS initiatives. While our current study has shed light on the restricting factors, we acknowledge the necessity of understanding the effective motivations and possible incentives that can drive individuals to actively participate. This study showed compensation alone may not be a significant deterrent, and a more nuanced exploration is required. To address this, we propose adopting robust data collection techniques, such as in-depth interviews, to gather qualitative insights into the economic aspects and other factors motivating individuals' decisions to engage in crowd shipping activities. This qualitative approach will provide a richer understanding of the complexities involved and contribute to the development of more reliable and effective CS initiatives. By extending our focus beyond the restricting factors and delving into the motivations for participation, future research can provide CS managers with a comprehensive toolkit for designing and implementing crowd-driven services. This holistic approach will not only enhance the reliability of CS initiatives but also contribute to the broader understanding of crowd participation dynamics in the evolving landscape of CS management.

## Appendix A

With respect to the variable referred to as the "sustainable role," a dedicated survey question was included to assess respondents' willingness to embrace sustainable delivery initiatives involving higher delivery fees, extended delivery times, or the use of alternative delivery locations like PLs. The precise wording of the question can be found in Figure 3.9. Accordingly, the "sustainable role" variable is defined as a binary indicator. If any of the first six suggested sustainable delivery approaches is chosen, the variable is assigned a value of one. Conversely, if the last option (none of the above) is selected, the variable is assigned a value of zero.

**Considering that home delivery using diesel trucks and vans contributes to climate change and traffic congestion, would you be open to any of the following sustainable options?**

- 1) I will shop more from e-commerce companies who have sustainable delivery programs. ☐
- 2) I accept longer delivery time if my parcel is delivered to my address with sustainable transport modes. ☐
- 3) I accept higher delivery fees if my parcel is delivered to my address with sustainable transport modes. ☐
- 4) I accept to pick up my parcels from post offices or lockers that are near my home (less than 1 km). ☐
- 5) I accept delivery to post office or locker if it can also improve delivery time. ☐
- 6) I accept delivery to post office or locker if it can also reduce shipping cost. ☐
- 7) None of the above. ☐

*Figure 3.9 The question for identifying individuals supporting sustainable urban freight initiatives.*

## **CHAPTER 4**

# **MODELING PACKAGE DELIVERY ACCEPTANCE IN CROWDSIPPING SYSTEMS BY PUBLIC TRANSPORTATION PASSENGERS: A LATENT CLASS APPROACH**

## **4 Modelling Package Delivery Acceptance in Crowdshipping Systems by Public Transportation Passengers: A Latent Class Approach**

### **Preface**

Chapter 4 explores the likelihood of PT passengers accepting package delivery tasks within the proposed PT-based CS system, focusing on those who have expressed an interest in participating as crowdshippers. In CS systems, delivery tasks are only visible to individuals who have registered and indicated a willingness to serve as crowdshippers. Therefore, the CS acceptance model is specifically developed for the subset of PT passengers who have demonstrated a positive willingness to participate in the system. Based on survey responses from 2,208 PT passengers in the Sydney metropolitan area (i.e., the same survey used in Chapter 3), this study establishes a model for task acceptance among PT passengers who are willing to participate as crowdshippers. A LC choice model is formulated and evaluated to investigate distinct classes of participant characteristics and preferences regarding the acceptance of CS delivery tasks. This analysis considers varying levels of offered incentives, package weight, and the required detour distance at the destination. The presented materials are based on an original journal paper published in *Travel Behaviour and Society* as follows:

Mohri, S.S., Nassir, N., Lavieri, P.S. and Thompson, R.G., 2024. Modeling package delivery acceptance in Crowdshipping systems by Public Transportation Passengers: A latent class approach. *Travel Behaviour and Society*, 35, p.100716..

<https://doi.org/10.1016/j.tbs.2023.100716>

This chapter is presented as a standalone research study in a journal publication format. There have been only minor changes to conform to the thesis style and section numbering.

## Abstract

The subject of this research is to model the probability of accepting package delivery tasks in CS systems focusing on shipping packages by PT passengers. Real-world implementation of such a PT-based CS initiative requires a proper grasp of the behaviour of crowd shippers, package receivers, and senders, among which crowdshippers are at the centre of attention. Given survey data collected from 2,208 PT passengers in the Sydney metropolitan area, this study constructs a model for package delivery task acceptance among PT passengers who express a willingness to participate as crowdshippers. A LC choice model is developed and estimated to explore different classes of participant characteristics and preferences for accepting CS delivery tasks, under different levels of offered incentive, package weight, and required detour distance at the destination. As a key finding, the model identifies three classes, namely “leisurely”, “avid”, and “sceptical” users with class sizes of 19%, 53%, and 28%, respectively. Leisurely users tend to be majorly employed with relatively higher ages and lower PT trip frequency per month. This class shows a potential desire to take CS tasks as long as they are not logistically burdensome. Avid users, forming the largest class of the population, are mostly younger PT passengers who are less sensitive to task difficulty and might accept even CS tasks with minimum incentives (around AU\$3). Sceptical users, displaying high PT trip frequency per month and high income, are unwilling to accept the CS tasks unless get compensated well.

## 4.1 Introduction

The e-commerce industry has grown rapidly in recent years. Working from home is becoming a new norm and online shopping and home deliveries are dominating retail markets (Vonage, 2021). Global e-commerce sale has soared from \$1.3 billion in 2014 to \$4.3 billion in 2020 and is estimated to grow to \$6.4 billion by 2024 (U.S. Department of Commerce, 2022). As part of this growth, customers’ expectations for quick, free, and flexible delivery services are changing rapidly (Mohri et al, 2022).

Given the emerging changes in retail markets, several innovative freight LMD initiatives have been launched in recent years, among which initiatives based on the concept of crowd logistics have gained great attention (Carbone et al., 2017). Crowd logistics is a type of crowdsourcing in which outsourcing logistics services is the subject of debate. CS is a segment

of crowd logistics in which only freight shipping services are outsourced to crowds, called crowdshippers. Crowdshippers are occasional carriers who conduct the whole or a part of a freight delivery task from its origin to its destination or between some intermediate points. Recent research has identified and envisioned a very significant, sustainable role in last mile freight delivery for crowdshippers (Mohri et al, 2023b)

The most popular and dominant type of CS in industry and academia is CS by occasional drivers which can reduce van- or truck-dedicated trips for package delivery. Amazon Prime, DHL, Walmart Spark Delivery, Deliveroo, UberEATS, DoorDash, and PiggyBee are some examples of these CS platforms in the industry (Alnaggar et al., 2021). The predominant focus of academic CS studies lies in the realm of CS with occasional drivers. Consequently, a substantial body of research has emerged, delving into various planning problems such as behavioural, design, and evaluation challenges within this domain (Le et al., 2019). With skyrocketing demands for LMD post-COVID-19, we are witnessing raising concerns over climate change and environmental issues, on top of economic, transport, or societal aspects. In this regard, promoting CS by occasional drivers is subject to criticism since it can induce additional car traffic in already congested metropolitan cities unless CS trips by occasional drivers have a small deviation from the drivers' original trips (Simoni et al., 2020; The New York Times, 2020). As the result, CS by PT is now at the centre of attention and aligned with sustainable development goals. In many large metropolitan cities<sup>5</sup>, PT passenger movements are in the order of millions, constituting a huge momentum to be utilized for LMD tasks.

As a nascent type of CS, the academic and empirical literature on PT-based CS is short, and as expected the focus is on exploring the behaviours of CS players because they are the foundation of the planning aspects (Mohri et al., 2023a). Exploring the intention to participate, and then, task acceptance probability of the participating PT passengers as crowdshippers are the basic behavioural problems in PT-based CS initiatives. Multiple papers have been published on these topics very recently (Marcucci et al., 2017; Serafini et al., 2018; Gatta et al., 2019a; Gatta et al., 2019b; Fessler et al., 2022; Mohri et al., 2023a, Mohri et al., 2023b). The contributions of this paper lay within the aforementioned domain and are elaborated in the following.

This paper models the task acceptance probability among the participating PT passengers in a locker-to-home PT-based CS initiative. The estimation of task acceptance probability is

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<sup>5</sup> In 2019, Seoul Metropolitan Subway, Tokyo Metro, Moscow Metro, New York City Subway, Hong Kong's Mass Transit Railway, and Shenzhen metro had an annual ridership of around 2.9, 2.7, 2.56, 1.69, 1.68, and 1.62 billion, respectively (Intelligent Transport, 2021).

specifically relevant to registered participants in CS initiatives. This is because CS tasks can be only offered to already existing crowdshippers in CS platforms and CS managers have the ability to collect basic socioeconomic information from passengers during the registration process for their involvement in the CS platform. As a result, understanding task acceptance behaviours and proposing tasks fit to participants would be very beneficial for the system.

To the best of our knowledge, no practical PT-based CS systems have been introduced thus far. While private companies predominantly serve as the primary CS platform providers in CS systems with occasional drivers, it is also possible for PT agencies or local governments to introduce PT-based CS systems. Furthermore, it is expected that there will be disparities in the business models between these two types of CS systems, as PT-based CS systems are integrated into the broader PT systems, necessitating the cooperation and agreement of PT agencies or establishing partnerships with them. Irrespective of the entity responsible for providing the CS system, it is crucial to examine the CS task acceptance model. The likelihood of CS task acceptance can significantly impact the underlying business models of such CS systems.

Locker-to-home CS delivery systems require less investment since packages are shipped directly to customers' homes and lockers around delivery destination points are no longer needed. However, since locker-to-home delivery is a heavier delivery task than locker-to-locker delivery, CS task acceptance is a question that is addressed by this paper. In this regard, moving packages to customers' homes by PT passengers would require a detour in their existing trips. Hence, the detour is considered as a new attribute for defining CS tasks in PT-based CS systems. Also, for the first time, Latent-Class (LC) choice models are utilized to model the acceptance probability. LC models have advantages over other DC models in terms of reducing computational costs, unbounding the specification of taste heterogeneity, and enhancing their usage for policymakers. Regarding its use by policymakers, LC models can provide more tangible insights for decision makers and CS businesses and direct them to discover the "classes of users" that are influenced by a given change or benefit from a specific incentive.

This paper is structured into five sections. Following the introduction presented in Section 4.1, in Section 4.2, the focus shifts towards examining CS behavioural models, where an in-depth literature review is conducted, and the contributions of this study are emphasized. The subsequent sections, namely Sections 4.3 and 4.4, presents the LC choice model methodology and the experimental design employed for conducting choice modelling, respectively. Section 4.5 is presents the process of survey data collection, and Section 4.6

presents a discussion of the model results. Finally, the paper is concluded in Section 4.7, summarizing the key findings and implications of the study.

## 4.2 Literature Review

In this section, the literature on behavioural CS studies is reviewed and summarized. On a high-level, Table 4.1 compares different aspects of this paper with existing studies in the literature. As Table 4.1 shows, this is the first study utilizing LC models to capture the package acceptance behaviour from the standpoint of crowdshippers in CS systems. Also, the proposed CS system targets PT passengers as crowdshippers for locker-to-home delivery structure. In the following, a detailed review of the papers is presented.

*Table 4.1 Review Table (main aspects of behavioural CS studies).*

| Reference               | Crowdshipper         | CS Task                  | Behavioural problem | DC method        | Case        |
|-------------------------|----------------------|--------------------------|---------------------|------------------|-------------|
| Miller et al. (2017)    | OD                   | Without TPs <sup>d</sup> | Acceptance          | Mixed logit      | The US      |
| Devari et al. (2017)    | OD <sup>a</sup>      | Without TPs              | Acceptance          | Binary logit     | The US      |
| Marcucci et al. (2017)  | General <sup>b</sup> | Without TPs              | Participation       | No DC model      | Italy       |
| Punel et al. (2018)     | OD                   | Without TPs              | Participation       | Binary logit     | The US      |
| Serafini et al. (2018)  | PT passenger         | Locker to locker         | Acceptance          | MNL <sup>c</sup> | Italy       |
| Le and Ukkusuri (2019a) | OD                   | Without TPs              | Participation       | Binary logit     | The US      |
| Gatta et al. (2019a)    | PT passenger         | Locker to locker         | Acceptance          | MNL              | Italy       |
| Wicaksono et al. (2021) | Cyclist              | Without TPs              | Acceptance          | MNL              | Netherlands |
| Fessler et al., (2022)  | PT passenger         | Locker to locker         | Acceptance          | Mixed logit      | Denmark     |
| Mohri et al., (2023a)   | PT passenger         | Locker-to-home           | Participation       | Binary logit     | Australia   |
| Current study           | PT passenger         | Locker-to-home           | Acceptance          | LC model         | Australia   |

a: Friends of package receivers in social platforms; b: Students traveling by any mode; c: Multinomial Logit (MNL); d: TPs: Transshipment points.

The success and efficiency of CS systems rely on attracting and maintaining a large supply (the number of crowdshippers) and demand (the number of package receivers).

The primary objective of this study revolves around examining the acceptance of CS systems in relation to supply size. However, it is imperative to acknowledge that a comprehensive implementation of a CS system necessitates a thorough understanding of its acceptance from the demand side as well. To address this aspect, previous studies, such as Gatta et al. (2019a) and Cebeci et al. (2023), have investigated the acceptance probabilities from the perspective of package receivers. Interested readers are encouraged to refer to these aforementioned studies.

To estimate the supply size for a CS system, it is of utmost importance to evaluate: 1) the probability of engagement (i.e., intention to participate) of potential crowdshippers in newly

introduced CS initiatives, and 2), the probability of accepting individual CS tasks by the engaged crowdshippers.

Marcucci et al. (2017), Punel et al. (2018), Le and Ukkusuri (2019a), and Mohri et al., (2023a) focus on modelling participation behaviour. Marcucci et al. (2017) investigate the conditions under which students in Rome would be willing to act as a crowdshipper. By surveying nearly 190 students, the authors show that most of the students are unfamiliar with CS, but after getting to know CS systems almost 87% of them would be willing to act as a crowdshipper. The participation of students as crowd-shipper would be decreased to 55% and 40%, if the package is large and the reward is less than 5 Euros, respectively. Also, the maximum acceptable detour distance was around 1.5 km for carless students and 3.1 km for students commuting by their private vehicles. Moreover, 57% of students acting as crowdshippers are not willing to be tracked. Contrary to Marcucci et al. (2017) in which descriptive analyses are used to represent the participation behaviour, Punel et al. (2018) use a predictive model to describe the participation behaviour using different explanatory variables. Given a dataset collected through an online survey in the US, Punel et al. (2018) calibrate a binary logit model and show that participation in CS is more common among younger individuals, men, and full-time employees. Moreover, CS would perform well in urban areas, where the delivery task requires medium-distance travel. Le and Ukkusuri (2019a) extend the study of Punel et al. (2018) and report more managerial implications based on modelling outputs. The authors reveal package delivery experience, socio-demographic characteristics, and social media usage are key factors that influence respondents' decisions to participate in CS. Furthermore, this study shows that crowdshippers' reimbursement expectation is correlated with their VoT.

While previous studies mainly focus on CS systems with occasional drivers, Mohri et al. (2023a) evaluate the participation behaviour for PT-based CS systems. Using survey data conducted in Sydney, Australia, and a binary logit model, it is observed that women, full-time employees, elderly, retirees, and low-income PT passengers hardly participate, while the youth, individuals with a positive attitude towards sustainable freight initiatives, and those who experienced working with PLs in the past would participate with a higher probability. The study found that a significant proportion, approximately 40% of the participants surveyed, expressed unwillingness to participate in the CS system. These respondents provided specific reasons underpinning their decision to reject participation. Through the utilization of inductive thematic analysis, Mohri et al. (2023a) evaluate the non-participation reasons and identify nine

categories<sup>6</sup> of the most important prohibiting factors in the way of participation of PT passengers in the PT-based CS initiative. It is observed that factors related to time availability/flexibility and physical health condition are much more important than the compensation level for passengers to participate in PT-based CS initiatives.

Miller et al. (2017), Devari et al. (2017), Serafini et al. (2018), Gatta et al. (2019a), Wicaksono et al. (2021), and Fessler et al., (2022) concentrated on modelling the package delivery acceptance probability by crowdshippers. Table 4.2 provides a review of the attributes and their levels considered in the CS task acceptance choice model by the previous studies.

*Table 4.2 Review Table (attributes and their levels in CS acceptance choice model)*

| Reference                                       | Alternative-specific attributes | Levels of attributes                                                                      |
|-------------------------------------------------|---------------------------------|-------------------------------------------------------------------------------------------|
| Miller et al. (2017)                            | Hourly generated profit         | 5 levels from \$6 to \$24                                                                 |
|                                                 | Additional travel time          | 3 levels from 5% to 60%                                                                   |
| Devari et al. (2017)                            | Incentive (compensation)        | 6 levels from \$0 to \$5                                                                  |
|                                                 | Additional travel time          | 6 levels: 5 min, 10 min, 15 min, 15+ min, will consider if paid more, No will never do it |
| Serafini et al. (2018) and Gatta et al. (2019a) | PL location                     | 2 levels: inside and outside metro stations                                               |
|                                                 | Incentive (compensation)        | 2 levels: 1 € and 3 €                                                                     |
|                                                 | Delivery booking                | 2 levels: on-line and off-line                                                            |
|                                                 | Payment mode                    | 2 levels: per one delivery and per five deliveries                                        |
| Wicaksono et al. (2021)                         | Time of Day                     | 2 levels: morning and evening                                                             |
|                                                 | Additional travel time          | 3 levels: 6, 10, 14, and 20 min                                                           |
|                                                 | Package Weight                  | 4 levels: 1, 3, 5, and 7 kg                                                               |
|                                                 | Incentive (compensation)        | 4 levels: 2, 4, 6, and 8 €                                                                |
| Fessler et al., (2022)                          | CO2 reduction                   | 4 levels: 0.9, 1.3, 1.7, and 2.1 kg                                                       |
|                                                 | Incentive (compensation)        | 5 levels: 5, 10, 20, 30, and 50 DKK                                                       |
|                                                 | Additional travel time          | 5 levels: 1, 2, 4, 6, and 8 min                                                           |
|                                                 | Number of packages              | 5 levels: 1, 2, 3, 4, and 5                                                               |
|                                                 | Package size                    | 5 levels: 0.5, 1, 2, 4, and 8 Liter                                                       |
| Current study                                   | Package weight                  | 5 levels: 0.5, 1, 2, 3, and 5 kg                                                          |
|                                                 | Incentive (compensation)        | 3 levels: 3, 5, and 8 AUD                                                                 |
|                                                 | Package weight                  | 3 levels: 1, 2, and 3 kg                                                                  |
|                                                 | Additional travel detour        | 3 levels: 200, 400, and 600 meters                                                        |

**CS systems with occasional drivers:** Miller et al. (2017) study the attributes of occasional drivers who work as part-time crowdshippers. They specifically examine the likelihood of accepting a package delivery and consider variables such as WTW. In contrast to the WTP, which measures the trade-off between money and time saving, WTW determines the trade-offs between an individual's time contribution and profit expectation. The acceptance likelihood is estimated by a mixed logit developed on survey data from the US. Results show people in the mid-income range with a graduate degree are more willing to accept CS tasks. Along with this issue, Devari et al. (2017) study a system in which friends or acquaintances of a customer in

<sup>6</sup> (1) Time, (2) physical/mental ability, (3) compensation, (4) responsibility, (5) safety and security, (6) social/labor aspects, (7) convenience, (8) infrequent PT passenger, and (9) not interested.

social networks act as a crowdshipper. In this study, the authors examine the attitude of people toward engaging in the system as a crowdshipper. The results reveal that nearly 72% of the respondents are willing to deliver a package to their friends. Among them, 60% are open to doing it for free, and 85% are willing to accept up to a 15-minute detour from their regular trip. To evaluate the proposed CS platform in real-world daily traffic, TRANSIMS, an agent-based transport simulator, is adopted, and the behaviours of customers and crowd-shippers as the agents are modelled. Results show this initiative could decrease truck movements as well as air pollution emitted by the delivery truck by 55-60%.

**CS systems with cyclists:** Wicaksono et al. (2021) explore how demand and supply functions for bike CS services meet in an urban delivery market. Two DC models are estimated to provide the acceptance of customers to use CS services and the willingness of cyclists to work as potential couriers. A market equilibrium model is developed and the equilibrium point is achieved and suggested to be used by CS platforms to develop their business models. A case study from the Netherlands is chosen and two surveys for customers and couriers are conducted. Several factors that can impact the acceptance of customers and couriers are considered based on those existing in the literature. Results show that profit, travel time, and package weight are the factors that significantly influence the attitude of couriers in accepting CS tasks. Furthermore, it is observed that customers are more sensitive to price changes than couriers.

**CS systems with PT passengers:** Studies such as Serafini et al. (2018) and Gatta et al. (2019a) benefit from survey data to develop DC models to explore the conditions under which the commuters on the PT systems (i.e., metro network) would accept locker-to-locker CS tasks as part of their daily travels. By applying an MNL model to the survey data, results show PT passengers favour lockers inside metro stations. Also, contrary to students having the largest marginal utility, older and high-income passengers are reluctant to accept CS tasks. Fessler et al., (2022) extend this research stream and conduct a survey in the Greater Copenhagen Area. They received 524 valid responses and developed a mixed logit model to explore whether PT users are willing to bring a package along on their trips. Results reveal younger individuals, students, and employed and self-employed individuals, in order, would show the highest willingness to accept CS tasks. Findings also show the marginal disutility of time spent retrieving and dropping off packages at lockers is higher for older individuals (aged +60) and individuals with higher income (i.e., earning more than 50,000 DKK/month), while it is lower for individuals with a short-term education (i.e., below 2 years education after high school).

The authors also observe that increasing compensation increases the acceptance probability while increasing the number, size, and weight of packages decreases it.

The research presented in this paper contributes to modelling the probability of package delivery acceptance in CS systems with PT passengers as crowdshippers. In contrast to the existing relevant studies, LC choice models are targeted to unbound the specification of taste heterogeneity and enhance the usage of modelling outputs for policymakers. Also, to economically make the CS initiative viable, a locker-to-home structure is investigated rather than the locker-to-locker structure considered by Serafini et al. (2018), Gatta et al. (2019a), and Fessler et al., (2022).

### 4.3 Method (LC choice Model)

LC models capture the preference heterogeneity across individuals by using discrete variations in taste parameters. Hence, the model makes  $S$  discrete but finite number of classes (i.e., segments) within each class, the preferences are homogenous but heterogeneous across classes. Therefore, the parameters used in the utility function of an alternative ( $j$ ) for an individual ( $n$ ) are specific to each class, as shown by Equation (4.1). Individuals belong to classes with different probabilities. The probabilities are calculated by “the class membership model”, Equation (4.2), depending on the class membership utility functions calculated based on individuals’ characteristics. Moreover, the probability of selecting an alternative ( $j$ ) by an individual ( $n$ ) is calculated conditionally on the class ( $s$ ) of the individual. In the literature, the model is called “the class-specific choice model”, Equation (4.3). Finally, by multiplying “the class-specific choice model” by “the class membership model” and making a summation over classes, the probability of selecting an alternative ( $j$ ) by an individual ( $n$ ) is calculated, Equation (4.4).

$$U_{nj|s} = \beta_s X_{nj} + \varepsilon_{nj|s} \quad (4.1)$$

$$M_n(s) = \frac{\exp(\gamma_s Z_n)}{\sum_{s=1}^S \exp(\gamma_s Z_n)} \quad (4.2)$$

$$P_n(j|s) = \frac{\exp(\beta_s X_{nj})}{\sum_{j \in C_n} \exp(\beta_s X_{nj})} \quad (4.3)$$

$$P_n(j) = \sum_{s=1}^S P_n(j|s) \cdot M_n(s) \quad (4.4)$$

Where,

- $U_{nj|s}$ : Utility function of alternative  $j$  for individual  $n$  in class  $s$ ,
- $\beta_s$ : Vector of class-specific parameters,
- $X_{nj}$ : Vector of observable variables used in the class-specific model,
- $\varepsilon_{nj|s}$ : Random error in the utility function of alternative  $j$  for individual  $n$  in class  $s$
- $M_n(s)$ : The probability that individual  $n$  belongs to class  $s$ ,
- $\gamma_s$ : Vector of class membership function parameters,
- $Z_n$ : Vector of observable variables used in the class membership model,
- $P_n(j|s)$ : Choice probability of alternative  $j$  for individual  $n$  within class  $s$ ,
- $C_n$ : The choice set (alternatives) for individual  $n$ ,
- $P_n(j)$  : Choice probability of alternative  $j$  for individual  $n$ .

LC choice models possess several notable advantages that contribute to their superiority in certain contexts. These advantages include capturing heterogeneity, improving model's predictive power, facilitating policy analysis, and enhancing model interpretability (Hensher et al., 2005; Train et al., 2009).

LC choice models are effective in capturing the inherent heterogeneity within a population. By categorizing individuals into distinct LCs based on their preferences, attitudes, or behaviours, these models can account for variations in decision-making processes across different segments of the population. By accounting for unobserved heterogeneity through LCs, these models often exhibit superior predictive power compared to traditional aggregate choice models. This enhanced predictive capability is particularly valuable in market segmentation, targeted marketing, and personalized recommendation systems. LC choice models can be instrumental in policy analysis and decision-making processes. By identifying distinct LCs, policymakers can gain insights into the preferences and behaviours of different segments of the population. This information can help guide the development and implementation of tailored policies and interventions, leading to more effective outcomes and improved resource allocation. LC choice models offer interpretability benefits by providing meaningful and interpretable LC profiles. These profiles can be associated with specific demographic, socio-economic, or psychographic characteristics, enabling researchers to understand the underlying drivers of different preferences and behaviours. This interpretability facilitates the identification of key factors that influence decision-making and supports more informed decision-making processes (Marcucci et al., 2015).

### 4.3.1 Willingness to work (WTW)

In this research, the WTW is defined as the incentive that PT passengers expect to receive for a desired level of weight or detour of CS tasks. This definition closely resembles those presented in previous studies within the scope of PT-based CS systems (Gatta et al., 2019a; Fessler et al., 2022). For LC models with a linear class utility function, WTW is calculated by Equation (4.5).

$$WTW_a^c = -\frac{\hat{\beta}_a^c}{\hat{\beta}_i^c} \quad \forall a \quad (4.5)$$

Where,  $\hat{\beta}_a^c$  and  $\hat{\beta}_i^c$  are the estimated coefficients of the targeted attribute ( $a$ ) and incentive ( $i$ ) in class  $c$ , respectively. In this paper,  $a \in \{weight, detour\}$ ; hence, only  $WTW_{weight}^c$  and  $WTW_{detour}^c$  are of concern.

The overall WTW for the sample is also the weighted average of the classes' WTWs, Equation (4.6), in which the probabilities of class membership or class size ( $\theta^c$ ) are the weights (Nguyen et al., 2015).

$$\overline{WTW}_a = \sum_{c \in C} \theta^c WTW_a^c \quad \forall a \quad (4.6)$$

Since WTW is derived as the ratio of two random variables, WTW is also a random variable. Thus, it is desirable to calculate confidence intervals (CIs) for values of WTWs, in addition to their point estimates calculated by Equations (4.5) and (4.6). There are several approaches in the literature to calculate CIs such as Delta, Krinsky and Robb and bootstrap methods, which are compared comprehensively in terms of their advantages and disadvantages by Gatta et al. (2015).

The bootstrap method, in contrast to the Krinsky and Robb method, avoids assumptions regarding the distribution of coefficients in the model. It generates a simulated distribution of WTW by drawing numerous samples (with replacement) from the estimated model. Each sample is utilized to estimate WTW by fitting the model and calculating WTW using equations (4.5) or (4.6). Similar to the Krinsky and Robb method, the bootstrap does not assume a symmetric distribution for WTW. However, unlike the Krinsky and Robb method, it does not necessitate the joint normal distribution of coefficients. As a result, the bootstrap method may outperform the Krinsky and Robb method in cases of small sample sizes. Nevertheless, the

bootstrap method is computationally intensive as it requires re-estimating the model for each bootstrap sample (Hole, 2007).

## 4.4 Designing a Stated Choice Experiment

The effectiveness of DC models in accurately representing choice behaviours is contingent upon the design of an appropriate stated preference choice experiment. In this section, the process and considerations taken to design the experiment are described. Firstly, the package delivery acceptance probability is intended to be measured only for those PT passengers showing an interest to participate in the proposed PT-based CS initiative and using PT at least once a month. Hence, a preliminary question (Q1), as shown in Figure 4.1, was asked of respondents travelling at least once a month in PT systems.

### **Crowd-shipping by public transport passengers**

**Note:** *Imagine, as part of a sustainable government-sponsored freight initiative program, you are offered a small package delivery task (i.e., 1 to 3kg) at your public transport station, near work or home location. You will be given a package, at your origin station locker, and you are asked to deliver it to an address close to your final destination within a short walking distance (i.e., 200 to 600 meters).*

**Q1:** Would you be interested to participate in the above program, and deliver packages in return for a monetary incentive (e.g., 3-8 AUD per delivery)?

Yes ☐ No ☐

Figure 4.1 The question for intention to participate.

This question (Q1) gives a summary of the initiative and stipulates the maximum and minimum levels of incentive, weight, and detour as the main attributes for the intended CS tasks. As shown in Table 4.2, previous research (Gatta et al., 2019a; Fessler et al., 2022) has identified three attributes - weight, detour, and incentive - as statistically significant factors affecting participation in PT-based collaborative shipping (CS) initiatives and the acceptance of CS tasks. However, Fessler et al. (2022) also suggest that the size and number of parcels may play a role, but these attributes are not examined in the current study for two reasons. Firstly, this study commenced with a preliminary consultation involving 12 professionals specializing in statistical analyses and last-mile logistics within the freight industry. In this regard, domain experts in last-mile freight and logistics expressed that there would likely be

correlations between weight, size, and the number of parcels. To simplify the choice question for respondents, it was recommended to retain weight as the sole attribute. Secondly, a pilot study using Qualtrics was conducted, where the initial survey design was sent to a 10% sample size. In this pilot, non-participants were asked a follow-up question regarding their reasons for not participating. The results indicated that the main deterrent factors for participation were a desire for higher incentives (13%), infrequent PT usage (26%), busy schedules (29%), and physical health (19%) (Mohri et al., 2023a). Based on these findings, it was concluded that weight addresses physical health concerns, detour accounts for time availability, and incentive relates to compensation expectations, which should be collectively adequate to explore the acceptance of CS tasks among PT passengers.

The levels of attributes were also set by reviewing previous studies and the average delivery cost per package imposed on carriers and e-commerce companies<sup>7</sup> (Gatta et al., 2019a; Fessler et al., 2022). It is worth mentioning that the incentive levels not only should encourage PT passengers to accept CS tasks, but also they should be less than the current delivery cost per package in traditional delivery systems by vans or trucks. Moreover, the attribute levels should be set so that when they combine and form alternatives, we do not have any “Potential implausible combinations” (Johnson et al., 2013). Accordingly, guided by preliminary inquiries and expert input derived from the consultation study, the attribute levels were established as delineated in Table 4.3. Statistics show more than 83% of package deliveries worldwide weigh less than 2 kilograms (Statistica, 2022). Hence, heavy packages have a small market share, and there is no necessity to estimate the probability of outsourcing them in CS initiatives. Consequently, the weight attribute levels were designated as 1kg, 2kg, and 3kg. To fine-tune the levels of incentive and detour attributes, a trial-and-error approach was employed, recommended by the experts in the consultation study. The primary consideration was to ensure the absence of implausible CS task scenarios during the experiment. Consequently, the formulation of alternatives by combining attribute levels necessitated two specific criteria: 1) an average hourly pay rate equal to or greater than the minimum national hourly wage in Australia and 2) a delivery fee lower than the average fee typically charged by Australian carriers. Taking this approach, the levels of incentive and detour were established as delineated in Table 4.3.

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<sup>7</sup> The research focus on carriers and e-commerce companies in Australia since the survey is intended to be launched there.

**Checking implausibility of extreme combinations:** Based on the levels, a CS task with 3 AUD incentive, 3 kg weight, and 600 meters detour is an extreme combination scenario of attribute levels. Assuming the average walking speed equals 5 km/h, this task takes 0.12 hours for the crowdshipper to be fulfilled. Therefore, the minimum hourly pay rate to crowdshippers in this initiative is around 25 AUD which is about 2 AUD more than the minimum national hourly wage in Australia considered by Fair Work Ombudsman organization (Fair Work Ombudsman, 2023). Therefore this extreme is considered plausible. Another extreme combination of attribute levels would be a scenario with an 8 AUD incentive, 1 kg weight, and 200 meters detour. In Australia, the average delivery fee requested by carriers for a small package is 8-12 AUD (8 AUD for shippers with more than 20 orders per month and 12 AUD for a shipper with only a single order) (Sendle, 2022). Therefore, this extreme scenario is not an implausible scenario and may be cost-effective for shippers, carriers, and parcel receivers. Considering these two extremes, and taking a full factorial design, 27 CS task alternatives are constructed.

In the context of experimental design for choice modelling, there is a prevailing preference to ensure a high degree of similarity between the experiment and the real-world context or situation that transpires following implementation. This pursuit of alignment with the post-implementation scenario aims to augment the generalizability and applicability of the results obtained from the experiment (Haghani et al., 2021). In most crowd-based systems such as ride-sourcing or CS systems, occasional service providers (e.g., crowdshippers in CS systems) typically encounter a single task offered at a time and asked if they accept or reject. Accordingly, we achieve this similarity in the survey by proposing a single alternative choice question.

Nevertheless, for the sake of reducing the cognitive effort of survey respondents, CS task alternatives are blocked. To block the alternatives, one of the CS task alternatives is replicated (i.e., repeated alternative: 3 AUD incentive, 1 kg weight, and 200 meters detour) making up a list of 28 tasks in total which are divided into four blocks (i.e.,  $b$  is an index for block) of 7 tasks each.

It is desirable to minimize the correlation among alternatives in each block although it may not hold for individual blocks (Johnson et al., 2013). Therefore, using a random draw process, alternatives are distributed among blocks and then the maximum pairwise correlation between any two alternatives in each block ( $O_b \forall b$ ) are enumerated. The process is iterated 2000 times and the blocking solution with  $\text{Min } \sum_{b=1}^4 O_b$  has chosen as the best set. An example

block of the choice questions is shown in Figure 4.2. The blocks are assigned randomly to respondents who have an intention to participate and responded “Yes” to Q1 so that each respondent only encounters one block.

**Q2:** Under which circumstances would you accept to deliver the (hypothetical) package?

(Incentive= Monetary incentive per task; Weight: Package weight; Distance: Extra walking distance at destination)

|                                                         |                           |                          |
|---------------------------------------------------------|---------------------------|--------------------------|
| Incentive = \$8 & weight = 2 kg & distance = 600 meters | Yes <input type="radio"/> | No <input type="radio"/> |
| Incentive = \$8 & weight = 3 kg & distance = 400 meters | Yes <input type="radio"/> | No <input type="radio"/> |
| Incentive = \$5 & weight = 1 kg & distance = 600 meters | Yes <input type="radio"/> | No <input type="radio"/> |
| Incentive = \$5 & weight = 2 kg & distance = 200 meters | Yes <input type="radio"/> | No <input type="radio"/> |
| Incentive = \$3 & weight = 1 kg & distance = 200 meters | Yes <input type="radio"/> | No <input type="radio"/> |
| Incentive = \$5 & weight = 3 kg & distance = 200 meters | Yes <input type="radio"/> | No <input type="radio"/> |
| Incentive = \$3 & weight = 2 kg & distance = 200 meters | Yes <input type="radio"/> | No <input type="radio"/> |

Figure 4.2 The question for exploring package delivery acceptance in the CS initiative.

Table 4.3 Levels of attributes in the choice experiment.

| Attributes | # Levels | Levels                                 |
|------------|----------|----------------------------------------|
| Incentive  | 3        | 3 AUD, 5 AUD, and 8 AUD                |
| Weight     | 3        | 1 kg, 2 kg, and 3 kg                   |
| Detour     | 3        | 200 meters, 400 meters, and 600 meters |

## 4.5 Case Study and Data Collection Procedure

Greater Sydney (GS) has an area of 12.4 thousand km<sup>2</sup> and is home to nearly 5.4 million people, according to the estimated population in June 2021 (Australian Bureau of Statistics, 2022). The PT system in Sydney includes train, bus, metro, light rail, and ferry whereby nearly 30% of total passenger trips are made by PT modes. Train and bus are the dominant PT modes in Sydney, where on average 53% (420 million passenger trips) and 41% (324 million passenger trips) of annual PT passenger trips (before COVID-19) were made by train and bus, respectively (TfNSW, 2022). The train system consists of 8 lines and 170 stations, while the

bus system has more than 600 routes and 4.2 thousand stops. Given the dense and attractive PT system, Sydney can be a viable option to launch PT-based CS initiatives.

To explore the package delivery acceptance probability of Sydney PT passengers, an online survey was conducted in February 2022. The survey asked respondents to provide information on their preferences for city logistics initiatives including the PT-based CS initiative. The choice questions related to the PT-based CS initiative were explained in Section 4.4. The survey was finalized and distributed in March 2022 through the Qualtrics platform.

The sample was aimed to be representative of Sydney's population in terms of age, gender, and level of income, and only included respondents older than 18. Through this survey, 2208 valid responses were collected. The demographic details of the collected sample and Sydney's population are summarized in Table 4.4, which shows that the collected sample is well representative of the population.

Data shows 1,589 of 2,208 respondents travel by PT services at least once a month, hence, 1,589 responses were collected from Q1 where 952 responded "Yes". It shows that the overall participation rate of PT passengers in this initiative is around 60%. Accordingly,  $952 \times 7 = 6,664$  responses are fed to the model for estimating package delivery acceptance probability by registered PT passengers in the initiative. In addition to the alternative specific variables (incentive, weight, and detour), several individual specific variables were also included based on survey outputs grouped as follows: **Demographics** (age, gender, dwelling type, employment status, and household size), **socio-economic** (income and sustainability attitude<sup>8</sup>), **e-shopping activity-related** (delivery volume, PL experience,<sup>9</sup> and acceptance<sup>10</sup>), and **PT mobility-related factors** (PT trip frequency per month). The variables utilized in the study are explicitly defined and their respective natures are stipulated within Appendix A. Except for PT trip frequency per month, which is a continuous variable, all other individual specific variables in the study are represented as dummy.

#### 4.5.1 Descriptive statistics

Before applying the LC model to the collected survey data (i.e., 1,589 valid responses),

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<sup>8</sup> Sustainability attitude: It is a binary variable indicating whether the respondent is willing to play a role in achieving sustainability in urban freight systems (e.g., accept higher delivery cost, accept longer delivery time, and accept PL or office post delivery if they contribute to reducing air pollution, congestion, and road accidents).

<sup>9</sup> PL experience: It is a binary variable indicating whether the respondent had any PL experience.

<sup>10</sup> PL acceptance: It is a binary variable indicating whether the respondent accepts using PLs.

some descriptive analyses were conducted with results displayed in Figure 4.3. Figure 4.3(a) shows that only 14% of the CS tasks are rejected by the participating PT passengers in this initiative. This indicates that offering CS tasks with an incentive, weight, and detour within the reasonable ranges of [\$3, \$8], [1kg, 3kg], and [200m, 600m] can be well accepted by registered PT passengers as crowdshipper in this system. Based on a preliminary analysis of survey data, it has been determined that the participation rate in this proposed CS initiative is approximately 60% (Mohri et al., 2023a). Consequently, it can be deduced that the expected acceptance rate among all PT passengers is approximately  $86\% \times 60\% = 52\%$ . A related study conducted by Fessler et al. (2022) found that nearly 54% of CS tasks in a locker-to-locker PT-based CS initiative was accepted by all passengers in Copenhagen. Despite the difference in CS system design and case studies, the acceptance rates observed in both studies are similar.

Figure 4.3(b) shows the frequency of accepted CS tasks in a block of 7 CS task alternatives. It shows nearly 62% of respondents have accepted all the alternatives meaning that even by changing the levels of packages' attributes, the acceptance probability would not be impacted. It is interesting because even with setting the incentive in a range to lead to saving delivery costs of traditional couriers, there still exists a desire to work with lower incentives by some PT passengers. Figure 4.3(c) illustrates how the rate of accepting CS tasks acceptance rate would change at different levels of the CS tasks' attributes. It indicates decreasing the incentive or increasing the weight or detour is associated with lessening the acceptance rate.

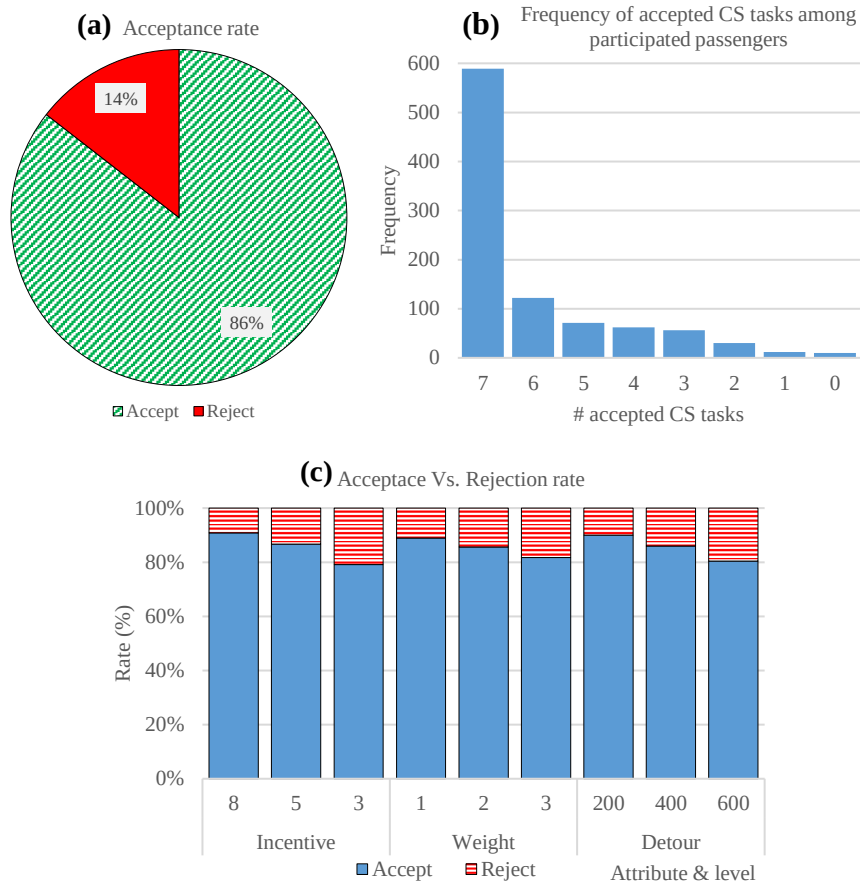


Figure 4.3 Descriptive statistics.

Table 4.4 Observed factors.

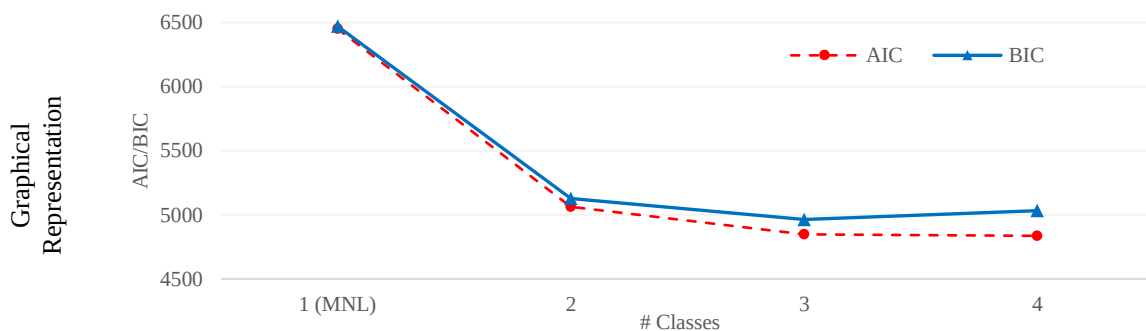
| Attribute                  | Frequency | Breakdown | Census 2016 | Attribute                                            | Frequency          | Breakdown | Census 2016 |
|----------------------------|-----------|-----------|-------------|------------------------------------------------------|--------------------|-----------|-------------|
| <b>Demographic factors</b> |           |           |             | <b>Socio-economic factors</b>                        |                    |           |             |
| <b>Gender</b>              |           |           |             | <b>Sustainability attitude</b>                       |                    |           |             |
| Male                       | 1061      | 48.05%    | 51.1%       | Yes                                                  | 1688               | 76.45%    | -           |
| Female                     | 1147      | 51.95%    | 49.90%      | No                                                   | 520                | 23.55%    | -           |
| <b>Age</b>                 |           |           |             | <b>Annual income</b>                                 |                    |           |             |
| 18-30                      | 476       | 41.56%    | 42.61%      | Less than \$30,000                                   | 484                | 27.92%    | 29.50%      |
| 31-40                      | 464       | 30.01%    | 31.09%      | \$30,000 to \$60,000                                 | 526                | 21.82%    | 22.10%      |
| 41-50                      | 460       | 8.83%     | 10.00%      | \$60,000 to \$90,000                                 | 511                | 23.14%    | 22.60%      |
| 51-60                      | 369       | 8.71%     | 7.28%       | \$90,000 to \$120,000                                | 373                | 13.89%    | 23.50%      |
| 61-70                      | 253       | 6.46%     | 5.22%       | More than \$120,000                                  | 314                | 12.22%    |             |
| 71 and older               | 186       | 4.42%     | 3.80%       | <b>E-shopping activity-related factors</b>           |                    |           |             |
| <b>Employment status</b>   |           |           |             | <b>Delivery volume</b>                               |                    |           |             |
| Full-time employee         | 1157      | 52.40%    | 51.20%      | Under 5 items                                        | 244                | 11.05%    | -           |
| Part-time employee         | 396       | 17.93%    | 38.6%       | 5-10 items                                           | 456                | 20.65%    | -           |
| Retired                    | 348       | 15.76%    |             | 11-20 items                                          | 534                | 24.18%    | -           |
| Disabled                   | 39        | 1.77%     |             | More than 20 items                                   | 974                | 44.11%    | -           |
| Student full time          | 89        | 4.03%     | -           | <b>PL experience</b>                                 |                    |           |             |
| Unemployed                 | 179       | 8.11%     | 5.90%       | Yes                                                  | 514                | 23.28%    | -           |
| <b>Dwelling type</b>       |           |           |             | No                                                   | 1694               | 76.72%    | -           |
| Stand-alone house          | 1341      | 60.73%    | 66.40%      | <b>PL preference</b>                                 |                    |           |             |
| Apartment                  | 727       | 32.93%    | 32.10%      | Yes                                                  | 1433               | 64.90%    | -           |
| Other                      | 140       | 6.34%     | 3.50%       | No                                                   | 775                | 35.10%    | -           |
| <b>Household size</b>      |           |           |             | <b>PT mobility-related factors</b>                   |                    |           |             |
| 1                          | 341       | 15.44%    | 16.00%      | PT trip frequency per month<br>(Continuous variable) | 2 trips (min)      |           |             |
| 2                          | 701       | 31.75%    | 36.60%      |                                                      | 34 trips (max)     |           | -           |
| 3 or 4                     | 934       | 42.30%    | 47.40%      |                                                      | 12 trips (average) |           |             |
| 5 or more                  | 232       | 10.51%    |             |                                                      |                    |           |             |

## 4.6 Results and Discussion

An LC model with a panel effect is developed to estimate the probability of accepting CS tasks in the proposed PT-based CS system. Different models are estimated in Pandas Biogeme 3.2.6 (Bierlaire, 2020), where a summary of the model's goodness of fit based on various indicators is presented in Table 4.5. In this table, four DC models including the best MNL model and LC models with 2, 3, and 4 classes are compared. The comparison shows the three-class model has the lowest BIC value. Although AIC and LL(B) are slightly improved in the four-class model and have smaller values than that of the three-class model, in the four-class model, two identical classes are observed. Hence, the three-class model is chosen as the best representative model.

Table 4.5 The goodness of fit measures for various LC models.

| # Classes | N    | K  | LL(B)    | R <sup>2</sup> | AIC      | BIC      | Identical class |
|-----------|------|----|----------|----------------|----------|----------|-----------------|
| 1 (MNL)   | 8141 | 4  | -3221.26 | 0.22           | 6450.527 | 6470.76  | No              |
| 2         | 8141 | 13 | -2518.36 | 0.34           | 5062.711 | 5128.475 | No              |
| 3         | 8141 | 19 | -2405.7  | 0.35           | 4847.402 | 4963.518 | No              |
| 4         | 8141 | 39 | -2378.91 | 0.35           | 4835.823 | 5033.114 | Yes             |



N: Number of observations; K: number of estimated parameters; LL(B) Final log-likelihood; R<sup>2</sup>: Adjusted R squared.

### 4.6.1 Model Interpretation

The class-specific choice and class membership models corresponding to the three-class model are presented in Tables 4.6 and 4.7, respectively. These models are used to determine the orientation of the three LCs to accepting CS tasks in the PT-based CS system. Based on exploring the socioeconomic characteristics of users and their preferences towards CS tasks' attributes, the three classes are labelled as follows: Class 1 (leisurely users), Class 2 (avid users), and Class 3 (sceptical users).

**Class 1 (leisurely users):** This class constitutes 19% of the population and is set as a reference when modelling the class membership functions. Hence, by looking at statistically significant variables used in membership functions of Classes 2 and 3, the characteristics of users in this class can be revealed. Accordingly, results show that low-income middle-aged employees with a household size of 3 or more, who may travel occasionally by PT services or have the desire to play a sustainable role in last-mile logistics systems would be likely to belong in this class. The class-specific choice model shows Class 1 and 2 both have positive constants in their utilities, and the coefficient for the incentive is not statistically significant in these classes. However, Class 1 has a smaller positive constant but a larger negative coefficient for both weight and detour attributes. This observation indicates that users in this class show a potential desire, however little, to take CS tasks as long as they are not logistically burdensome. Hence, this class is labelled “leisurely users” because having low-income and sustainable attitude encourage them to accept CS tasks but being old and occasionally travelling by PT services propel them to low weight/detour CS tasks.

Table 4.6 The class-specific choice model.

| Variable  | MNL<br>Co-eff. (t-stat) | LC 1: leisurely users<br>(Prob. 19%)<br>Co-eff. (t-stat) | LC 2: Avid users (Prob. 53%)<br>Co-eff. (t-stat) | LC 3: sceptical users<br>(Prob. 28%)<br>Co-eff. (t-stat) |
|-----------|-------------------------|----------------------------------------------------------|--------------------------------------------------|----------------------------------------------------------|
| Constant  | 2.191 (15.88)           | 2.042 (8.3)                                              | 5.671 (14.44)                                    | -3.908 (-4.65)                                           |
| Incentive | 0.178 (10.7)            | 0.054 (1.26)                                             | 0.08 (1.52)                                      | 1.616 (8.41)                                             |
| Detour    | -1.948 (-9.7)           | -3.12 (-7.2)                                             | -2.846 (-4.38)                                   | -4.893 (-5.34)                                           |
| Weight    | -0.205 (-8.07)          | -0.452 (-7.41)                                           | -0.283 (-3.49)                                   | -0.355 (-3.02)                                           |

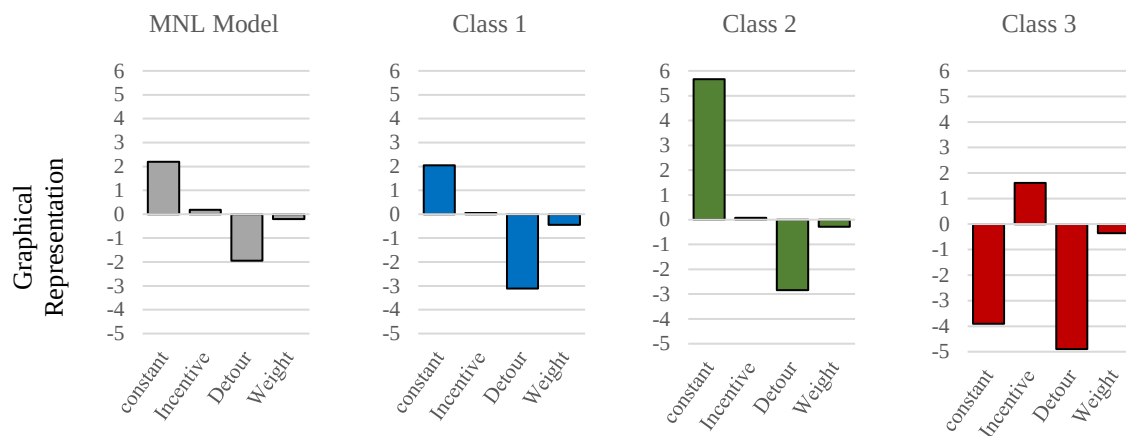


Table 4.7 The class membership model.

| Variable | MNL<br>Co-eff.<br>(t-stat) | LC 1: leisurely users<br>(Prob. 19%)<br>Co-eff. (t-stat) | LC 2: avid users<br>(Prob. 53%)<br>Co-eff. (t-stat) | LC 3: sceptical users (Prob. 28%)<br>Co-eff. (t-stat) |
|----------|----------------------------|----------------------------------------------------------|-----------------------------------------------------|-------------------------------------------------------|
|----------|----------------------------|----------------------------------------------------------|-----------------------------------------------------|-------------------------------------------------------|

|                       |   |           |                      |                       |
|-----------------------|---|-----------|----------------------|-----------------------|
| constant              | - | Reference | <b>1.3 (7.85)</b>    | <b>0.709 (3.06)</b>   |
| Low PT trip frequency | - |           | 0.257 (1.05)         | <b>-0.785 (-2.11)</b> |
| Low income            | - |           | -0.126 (-0.67)       | <b>-0.501 (-1.96)</b> |
| Sustainable role      | - |           | -0.077 (-0.24)       | <b>-1.158 (-2.76)</b> |
| Unemployed            | - |           | <b>-0.25 (-2.74)</b> | 0.602 (1.26)          |
| Family                | - |           | -0.03 (-0.18)        | <b>-0.82 (-3.54)</b>  |
| Young adults          | - |           | <b>0.738 (3.9)</b>   | <b>1.096 (3.17)</b>   |

**Class 2 (avid users):** this class constitutes 53% of the population and is the largest class. The class membership function shows being a young employee would be associated with increasing the likelihood of belonging to this class. In the class-specific choice model, the incentive is statistically insignificant similar to Class 1, but this class has a larger positive constant and lower negative coefficients for the weight and detour attributes than Class 1. This shows that users in Class 2 are eager to work as crowdshipper even when offered incentives at lower bound (\$3). In this class, increasing weight and detour would be associated with reduced utility of accepting CS tasks, but the reduction is less than what occurs in Class 1. Hence, this class is labelled “avid users”, who are less sensitive to CS task attributes than other classes.

**Class 3 (sceptical users):** The second largest class, Class 3, constitutes nearly 28% of the population. PT passengers who are young, living in small households with a maximum of 2 members, travelling frequently by PT services, having mid-level income, and not necessarily supporting a sustainable freight initiative may be more likely to belong to this class. In the class-specific choice model, all three CS task attributes (incentive, weight, and detour) are statistically significant. Users of this class show a strong but expected response to the tasks attributes; i.e. increasing incentive contrary to reducing weight or detour would be associated significantly with improving the probability of accepting CS tasks. In distinction to users categorized under Classes 1 and 2, users classified within this particular class exhibit diminished inclination towards accepting CS tasks that offer low incentives, with substantial weight, and significant detours. This behaviour was expected to be predominant in the population before conducting the survey, but the results show only 28% of the population display such significant behaviours. In this class, in addition to the large negative constant in the class-specific choice model, the coefficients of weight and detour are quite large and negative; however, incentive acts as a motivation whereby CS businesses can also encourage users of this class to accept CS tasks as well. Hence, this class is labelled “sceptical users” because of the scepticism observed in their decisions.

In general, the findings indicate that the incentive factor influences more on the decision of passengers who exhibit a lower inclination to engage as crowdshippers (specifically, those

classified as class 3: sceptical users). In the case of PT passengers who possess a favourable disposition towards CS (i.e., belonging to class 1 or 2), other factors such as weight and detour play a significant role and exert an influence on their decision-making process.

#### **4.6.2 Scenario analysis**

In this section, a scenario analysis is performed to compare the acceptance probabilities of various CS tasks using two different models: the LC model's classes and the MNL model. The analysis involves varying the attribute levels within the predefined ranges specified in the experimental design, resulting in the construction of 2000 distinct scenarios. Subsequently, the acceptance probabilities are computed based on the estimated parameters of the MNL model and the class-specific choice models of the LC model, as presented in Table 4.8. To present the findings, Table 4.8 showcases the acceptance probabilities for a subset of scenarios that encompass extreme attribute levels and intermediate attribute levels. Additionally, the graphical representation of the data is provided through a box plot (Figure 4.4), offering an intuitive visualization of the ranges within which the acceptance probabilities fluctuate in the respective models.

Table 4.8 The probabilities of accepting CS tasks in MNL and LC models

| CS task scenario (Incentive (I), Weight (W), Detour (D)) | Acceptance probability (%) |                    |                    |                    |
|----------------------------------------------------------|----------------------------|--------------------|--------------------|--------------------|
|                                                          | MNL model                  | LC model (class 1) | LC model (class 2) | LC model (class 3) |
| (I=8 AUD, W=1 Kg, D=0.2 Meter)                           | 95%                        | 72%                | 99%                | 100%               |
| (I=8 AUD, W=2 Kg, D=0.2 Meter)                           | 94%                        | 63%                | 99%                | 100%               |
| (I=8 AUD, W=3 Kg, D=0.2 Meter)                           | 93%                        | 52%                | 99%                | 100%               |
| (I=8 AUD, W=1 Kg, D=0.4 Meter)                           | 93%                        | 58%                | 99%                | 100%               |
| (I=8 AUD, W=2 Kg, D=0.4 Meter)                           | 92%                        | 47%                | 98%                | 100%               |
| (I=8 AUD, W=3 Kg, D=0.4 Meter)                           | 90%                        | 36%                | 98%                | 100%               |
| (I=8 AUD, W=1 Kg, D=0.6 Meter)                           | 90%                        | 43%                | 98%                | 100%               |
| (I=8 AUD, W=2 Kg, D=0.6 Meter)                           | 88%                        | 32%                | 97%                | 100%               |
| (I=8 AUD, W=3 Kg, D=0.6 Meter)                           | 86%                        | 23%                | 96%                | 99%                |
| (I=5 AUD, W=1 Kg, D=0.2 Meter)                           | 92%                        | 72%                | 99%                | 94%                |
| (I=5 AUD, W=2 Kg, D=0.2 Meter)                           | 91%                        | 63%                | 99%                | 92%                |
| (I=5 AUD, W=3 Kg, D=0.2 Meter)                           | 89%                        | 52%                | 99%                | 89%                |
| (I=5 AUD, W=1 Kg, D=0.4 Meter)                           | 89%                        | 58%                | 99%                | 87%                |
| (I=5 AUD, W=2 Kg, D=0.4 Meter)                           | 87%                        | 47%                | 98%                | 82%                |
| (I=5 AUD, W=3 Kg, D=0.4 Meter)                           | 84%                        | 36%                | 98%                | 76%                |
| (I=5 AUD, W=1 Kg, D=0.6 Meter)                           | 85%                        | 43%                | 98%                | 71%                |
| (I=5 AUD, W=2 Kg, D=0.6 Meter)                           | 82%                        | 32%                | 97%                | 63%                |
| (I=5 AUD, W=3 Kg, D=0.6 Meter)                           | 79%                        | 23%                | 96%                | 54%                |
| (I=3 AUD, W=1 Kg, D=0.2 Meter)                           | 89%                        | 72%                | 99%                | 40%                |
| (I=3 AUD, W=2 Kg, D=0.2 Meter)                           | 87%                        | 63%                | 99%                | 32%                |
| (I=3 AUD, W=3 Kg, D=0.2 Meter)                           | 85%                        | 52%                | 99%                | 25%                |
| (I=3 AUD, W=1 Kg, D=0.4 Meter)                           | 85%                        | 58%                | 99%                | 20%                |
| (I=3 AUD, W=2 Kg, D=0.4 Meter)                           | 82%                        | 47%                | 98%                | 15%                |
| (I=3 AUD, W=3 Kg, D=0.4 Meter)                           | 79%                        | 36%                | 98%                | 11%                |
| (I=3 AUD, W=1 Kg, D=0.6 Meter)                           | 79%                        | 43%                | 98%                | 9%                 |
| (I=3 AUD, W=2 Kg, D=0.6 Meter)                           | 76%                        | 32%                | 97%                | 6%                 |
| (I=3 AUD, W=3 Kg, D=0.6 Meter)                           | 72%                        | 23%                | 96%                | 4%                 |

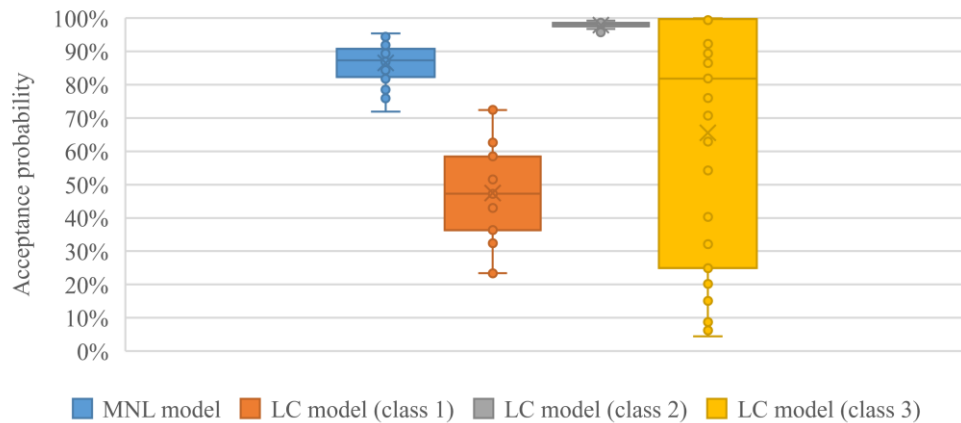


Figure 4.4 The ranges of CS task acceptance probability for various CS tasks.

Table 4.8 shows the acceptance probabilities derived from the MNL model cover a range of values between 72% and 95%. However, Figure 4.4 reveals that the interquartile range (IQR) of these probabilities is more narrowly confined, spanning from 82% to 91%. A comparison

with the probabilities calculated by the class-specific choice models demonstrates that the MNL model generally performs closely to the choice model for Class 2, which represents avid users. Nonetheless, it is evident from both Table 4.8 and Figure 4.4 that the probabilities obtained through the Class 2 choice model consistently surpass those computed by the MNL model.

Specifically, within Class 1, scenarios involving light packages and short detours exhibit a high acceptance probability of 72%. However, increasing the package weight to 3 kg and the detour length to 600 meters significantly diminishes the acceptance probability to 23%. The IQR for the acceptance probabilities among users in Class 1 ranges from 36% to 58%, as illustrated in Figure 4.4. In contrast, Class 3 demonstrates a pronounced dependence on incentives to influence acceptance probabilities, resulting in a wide variation range from 4% to 100%. As indicated in Table 4.8, scenarios with an incentive of 8 AUD consistently achieve full acceptance within this class. However, reducing the incentive to 5 AUD and 3 AUD correspondingly reduces the acceptance probabilities to 54% and 4%. Consequently, the IQR in Class 3 spans from 25% to 100%.

### 4.6.3 WTW estimation

The point estimates and CIs of WTW measures for the MNL and the three LCs are presented in Table 4.9. The estimates made herein are based on considering the coefficient of the incentive attribute as  $\hat{\beta}_i^c$  and the coefficient of either the weight or detour attribute as  $\hat{\beta}_{weight}^c$  and  $\hat{\beta}_{detour}^c$ , respectively. Therefore, the amount of Australian dollars that PT passengers are willing to earn for a level of weight or detour in a CS task can be calculated. In the LC model, because the incentive is not statically significant in Class 1 and Class 2, the WTW cannot be calculated for them. Also, the WTW for the whole model, according to Equation (4.6), is also impossible to be estimated. Accordingly, the WTWs are calculated only for Class 3 constituting 28% of the population.

Table 4.9 WTW measures (point estimates and 95%-level CIs).

| WTW measure      | Unit     | MNL (point estimate) | MNL (95%-level CI) | Class 3 (point estimate) | Class 3 (95%-level CI) | Class 2 | Class 1 |
|------------------|----------|----------------------|--------------------|--------------------------|------------------------|---------|---------|
| Weight/Incentive | A\$/kg   | 1.15                 | [\$0.79,\$1.49]    | 0.20                     | [\$0.07,\$0.37]        | na      | na      |
| Detour/Incentive | A\$/100m | 1.09                 | [\$0.78, \$1.39]   | 0.29                     | [\$0.17,\$0.43]        | na      | na      |

The findings indicate that users belonging to Class 3 express an increment of \$0.20 in their WTW for each additional one-kilogram increase in the weight of the package. The corresponding CI for this estimate is [\$0.07, \$0.37], signifying that with 95% confidence, the true WTW associated with the weight attribute lies within this range on repeated sampling. It should be highlighted that this WTW is valid as long as the final weight of the package is within the range defined in the choice experiment, [1kg, 3kg]. In the MNL model, which is not as accurate as the LC model, the expected value of WTW based on weight attribute is around \$1.15, which is still not a challenging reward expectation by PT passengers. Based on the values of CI for this WTW measure, passengers expectation of additional incentive for one kilogram increase in the package weight would vary from \$0.79 to \$1.49.

The point estimate for WTW related to the detour attribute of CS tasks is around \$0.29 per 100 meters in Class 3. It means PT passengers in this class expect to receive \$0.29 for every 100 meters detour imposed on their original trips. The CI of this estimation indicates that the expectation would be at least \$0.17 and at most \$0.43. This observation shed light on the high potential of saving costs of delivery to dense residential areas (e.g., central parts of cities) to which many PT passengers are attracted and high access to PT stations exists. Also, because these areas suffer from high congestion and air pollution, this initiative can substantially decline the movement of vans to these areas and brings some sustainable benefits.

## 4.7 Conclusion

This paper proposes a PT-based CS system in which PT passengers engage as crowdshippers and move delivery packages from some lockers to customer homes. In contrast to CS systems with occasional drivers, PT-based CS systems present distinct advantages and disadvantages. CS systems involving occasional drivers may impact the mobility patterns of drivers and even introduce new trips into the transport system. Although substituting dedicated freight movements with existing mobilities of travellers in the transport system may appear ecologically beneficial, the widespread adoption of such solutions could lead to adverse effects if they become a new source of trip generation (The New York Times, 2020; Rai et al., 2018; Allahviranloo and Baghestani, 2019; Qi et al., 2018). This concern can be mitigated in PT-based CS systems, wherein dedication of PT trips to parcel delivery would no longer be a drawback. Nevertheless, the transfer of delivery packages to PT passengers presents greater challenges than to occasional drivers. As a result, PT-based CS systems necessitate the

establishment of TPs (e.g., PLs) to facilitate the process, consequently increasing the total fixed cost of implementing the CS system. Prior PT-based CS initiatives proposed in academic literature have predominantly focused on a locker-to-locker delivery structure for PT passengers. In this study, we introduce a novel locker-to-home delivery structure, which holds potential economic advantages and system-wide benefits over traditional locker-to-locker CS initiatives. This is due to fewer lockers needed to run the system and improved quality of service for at-door delivery service. To explore how PT passengers accept to move packages in the lockers system, with different attributes such as incentive, weight, and detour, a survey is conducted in Sydney metropolitan area and its data is used to model the package delivery acceptance probability. LC models are preferred not only for their technical rigor but also, to capture tastes and preference heterogeneities in accepting CS tasks. The model shows the target population consists of mainly three different classes with different preferences. By investigating the significant variables used in the class-specific choice and class membership models, the classes are labelled as follows: leisurely users (19% of the population), avid users (53% of the population), and sceptical users (28% of the population). Leisurely users seem to be some employees with relatively high age and low PT trip frequency per month, who show a potential desire, however little, to take CS tasks as long as it is not a burdening task. Avid users would be some young PT passengers who are less sensitive to tasks' attributes and surprisingly might accept even CS tasks with minimum incentives of around A\$3. Sceptical users who probably have high PT trip frequency per month and good income are unwilling to accept the CS tasks unless get compensated well.

#### 4.7.1 Policy implications

The results of the LC model show that even by excluding lockers around destination points and defining more demanding CS tasks for crowdshippers, still PT passengers show a tendency to engage and even accept CS tasks. Therefore, there is some room for evaluating the performance of such PT-based CS systems and optimally designing them. However, some key policy implications can be derived from the empirical findings of this research.

**Bundle Delivery Policy:** The LC model shows that PT passengers are less sensitive to the weight of packages compared to the required detours. Given the point that nearly more than 67% of package deliveries in urban areas are less than 2 kilograms (Statistica, 2022), it is suggested to offer PT passengers some bundles of deliveries or allow them to form a bundle

by their preferences. Therefore, a PT passenger can do multiple deliveries to neighbours without significant detour required.

**Partial Delivery Policy:** partial delivery policy allows dividing a delivery path into different segments and outsourcing CS over every segment to an individual crowdshipper. In the proposed PT-based CS system, two different segments can be defined: (1): station to station and (2): station to home. By allowing users to only work on either Segments 1 or 2, CS managers can better benefit from the heterogeneities observed in crowdshippers behaviours. It is important to emphasize that the CS acceptance model has been specifically designed for individuals who have expressed an intention to participate in the initiative and have willingly registered to work for the CS platform. As a result, CS managers are granted access to basic socio-economic characteristics. Therefore, the managers would be able to estimate the size of passenger markets in all behavioural classes. The detour plays a significant role in the estimated LC model, and its magnitude depends on the passenger destinations. To calculate the detour, CS managers have the ability to estimate the distribution of walking distances from PT stations (Daniel and Mully, 2013) based on catchment area of a PT station. This allows them to estimate the anticipated detour for each parcel delivery in the vicinity of a PT station.

Accordingly, Classes 1 and 3 constitute nearly half of the population, with users very sensitive to detours. Therefore, it may be recommended to employ class 1-2 users on Segment 1 (station to station), where no detour is required. Then, users of Class 2 (Avid) who may be very likely to accept CS tasks even with a detour may be employed in Segment 2 (station to home). This policy can also get the packages closer to their delivery locations faster because the popularity of CS tasks on Segment 1 (station to station) is high. Therefore, some package receivers might decide to pick up at their neighbouring PT station.

Given the intrinsic nature of stated choice experiments, which involve participants expressing their preferences and making decisions within simulated or hypothetical contexts instead of real-life scenarios, the presence of hypothetical biases becomes inevitable. These biases have the potential to influence policy interventions within DC models. Consequently, prior to the implementation of the CS system, it is imperative to conduct validation studies aimed at assessing the extent and direction of these biases. Such studies serve to ascertain the reliability and validity of the findings obtained from stated choice experiments and ensure accurate policy implications and decision-making.

#### 4.7.2 Limitations and Future research

The integration of CS within PT systems has shown potential in enhancing sustainability compared to CS systems relying on occasional drivers. However, there exist certain risks, limitations, and implementational challenges that must be acknowledged before commercializing such an initiative. In terms of risk, PT-based CS can be susceptible to both planned and unplanned disruptions in the system, including scheduled maintenance and unforeseen incidents. As an example, COVID-19 pandemic and its associated mobility and social interaction restrictions substantially dropped the ridership in PT systems in different parts of the world (Mohri et al., 2021). Consequently, it is recommended that future research focus on examining the measurement and management of system resilience within the context of CS implementation.

It is important to recognize that PT-based CS systems cannot completely replace traditional carrier delivery systems, as their operational scope is confined to the transport of small and lightweight packages. Consequently, it is pertinent to investigate the cost-effectiveness of implementing CS systems from the perspective of carriers. Understanding the economic implications and feasibility of integrating CS within existing carrier networks would provide valuable insights for decision-making processes.

The outsourcing of package deliveries to PT passengers necessitates the establishment of relay points, commonly referred to as transfer or TPs. Previous research (Marcucci et al., 2017; Serafini et al., 2018; Gatta et al., 2019a; Gatta et al., 2019b; Fessler et al., 2022; Mohri et al., 2023a) has proposed PLs as the optimal relay points for this purpose. However, the implementation of PLs is associated with significant costs. Although this study introduces a novel approach of a PT-based CS system that operates between lockers and recipients' homes, requiring a reduced number of PLs located at or near PT stations, the financial burden of implementing such an initiative would still exceed a carrier's budget capacity. Therefore, future studies can employ cost-benefit analyses and revenue models to identify potential stakeholders responsible for providing the necessary PLs. In this regard, local or national governments, as well as TPL entities, can play a crucial role, similar to the Singaporean "Locker Alliance" program in which the Singaporean government financially supports the establishment of an extensive PL delivery network (Lin et al., 2020).

Most CS systems assign singular tasks to their crowdshippers, expecting binary responses (accept or reject). While single-alternative questions align with post-implementation choices and can reduce hypothetical bias in choice modelling, multiple-alternative ones can

offer more robust statistical models. Given certain CS platforms present task menus (Ausseil et al., 2022), employing multiple-alternative questions harmonizes with system characteristics. Future research should explore task acceptance in menu-based CS systems using this approach.

In this research, only three attributes for the CS tasks are considered: incentive, weight, and detour. While the conducted consultation and pilot studies have informed the research and led to the consideration of the three primary attributes, it is important to acknowledge that there may be additional attributes that influence the decision-making process of crowdshippers when accepting or declining a CS task. For instance, findings from the pilot study have indicated that some PT passengers have concerns related to safety (e.g., handling unknown products or interacting with unfamiliar receivers), security (e.g., CS platform or receiver tracking), and liability (e.g., costs borne by crowdshippers in cases of product theft or damage) (Mohri et al., 2023a). Moreover, the trip purpose and time pressure experienced by PT passengers would impact their decisions on accepting CS delivery tasks. Consequently, we recommend for future research to investigate the impact of other attributes, such as traceability, delivery insurance, level of complexity as well as the size, quantity, type, and value of CS tasks, on the acceptance decision. Given that some of these variables may encompass attitudinal aspects, it is imperative to define them appropriately utilizing latent variables in order to capture their underlying unobservable nature accurately.

In the proposed PT-based CS system, it is assumed that passengers pick up packages from a locker in a particular PT station, then move to another PT station, get out of the PT system and carry packages to their destinations, while heading to their homes as well. Another alternative system could be excluding the station-to-station movement of packages from crowdshippers' tasks and doing it by moving lockers between stations. Therefore, in-vehicle crowding in some segments of PT lines would not impact the acceptance decision. Furthermore, the research's focus is on behavioural aspect of the initiatives while evaluating the performance of the PT-based CS systems and then designing them can be the subject of future studies.

## Appendix A1

Variable definitions and types:

- **Female:** Women (type: binary variable)
- **Young adults:** Individuals aged less than 40 (type: binary variable)
- **Middle-aged adults:** Individuals aged between 40 to 60 (type: binary variable)
- **Senior adults:** Individuals aged more than 60 (type: binary variable)

- **Low income:** Individuals with an income of less than 30k AUD per year (type: binary variable)
- **Medium income:** Individuals with an income between 30k AUD to 90k AUD per year (type: binary variable)
- **High income:** Individuals with an income of more than 90k AUD per year (type: binary variable)
- **Full-time employee:** Individuals working full time (type: binary variable)
- **Part-time employee:** Individuals working part-time (type: binary variable)
- **Unemployed:** Unemployed individuals (type: binary variable)
- **Retired:** Individuals who are retired (type: binary variable)
- **Disable:** Individuals with a disability (type: binary variable)
- **Single:** Individuals living in households with a maximum 1 member (type: binary variable)
- **Couple:** Individuals living in households with 2 members (type: binary variable)
- **Family:** Individuals living in households with 3 or more members (type: binary variable)
- **Low PT trip frequency per month:** Individuals travelling by PT less than or equal to 3 trips per month (type: binary variable)
- **Medium PT trip frequency per month:** Individuals travelling by PT more than 3 trips but less than or equal to 12 trips per month (type: binary variable)
- **High PT trip frequency per month:** Individuals travelling by PT more than 12 trips per month (type: binary variable)
- **Sustainable role:** Individuals supporting sustainable urban freight initiatives (type: binary variable)
- **Locker preference:** Individuals not having an opposition to contact with PL facilities (type: binary variable)
- **Locker experience:** Individuals having has working experience with PLs (type: binary variable)
- **Low-volume delivery:** Individuals having less than 5 deliveries per year (type: binary variable)
- **Medium-volume delivery:** Individuals having between 5 to 20 deliveries per year (type: binary variable)
- **High-volume delivery:** Individuals having more than 20 deliveries per year (type: binary variable)
- **Apartment dwellers:** Individuals living in an apartment (type: binary variable)
- **House residents:** Individuals living in a house (type: binary variable)

In relation to the variable denoted as "sustainable role," a dedicated question was included in the survey. This question sought to ascertain respondents' acceptance of sustainable delivery initiatives that entail higher delivery fees, longer delivery times, or the utilization of alternative delivery addresses, such as PLs. The specific wording of the question is presented in Figure 4.5. Consequently, the variable "sustainable role" is defined as a binary indicator. If any of the first six suggested sustainable delivery approaches is selected, the variable is assigned a value of one. Conversely, if the last option (none of the above) is chosen, the variable is assigned a value of zero.

**Considering that home delivery using diesel trucks and vans contributes to climate change and traffic congestion, would you be open to any of the following sustainable options?**

- 8) I will shop more from e-commerce companies who have sustainable delivery programs. ☐
- 9) I accept longer delivery time if my parcel is delivered to my address with sustainable transport modes. ☐
- 10) I accept higher delivery fees if my parcel is delivered to my address with sustainable transport modes. ☐
- 11) I accept to pick up my parcels from post offices or lockers that are near my home (less than 1 km). ☐
- 12) I accept delivery to post office or locker if it can also improve delivery time. ☐
- 13) I accept delivery to post office or locker if it can also reduce shipping cost. ☐
- 14) None of the above. ☐

*Figure 4.5 The question for finding individuals supporting sustainable urban freight initiatives.*

## **CHAPTER 5**

# **CROWD-SHIPPING SYSTEMS WITH PUBLIC TRANSPORT PASSENGERS: STRATEGIC AND OPERATIONAL PLANNING**

## 5 Crowd-shipping Systems with Public Transport Passengers: Strategic and Operational Planning

### Preface

Chapters 3 and 4 witnessed the development of crucial behavioural models for planning PT-based CS systems. Within this chapter, a design model is introduced at both the strategic and operational decision-making levels to architect the CS system. A probabilistic mathematical model is presented, which incorporates the behavioural models as equations to optimize the allocation of delivery tasks to the CS system and PLs. This entails incentivizing passengers for CS-allocated tasks and directing delivery vehicles to handle non-allocated parcels, including heavier items. Subsequently, a heuristic solution algorithm is proposed to optimize decisions pertaining to allocation, routing, and incentivization. The effectiveness of this algorithm is evaluated through application to a real case study within the Greatest Sydney (GS) area. The presented materials are based on an original journal paper which is under review in *Transportation Research Part E: Logistics and Transportation Review* as follows:

Mohri, S.S., Nassir N., and Thompson, R., Lavieri, PS., Crowd-shipping with Public Transportation Passengers: Operational Planning, *Transportation Research Part E: Logistics and Transportation Review* (Status: Under review)

This chapter is presented as a standalone research study in a journal publication format. There have been only minor changes to conform to the thesis style and section numbering.

## Abstract

This study designs a CS delivery system with PT passengers at the operational decision-making level. In this system, PLs are positioned in PT stations, through which small and light parcels are allocated to passengers for delivery to their final delivery addresses (i.e., performing the last-mile delivery). A probabilistic mathematical model is formulated with behavioural constraints to estimate the probabilities of accepting CS tasks by passengers. The probability estimated based on a logit function, sensitive to the parcel's weight, reimbursement amount, and the walking detour required to deliver the parcel to its final destination. The logit model is constructed based on survey data collected from the GS area, Australia. The mathematical model optimises the allocation of delivery tasks to the CS system and PLs, subsequently, incentivising CS-allocated tasks for participating passengers. Furthermore, the model performs the routing of vehicles to deliver non-allocated parcels, including heavy parcels. A heuristic solution algorithm is then proposed to optimise decisions related to allocation, routing, and incentivisation, which was tested on a real case study. By conducting sensitivity analysis on various model parameters, results show that for a small carrier, utilising a PT-based CS system could minimise daily delivery costs by up to 36%, depending on passengers' rate of familiarity with the CS initiative and the number of PT stations equipped with PLs. Vehicle delivery cost in the CS-integrated delivery system is also reduced between 50% to 65%, in comparison to the conventional vehicle-only system. Our study reveals that a CS system should offer higher incentives at the beginning, and as CS familiarity grows, figures could be reduced depending on other market and operational conditions. Furthermore, simulated experiments suggest that denser PL networks enable carriers to reduce incentives even at earlier stages with lower familiarity rates.

## 5.1 Introduction

The global ecommerce market was estimated at USD18.98 Trillion in 2022 and is projected to reach USD 47.73 Trillion by 2030 (Research & Markets, 2023). This unprecedented growth and popularity of online shopping brings along significant implications for direct B2C deliveries, including increased traffic congestion and capacity constraints in urban systems (Su et al., 2024). Aligned with these challenges facing retailers, customers are increasingly expecting fast and low-cost delivery services (Su et al., 2024). A recent consumer

survey from the US indicates that nearly half of consumers expect to receive their parcels within two days as a standard delivery time (Statista, 2021). Similarly, couriers encounter operational difficulties to meet the growing demand and remain commercially viable (Pan et al., 2021).

On the other hand, millions of people travel on PT networks across the globe. In 2019, the annual ridership for the Seoul Metropolitan Subway, Tokyo Metro, Moscow Metro, New York City Subway, Hong Kong's Mass Transit Railway, and Shenzhen Metro collectively exceeded 1.62 billion passengers (Intelligent Transport, 2021). PT systems are inherently designed to provide reliable and cost-effective connectivity across main economic zones. While the main purpose of such systems is to facilitate personal mobility, emerging research highlights that urban freight companies (i.e., carriers) can immensely benefit from them to move cargo, sustainably and efficiently (Gatta et al., 2019a). By leveraging on the concept of 'existing mobility' and utilising PT systems capacity, carriers can reduce the number of dedicated delivery trips and vehicles. However, an essential ingredient for the success of such systems is the availability and participation of PT passengers, or in our case 'crowdshippers'. In PT-based CS, passengers are able to generate additional revenue and customers could receive their products quicker and cheaper, while PT agencies could potentially benefit from additional ridership. Figure 5.1(a) illustrates an ordinary UFDS, in which a delivery vehicle departs the depot, visits delivery points, and returns to the depot. Figure 5.1(b) shows an UFDS including PT-based CS. In Figure 5.1(b), three PT stations (A, B, and C) within the delivery area are identified where major passenger flows between A and B, and A and C. Consequently, parcel deliveries encircling stations B and C can be assigned to passengers commuting from A to these stations. As depicted in Figure 5.1(b), station A is equipped with a PL to streamline the transfer of parcels between carriers and PT passengers, which are subsequently delivered to final points around Stations B and C.

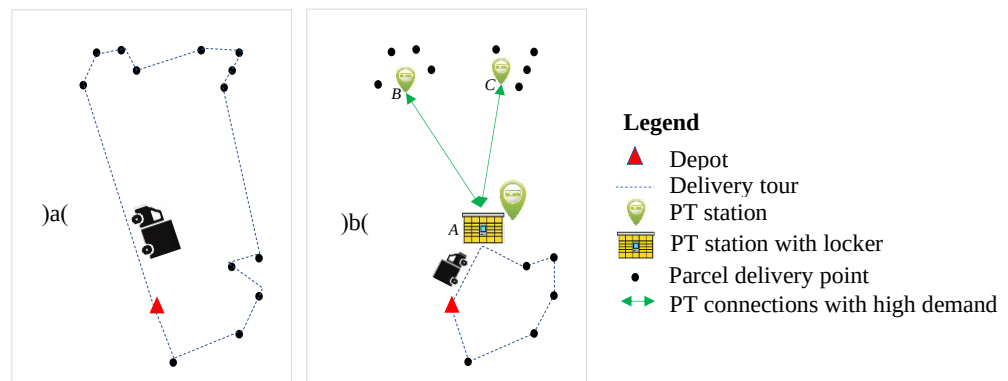


Figure 5.1 (a) Conventional UFDS; (b) UFDS including PT-based CS

In this system, carriers will no longer need to provide frequent deliveries to low-density zones that are distanced from their depots. Instead, part of the service is outsourced to PT passengers using PLs at stations, providing same-day delivery service for most parts of a city at a lower cost. The literature also highlights the potential benefits of such CS systems for low-income passengers and students to cover their transport expenses (Mohri et al., 2024a). Furthermore, besides improved ridership, the installation of PLs could lead to additional revenue for PT agencies. More broadly, the benefits of PT-based CS systems for the general public and government are realised through reduced congestion, emission, and other externalities as the result of lower number of dedicated freight trips within densely populated urban areas (Mohri et al., 2023). While PT-based CS appears to be a commercially and environmentally viable model for parcel delivery within urban areas, the question remains open on whether such an approach is operationally feasible, and if yes, what are the optimal systems configuration and behavioural considerations to ensure sufficient uptake by both crowdshippers and carriers. In this study, we respond to the call in the literature (Fessler et al., 2022; Mohri et al., 2024b) to determine the characteristics of an optimal design. Objectively, the assignment of parcels to PLs, PT passengers, and vehicles for optimal systems performance is examined. Next, the optimal values of financial incentives to PT passengers are measured. Finally, we compare the performance of PT-based CS against a conventional vehicle-only model.

To address the abovementioned objectives, we develop an operational PT-based CS model incorporating the assignment, routing and incentivisation decisions. More specifically, to reflect the probability of PT passengers' acceptance and rejection of delivery tasks, we opt for a probabilistic combinatorial optimisation model using a MNL approach. This allows us to characterise the operational uncertainties of the system. The utility function of the MNL model reflects the behaviour of PT passengers to accept a delivery task given various considerations (e.g., parcel weight, incentive, and detour), estimated using survey data collected in Sydney, Australia. A heuristic solution algorithm is then developed to tackle the complexity of our optimisation model and to solve large-scale instances with reasonable speed and accuracy. We then test our model on a real case study of GS.

Our work provides several contributions to the literature of city logistics, particularly the growing stream examining the applications of crowdsourcing for last-mile delivery using PT systems. This study is one of the first that validates the feasibility of PT-based CS systems using both survey and real-world urban freight data. Furthermore, we empirically study the

implications of CS familiarity in relation to delivery task acceptance and systems performance. Importantly, our study incorporates the behavioural consideration such as PT passengers' participation and acceptance into the CS system design. And finally, from a modelling perspective, our work contributes to the literature of CS by developing an integrated optimisation model that takes into account decisions related to parcel assignment, vehicle routing, and incentivising. In terms of network structure, the proposed model differs from previous PT-based CS studies, given its locker-to-home delivery structure. Such design is considerably more complex, yet practical for both carriers and PT passengers. The organization of this paper is as follows. Section 5.2 provides a summary of relevant literature. Section 5.3 formulates the problem and Section 5.4 presents the solution approach. In Section 5.5 we determine the case study and related model parameters. Section 5.6 presents the results, and finally, conclusions are drawn in Section 5.7.

## 5.2 Literature Review

The sharp increase in e-commerce and home delivery volumes has significantly contributed to the rise in freight vehicle activity within urban areas and associated externalities (Janjevic et al., 2021). As the result, several innovative last-mile logistics solutions and interventions have been proposed by academia and industry to address these growing concerns, of which, crowdsourced parcel delivery or CS standing out as a promising one. The literature presents diverse interpretations of CS (Gläser et al., 2021). Here we borrow the definition by Buldeo Rai et al. (2017): *“Crowdshipping is an information connectivity enabled marketplace concept that matches supply and demand for any kind of transportation of goods with an undefined and external crowd that has free capacity with regards to time and/or space, participates on a voluntary basis, and is compensated accordingly”*.

The benefits of CS for both direct and indirect stakeholders within UFDSs are known (Mohri et al., 2023; Le et al., 2019). It allows carriers to reduce their delivery costs, and at the same time, it could improve delivery service quality for customers (Ghaderi et al., 2022a). Moreover, retailers can expand their service coverage by utilising such services. CS is anticipated to minimise the environmental impacts of freight task within urban areas by reducing truck movement, hence, reducing emissions, traffic congestion, and social externalities (Mohri et al., 2023). Despite these benefits, the design of eco-friendly CS systems has been minimally studied in the literature. In the past, e-commerce platforms have mainly

focused on systems involving occasional drivers. Examples of such platforms include Amazon Prime, Walmart Spark Delivery, DHL MyWays, Deliveroo, UberEATS, DoorDash, and PiggyBee (Alnaggar et al., 2021). Similarly, academic studies have focused on planning decisions of CS with occasional drivers, particularly examining the behavioural aspects, systems design, and evaluation aspects (Le et al., 2019; Mohri et al., 2023). Meanwhile, studies such as Qi et al. (2018), Gatta et al. (2019a), and Simoni et al. (2020) illuminate the less favourable facets of CS systems, revealing potential environmental concerns often referred to as the "dark side" of the system. The literature on CS emphasises that poor system design and reliance on dedicated trips would yield adverse environmental effects, in some cases worse than conventional courier-based delivery systems (Rai et al., 2018; Qi et al., 2018).

Qi et al. (2018) investigated the environmental performance of CS systems involving occasional drivers, contrasting them to truck-only delivery systems based on a San Francisco case study. The findings indicate that in terms of operating costs, CS lacks the same scalability as conventional systems. Yet, integrating CS could reduce fleet size and enhance operational adaptability, granting improved entry to peak-demand zones and hours. Moreover, Qi et al. (2018) inferred that CS systems could potentially amplify emissions due to longer travel distances for crowdshippers, if they rely on private vehicles. Rai et al. (2018) explored the environmental aspect of CS utilising occasional drivers based on historical data from the operations of a crowd logistics company in Belgium. Results indicate that the CS platform led to larger environmental impacts associated with high number of dedicated trips. These studies have sparked an interest in improving the sustainability of the CS system, particularly by leveraging the concept of 'existing mobility' and PT-based approaches. Early studies on PT-based CS primarily delve into understanding how passengers engage and accept CS delivery tasks (Marcucci et al., 2017; Serafini et al., 2018; Gatta et al., 2019a; Gatta et al., 2019b). For example, Marcucci et al. (2017) investigated the conditions under which students in Rome would be willing to act as crowdshipper in PT-based CS systems. By surveying nearly 190 students, authors indicate that most students are unfamiliar with CS, while 87% of them would be willing to act as crowdshipper. The participation of students as crowdshipper would lower to 55% and 40%, if the parcel is large and the reward is less than 5€, respectively. Serafini et al. (2018) and Gatta et al. (2019a) employed discrete choice models to explore the behaviour and expectation of commuters on the metro network to participate in CS initiatives. Later on, Fessler et al., (2022) studied PT passengers' parcel delivery acceptance in the Greater Copenhagen Area, based on varying weight, size, incentives, number of parcels, and detour considerations. Using survey data and applying a mixed logit model, the results of Fessler et

al. (2022) show that a higher compensation rate has direct correlation with acceptance level, while increasing the number, size, and weight of parcels negatively impacts the acceptance rate. Predominantly, the abovementioned studies explore the acceptance behaviour of crowdshippers for locker-to-locker delivery with lockers installed inside or near PT stations. Mohri et al. (2024a) and Mohri et al. (2024b) suggest a centralised network of locker facilities in which passengers pick up parcels from lockers and deliver them to their final destinations, within the passengers' destination neighbourhood. These recent studies explore how delivery structure, behavioural considerations, participation rate, and acceptance probability could improve the design of PT-based CS systems.

Besides behavioural studies, modelling studies on PT-based CS are limited. Giuffrida et al. (2021) explore the spatial feasibility of outsourcing parcel delivery to university students who commute in the network with PT services and other active modes of transport. A case study from the city of Catania, Italy, is used to examine the feasibility of matching deliveries with student movements by considering their mobility patterns, the proximity of delivery points to students' home addresses, and the mode of transport. By assuming a maximum walking distance of 500 meters for detouring, a potential pool of candidates could be formed. Simoni et al. (2020) employed dynamic traffic simulation to explore how parcel delivery by private transport and PT services could reduce air pollution and traffic delays. Based on a case study of Rome, Italy, it was found that when matched demand is higher, PT-based CS is more beneficial than private vehicles from environmental and congestion perspectives. The study by Simoni et al. (2020) also found that CS with cars entails higher negative externalities compared to a traditional delivery system, both in terms of pollution and congestion. It is important to note that Simoni et al. (2020) and Giuffrida et al. (2021) follow simulation and GIS-based approaches, respectively, while the present study benefits from mathematical modelling and optimisation techniques to design and develop a PT-based CS system. Leveraging trajectory data from a CS platform in Australia, Ghaderi et al. (2022b) explored how PLs could improve successful deliveries. Their result indicated that PLs could support joint deliveries made by multiple participants, consequently reducing the deviation distance and improving the acceptance rate. While being an optimisation-based study, Ghaderi et al. (2022b) did not consider PT-based CS. Furthermore, while previous studies provide insights into the behavioural considerations of passengers, particularly by exploring the probability of accepting delivery tasks (Punel et al., 2018; Le and Ukkusuri, 2019; Miller et al., 2017; Devari et al., 2017), their findings have not been well incorporated into operational decisions. For example, Feng et al. (2019) and Archetti et al. (2021) assume heterogeneities in crowdshippers'

travelling cost, time window, and vehicle capacity decisions. In other words, behavioural and optimisation decisions have been largely studied in isolation. The literature of crowdsourcing demonstrate examples on how such problems could be integrated, synergistically (Moayedikia et al., 2020). To address this gap, we propose a probabilistic optimisation model, in which the likelihood of PT passengers' participation in CS and job acceptance are incorporated. These probabilities are calculated based on a discrete choice analysis, driven from a survey of 2208 respondents in the GS area, Australia.

### 5.3 Problem Definition and Formulation

We formulate a PT-based CS system, at an operational level, which aims to minimise the parcel delivery costs of a carrier. To design the system three operational decisions are considered: (1) the assignment of parcels to selected lockers in the CS system or vans in the home delivery system, (2) the routing decision of delivery vehicles for visiting parcels assigned to home delivery and the lockers, and (3) incentivisation of PT passengers participating in the initiative. These decisions are simultaneously optimised to minimise total delivery costs of the carrier. Moreover, it is a prerequisite to integrate the behaviours of PT passengers in terms of participation in the CS system and task acceptance. Therefore, we propose a monolithic mathematical model, integrating probabilistic behavioural choice models with an operational design problem. To reflect decision uncertainty, we utilise an “expected value” calculation technique. Expected value calculation in decision theory involves determining the average outcome of a decision (strategy) in uncertain situations (Gigerenzer, 2008). It is computed by multiplying the value of each possible outcome by its occurrence probability and summing them up. This calculation is used to evaluate different decision options and choose the one with the lowest expected costs. It provides a systematic way to assess and compare various alternatives in the face of uncertainty. Mathematically, it is expressed as  $Expected\ Cost = \sum_i P(Outcome_i) \times Cost(Outcome_i)$ . Here,  $P(Outcome_i)$  represents the probability of each possible outcome and  $Cost(Outcome_i)$  represents the cost associated with that outcome.

Figure 5.2 illustrates how the expected cost calculation method can be applied to the problem under investigation in this study. Figure 5.2(a) illustrates the decision-making process for the carrier, while Figure 5.2(b) shows the potential cost terms incurred by a carrier during the decision-making process for delivering a parcel. As shown by Figure 5.2(a), each parcel can be delivered by CS or conventional carrier-based delivery model. A total routing cost ( $C_2$ )

is incurred for the conventional delivery method. In Figure 5.2(b), the arrow from depot to parcel destinations shows  $C_2$ . If a parcel is considered for CS, the expected costs ( $EC = C_3 + C_4 + C_5$ ), as well as a deterministic cost ( $C_1$ ) are incurred. This study considers all cost terms along with their associated probabilities to calculate the total costs incurred by a carrier using a PT-based CS system. The detailed explanation of cost terms and the methods are explained further. The carrier considers a selected set of PT stations for placing lockers to move the parcels involving CS (i.e., these stations are called PT hub stations throughout the paper). Therefore, as shown in Figure 5.2(b),  $C_1$  is the cost of moving parcels from depot to lockers in PT stations.

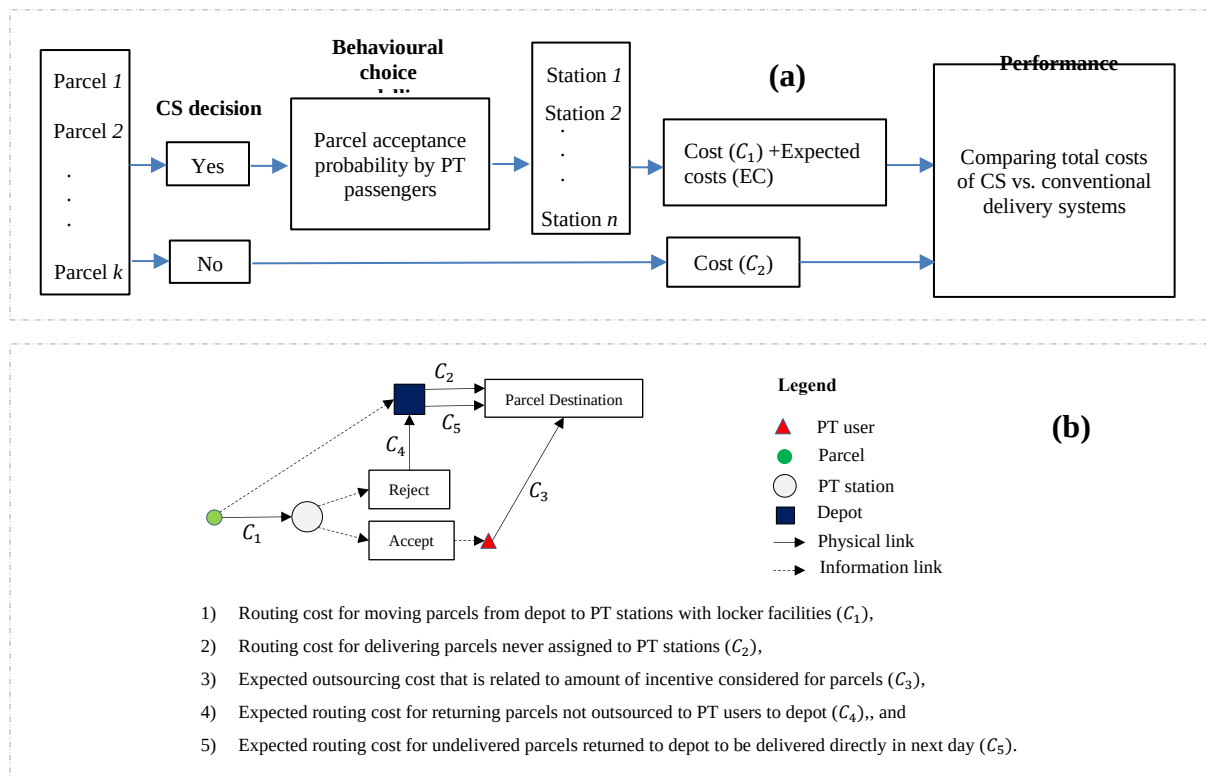


Figure 5.2 The decision-making process framework

After assigning a parcel to a locker, the probability of delivery acceptance by at least one PT passenger must be measured, travelling from the station to the neighbourhood of the parcel's destination. In measuring such probability, we consider parcel characteristics such as weight, delivery address, and incentive. Therefore, three expected cost terms of  $C_3$ ,  $C_4$ , and  $C_5$ , are incurred.  $C_3$  is the expected cost of successfully outsourcing the parcel to PT passengers, which depends on the incentive value.  $C_4$  and  $C_5$  are the expected costs associated with the probability of rejecting the parcel by PT passengers. Accordingly,  $C_4$  indicates the expected cost of returning the parcel to the depot and  $C_5$  indicates the expected routing cost for delivering

the rejected parcel using delivery vehicles in the next day. Using this approach, a carrier can effectively quantify the average expected cost for each decision scenario, considering the probabilities associated with different outcomes. This process facilitates informed decision making in situations where outcomes are uncertain.

As shown in Figure 5.2, the behavioural part of the model captures the probability of at least one PT passenger accepting the parcel delivery with particular characteristics (e.g., incentive, weight, detour). This is a critical step, as such probability largely affects the performance of the system and sequential decisions. To measure this probability, we consider the effects of three (interrelated) factors. First, we account for the familiarity rate among PT passengers with CS initiatives, which can increase over time by advertising the CS initiative and wider interactions among crowdshippers and other PT passengers. Given the temporal rate of familiarity, a varying percentage of PT passengers participate in the initiative, which eventually impacts task availability. Second, the rate of participation by PT passengers who are familiar with the initiative should be calculated. This is to account for PT passengers who are familiar with the initiative but unwilling to get involved. Leveraging on the study of Mohri et al. (2024a), the participation rate of different socioeconomic groups of a community can be approximated. By multiplying the familiarity and participation rates, the expected daily number of potential PT passengers to move parcels between the pair of PT stations is estimated. Third, the probability of accepting or rejecting CS tasks by participating PT passengers in the initiative is calculated. The CS parcel acceptance probability modelled by the study of Mohri et al. (2024b) is borrowed. In the following subsection, the familiarity and participation rates, as well as acceptance probability, are presented to derive the appropriate equations to estimate the total parcel delivery acceptance rate.

### 5.3.1 Parcel delivery acceptance probability

A participating PT passenger in the CS initiative has two choices: A: Accept and R: Reject. Therefore, we assume  $f_{ij}^{km}$  is the probability that PT passenger  $m$ , travelling from PT station  $i$  to  $j$ , accepting to deliver a parcel, located in a locker at station  $i$  and delivery address ( $k$ ) around station  $j$  (i.e.,  $j \in D(k)$ ). We assume the choice probability follows a logit function as shown by Equation (5.1). Therefore,  $f_{ij}^{km}$  is a function of  $g_{ij}^{km}$ . In discrete choice problems with two alternatives,  $g_{ij}^{km}$  is equal to  $U(R) - U(A)$ , where  $U(R)$  and  $U(A)$  are the utilities that passenger  $m$  obtain by rejecting and accepting parcel delivery to point  $k$ , respectively. Generally,  $g_{ij}^{km}$  can be a function of observed alternative specific variables (e.g., characteristics

of parcel delivery task to point  $k$ , such as weight and incentive), individual specific variables (e.g., characterises of passenger  $m$  such as age, gender, income, etc.), interactive variables (e.g., a parcel address distance from a PT passenger trip destination) and an unobserved error term as shown by Equation (5.2).

$$f_{ij}^{km} = \frac{1}{1 + e^{-g_{ij}^{km}}} \quad \forall i, j \in N, k \in K, j \in D(k), m \in M \quad (5.1)$$

$$g_{ij}^{km} = \alpha + \sum_{a \in A1} \beta_a e_a^k + \sum_{a \in A2} \beta_a e_a^m + \sum_{a \in A3} \beta_a e_a^{k,m} + \epsilon \quad \forall i, j \in N, k \in K, j \in D(k), m \in M \quad (5.2)$$

In this equation,  $a \in A$  is an index for all explanatory variables used in the utility function. Set  $A$  consists of three non-intersecting subsets:  $A1$ ,  $A2$ , and  $A3$ , which are the explanatory variables related to parcel characteristics, passenger characteristics, and passenger-parcel interactive characteristics, respectively. Accordingly,  $e_a^k, \forall k, a \in A1$  is an explanatory variable attributed to characteristic  $a$  of the parcel for delivery point  $k$  (an alternative specific variable),  $e_a^m, \forall m, a \in A2$  is an explanatory variable attributed to characteristic  $a$  of passenger  $m$  (an individual specific variable), and  $e_a^{k,m}, \forall m, k, a \in A3$  is an explanatory variable attributed to the interactive variable  $a$  between characteristics of passenger  $m$  and the parcel for delivery to point  $k$ . Now, assume that  $g_{ij}^{km}$  is estimated based on the information of participated passengers which are collected by the CS platform and the characteristics of parcel deliveries. Using  $g_{ij}^{km}, f_{ij}^{km} \quad \forall i, j \in N, k \in K, j \in D(k), m \in M$  is calculated.

The carrier should distribute existing parcels to either potential PT stations for CS or a virtual node (node 0 standing for carrier's depot for delivery through the carrier-owned vehicles). Therefore,  $|N| + 1$  options for assigning parcels are available. Parcels may be dropped at PT station  $i$  to be outsourced to passengers traveling from  $i$  to  $j \in N$ , with a detour to visit delivery point  $k$  near PT station  $j$ . The number of PT passengers traveling daily from  $i$  to  $j$  is denoted as  $h_{ij}$ .  $h'_{ij}$  represents a fraction of  $h_{ij}$ , signifying PT passengers are familiar with and willing to participate in the CS initiative. It can be calculated through preprocessing using Equation (5.3) and subsequently used as a parameter in the operational design model. In this equation,  $F_{rate}$  and  $P_{rate}$  denote familiarity and participation rates, respectively.

$$h'_{ij} = \lfloor F_{rate} \times P_{rate} \times h_{ij} \rfloor \quad \forall i, j \in N \quad (5.3)$$

The CS platform has information about  $h'_{ij}$  passengers as they have already registered with CS and shared personal or intention-to-participate data. Consequently, set  $M_{ij}$  is established, comprising the  $h'_{ij}$  passengers. The carrier needs to determine the probability that at least one PT passenger from  $M_{ij}$  will agree to carry the parcel destined for address  $k$ . This probability is denoted as  $P_{ij}^k$ . Following the complementary probability principle,  $P_{ij}^k$  equals one minus the probability of all PT passengers from  $M_{ij}$  refusing parcel delivery to address  $k$ . PT passengers independently decide whether to accept or reject a parcel delivery. Accordingly, given  $f_{ij}^{km}$  as the probability of passenger  $m$  accepting parcel delivery to  $k$ ,  $P_{ij}^k$  can be computed using Equation (5.4).

$$P_{ij}^k = 1 - \prod_{m \in M_{ij}} (1 - f_{ij}^{km}) \quad \forall i, j \in N, k \in K, j \in D(k) \quad (5.4)$$

Therefore,  $P_{ij}^k$  and  $(1 - P_{ij}^k)$  are the probabilities that parcel delivery to  $k$  is to be outsourced or not, respectively. Now, using the estimated probability formulas, a mathematical model of the decision-making process is proposed in the following section.

### 5.3.2 Decision making model formulation

In this subsection, we propose a mathematical model responsible for assignment, routing, and incentivisation decisions. The model incorporates the acceptance probability of parcel deliveries by PT passengers working as crowdshippers in the CS system. Hence, the model is able to determine not only the optimal assignment of parcels to the lockers at predefined PT stations, but also the incentive for CS-delivered parcels and routing of non-outsourced parcels from carrier's depot to their destination. The objective function minimises total expected parcel delivery costs in the delivery system with carrier's fleet and crowdshippers. Accordingly,  $C_1$  and  $C_2$  are pertinent to conventional parcel delivery with vehicles and  $C_3$ ,  $C_4$ , and  $C_5$  are the expected costs through CS. Before presenting the model, the total sets, indices, parameters, and decision variables used in the model are defined.

- **Sets/indices/input parameters**

- $N$  : Set of the PT stations
- $N_1$  : Subset of  $N$  with PL (i.e., PT hub stations)
- $K$  : Set of the parcel delivery points in one day,  $K = K_1 \cup K_2$

|                           |                                                                                                                                                                  |
|---------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| $K_1$                     | : Subset of the ‘final’ parcel delivery points in $K$ (e.g., home addresses)                                                                                     |
| $K_2$                     | : Subset of “virtual” parcel delivery points in $K$ (i.e., for hub stations)                                                                                     |
| $K_3$                     | : Subset of final parcel delivery points $K_1$ with heavy parcels which are not eligible for CS delivery                                                         |
| $V$                       | : Set of delivery vehicles                                                                                                                                       |
| $M$                       | : Set of PT passengers                                                                                                                                           |
| $M_{ij}$                  | : Set of PT passengers who participate in the CS system and travel from PT station $i$ to $j$ daily                                                              |
| $i, j$                    | : Index of PT stations                                                                                                                                           |
| $k, k'$                   | : Index of parcel delivery points, $k \& k' \in K$                                                                                                               |
| $v$                       | : Index of delivery vehicles                                                                                                                                     |
| $m$                       | : Index of PT passengers                                                                                                                                         |
| $0, \pi$                  | : Representing depot                                                                                                                                             |
| $D(k)$                    | : Set of PT stations with the final parcel delivery point $k$ in its proximity                                                                                   |
| $O(k)$                    | : Corresponding index of $k \in K_2$ in set $N_1$                                                                                                                |
| $U$                       | : A large positive number                                                                                                                                        |
| $\overline{OC}$           | : The cost of operating the carrier’s delivery vehicle for one hour of service                                                                                   |
| $\bar{c}_k$               | : Average delivery cost by delivery vehicles for rejected parcel delivery to $k$ in CS system                                                                    |
| $\alpha, \beta_{1,...,n}$ | : Coefficient of explanatory variables in the logit model (parcel’s weight, incentive, distance to PT stations, and characteristics of PT passengers)            |
| $\omega_k$                | : Parcel weight at delivery address $k \in K$ before outsourcing parcels to the CS system; hence, $\omega_k = 0$ for virtual delivery points $\forall k \in K_2$ |
| $\omega_{max}$            | : Maximum parcel weight eligible for CS delivery                                                                                                                 |
| $h_{ij}$                  | : Number of PT passengers travelling from PT station $i$ to $j$ daily                                                                                            |
| $h'_{ij}$                 | : Number of PT passengers participating in the CS and travelling between PT stations $i$ to $j$ daily                                                            |
| $b_{n+1}$                 | : A maximum threshold for limiting route durations                                                                                                               |
| $Q$                       | : Vehicle capacity (kg)                                                                                                                                          |
| $t_{kk'}$                 | : Travel time from $k$ to $k'$ by delivery vehicles                                                                                                              |
| $s_k$                     | : Service time on delivery $k \in K$ before outsourcing parcels to the CS system; hence, $s_k = 0$ for virtual delivery points $\forall k \in K_2$               |

$\mu$  : Reduction in servicing cost at delivery points as the result of using PLs, compared to direct customer handling. Therefore,  $0 \leq \mu \leq 1$  adjusts service cost for PL delivery.

• **Decision variables**

$x_{ij}^k$  : A binary decision variable that is equal to one if the parcel for delivery point  $k$  is placed in lockers of PT station  $i$  for outsourcing to PT passengers travelling from  $i$  to  $j$ ; otherwise, it is equal to zero.

$x'^k$  : A binary decision variable that is equal to one if parcel delivery point  $k$  is serviced by delivery vehicles; otherwise, it is zero (i.e., serviced by passengers).

$y_{kk'}^v$  : A binary decision variable that is equal to one if vehicle  $v$  travels from  $k$  to  $k'$ ; otherwise, it is zero.

$P_{ij}^k$  : The probability of a parcel with delivery point  $k$ , located in PT station  $i$  for outsourcing to PT passengers travelling from  $i$  to  $j$ , is successfully outsourced.

$I_k$  : The incentive offered to PT passengers to deliver to  $k$

$p_i$  : The total number of parcels left at PT hub station  $i$  for CS

$w_k^v$  : Time when vehicle  $v$  leaves parcel delivery point  $k$

$\omega'_{k'}$  : Updated weight of parcels at delivery address  $k' \in K$  after outsourcing parcels to the CS system; for  $k' \in K_1$ , the decision is fixed and  $\omega'_{k'} = \omega_{k'}$

$s'_{k'}$  : Updated service time of delivery address  $k' \in K$  after outsourcing some parcels to the CS system; for  $k' \in K_1$ , the decision is fixed and  $s'_{k'} = s_{k'}$

Next, we present the mathematical model and related equations.

$$\text{Min } C_1 + C_2 + C_3 + C_4 + C_5 \quad (5.5)$$

Subject to:

$$C_1 + C_2 = \overline{OC} \left( \sum_{v \in V} \sum_{k \in K \cup \{0\}} \sum_{k' \in K \cup \{\pi\}, k \neq k'} y_{kk'}^v t_{kk'} \right. \\ \left. + \sum_{i \in N_1} \sum_{j \in N, j \in D(k)} \sum_{k \in K_1} x_{ij}^k \mu s_k + \sum_{k \in K_1} x'^k s_k \right) \quad (5.6)$$

$$C_3 = \sum_{i \in N_1} \sum_{j \in N, j \in D(k)} \sum_{k \in K_1} x_{ij}^k P_{ij}^k I_k \quad (5.7)$$

$$C_4 = \overline{OC} \sum_{i \in N_1} \sum_{j \in N, j \in D(k)} \sum_{k \in K_1} \mu S_k x_{ij}^k (1 - P_{ij}^k) \quad (5.8)$$

$$C_5 = \sum_{i \in N_1} \sum_{j \in N, j \in D(k)} \sum_{k \in K_1} \bar{c}_k x_{ij}^k (1 - P_{ij}^k) \quad (5.9)$$

$$g_{ij}^{km} = \alpha + \beta_1 \omega_k + \beta_2 I_k + \beta_3 d_j^{km} + \sum_{a \in A_2} \beta_a e_a^m \quad \forall i \in N_1, j \in N, k \in K_1, j \in D(k), m \in M \quad (5.10)$$

$$f_{ij}^{km} = \frac{1}{1 + e^{-g_{ij}^{km}}} \quad \forall i \in N_1, j \in N, k \in K_1, j \in D(k), m \in M \quad (5.11)$$

$$P_{ij}^k = 1 - \prod_{m \in M_{ij}} (1 - f_{ij}^{km}) \quad \forall i \in N_1, j \in N, k \in K_1, j \in D(k) \quad (5.12)$$

$$\sum_{i \in N_1} \sum_{j \in N, j \in D(k)} (x_{ij}^k) + x'^k = 1 \quad \forall k \in K_1 \quad (5.13)$$

$$x'^k = 1 \quad \forall k \in K_3 \quad (5.14)$$

$$\sum_{k \in K_1} \sum_{j \in N, j \in D(k)} \omega_k (x_{ij}^k) = \omega'_{k'} \quad \forall i \in N_1, k' \in K_2, O(k') = i \quad (5.15)$$

$$\omega'_{k'} \leq U x'^{k'} \quad \forall k' \in K_2 \quad (5.16)$$

$$\sum_{k \in K_1} \sum_{j \in N, j \in D(k)} s_k (x_{ij}^k) = s'_{k'} \quad \forall i \in N_1, k' \in K_2, O(k') = i \quad (5.17)$$

$$\sum_{v \in V} \sum_{k' \in K, k \neq k'} y_{kk'}^v = x'^k \quad \forall k \in K \quad (5.18)$$

$$\begin{cases} \sum_{k' \in K} y_{0k'}^v = 1 \\ \sum_{k' \in K} y_{k', n+1}^v = 1 \end{cases} \quad \forall v \in V \quad (5.19)$$

$$\sum_{k \in K, k \neq k'} y_{kk'}^v - \sum_{k \in K, k' \neq k} y_{k'k}^v = 0 \quad \forall v \in V, k' \in K \quad (5.20)$$

$$y_{kk'}^v (w_k^v + s'_{k'} + t_{kk'} - w_{k'}^v) \leq 0 \quad \forall v \in V, k, k' \in K \cup \{0, \pi\}, k \neq k' \quad (5.21)$$

$$w_{n+1}^v \leq b_{n+1} \quad \forall v \in V \quad (5.22)$$

$$\sum_{k \in K} \sum_{k' \in K \cup \{n+1\}, k \neq k'} \omega'_{k'} y_{kk'}^v \leq Q \quad \forall v \in V \quad (5.23)$$

$$x_{ij}^k \in \{0, 1\} \quad \forall i, j \in N, k \in K, j \in D(k) \quad (5.24)$$

$$y_{kk'}^v \in \{0, 1\} \quad \forall k, k' \in K \cup \{0, \pi\}, v \in V \quad (5.25)$$

The objective function in Equation (5.5) minimises total and expected costs associated with the CS program. This objective is consistent with the technique of minimising expected costs, as explained in Subsection 5.3.2, to address the uncertainty associated with accepting CS tasks by PT passengers. Equation (5.6) calculates  $C_1 + C_2$ , which stands for total routing costs with delivery vehicles in the system. It accumulates routing costs (the first cost term) and service costs (the second and third cost terms) on visiting delivery points assigned to PT hub stations and vehicles, respectively. In the second term,  $\mu$  adjusts the service cost for locker delivery, as delivering to lockers requires less time for delivery workers compared to handing parcels directly to customers. Hence,  $\mu s_k$  estimates the adjusted service cost for delivery point  $k$ , which is no longer visited by vehicles and is allocated to the CS system. However, only delivery workers need to load parcels into PLs. Equations (5.7-5.9) estimate the total expected costs of parcel delivery in the CS system. These equations capture the interdependencies between individual parcel delivery decisions in the CS system as shown in Figure 5.2(b). Once,  $x_{ij}^k$  is equal to one, meaning that parcel  $k$  is allocated to the CS system, these equations would have non-zero values. Equation (5.7) is the expected cost resulting from incentivising delivery tasks assigned to CS delivery ( $C_3$ ). In this equation,  $P_{ij}^k I_k$  represents the expected CS delivery cost for parcel delivery point  $k$ . Equation (5.8) calculates the expected cost of returning non-outsourced delivery tasks from the lockers to the depot ( $C_4$ ). We assume the carrier has to visit the PT hub stations to load new parcels; hence, only one additional service cost for unloading parcels is incurred. In this equation,  $\mu s_k (1 - P_{ij}^k)$  estimates the additional service cost, where  $\mu$  is incorporated as an adjustment factor for locker delivery. Equation (5.9) approximates home delivery cost for rejected delivery tasks from depot/hubs to their customers in the next day ( $C_5$ ). Here,  $\bar{c}_k$  represents the average vehicle delivery cost to delivery point  $k$ . Equations (5.10) and (5.11) describe the utility and probability functions for the logistic regression model, respectively. Accordingly, the probability of outsourcing parcel delivery for point  $k$  through hub station  $i$  to PT passenger  $m$  travelling from  $i$  to  $j$  is defined by  $f_{ij}^{km}$ , and calculated in Equation (5.11). The probability is a function of an acceptance utility,  $g_{ij}^{km}$ , Equation (5.10), which includes variables related to delivery tasks such as weight and incentive, passengers (e.g., age and gender), and interactions between tasks and passengers such as distance between delivery points and passengers' destinations. The delivery task for point  $k$  can be successfully outsourced if at least one PT passenger accepts. Hence, Equation (5.12) estimates the probability of outsourcing parcel delivery for point  $k$  to at least one PT passenger.

Equation (5.13) assures that each final parcel delivery point,  $k \in K_1$ , must be visited by carrier vehicles or outsourced to PT passengers through a hub station. Using this equation, parcel delivery points are divided into CS or vehicle deliveries. Equation (5.14) ensures that delivery points with heavy parcels (i.e.,  $\forall k, \omega_k > \omega_{max}$ ) can only be visited by carriers. In addition to the final parcel delivery points assigned to vehicles (i.e.,  $\forall k \in K_1, x'^k = 1$ ), virtual delivery points representing PT hub stations are utilised for outsourcing parcels to passengers and visited by vehicles. In this regard, Equation (5.15) calculates the total weight of parcel deliveries assigned to virtual delivery point  $k \in K_2$ . Next, Equation (5.16) forces the delivery vehicles to visit the virtual points with positive parcel delivery weight. Similar to (5.15), Equation (5.17) accumulates the total required service time at these virtual points.

Equations (5.18) to (5.23) are common restrictions in Capacitated Vehicle Routing Problems (CVRPs). This set of equations is considered to identify the required routes for delivering parcels by carriers. Hence, the vehicles are forced to service the parcel delivery points that are not considered for the CS program ( $x'^k = 1$ ) and the virtual delivery points with non-zero demand (Equation 18). Moreover, Equation (5.19) states that each vehicle must depart and arrive the depot only once. Equation (5.20) satisfies the flow conservation at each delivery address for each parcel. Equation (5.21) ensures the consistency of arrival and departure time to and from delivery points. Also, this equation eliminates subtours. Equation (5.22) is a time-window constraint that bounds the route durations. Equation (5.23) enforces the vehicle capacity restriction. Finally, Equations (5.24) and (5.25) represent the nature of decision variables.

## 5.4 Solution Algorithm

The literature acknowledges the NP-hard nature of CVRP and its resolution through exact methods is restricted to scenarios of smaller scale. The inherent complexity in the articulated problem goes beyond the conventional CVRP scope, as it encompasses supplementary decisions such as the allocation of parcels to vehicle delivery or collection points, coupled with the introduction of incentives for collection point tasks. Since the proposed study aims to apply the model to a large-scale real-world scenario, it is important to employ a solution algorithm that embodies both efficiency and speed.

Without losing generality, we assume that  $g_{ij}^{km}$  is only a function of parcels' characteristics. The effects of other factors such as passengers' characteristics can be captured

aggregately by the error term. Therefore,  $g_{ij}^{km}$  will have three explanatory variables: incentive, weight, and detour of parcel delivery to  $k$ . However, the detour ( $d_j^{km}$ ) used in Equation (5.10) still depends on the passengers' trip destinations, hence, it is impossible to exclude index  $m$  from Equation (5.10). To adjust the equation, the detour on CS tasks for every passenger is approximated as the function of a parcel distance to a PT station ( $d_j^k$ ), which is around the parcel's delivery point.

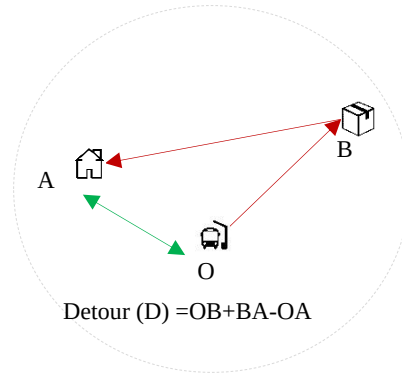


Figure 5.3 A schematic view of an imposed detour to a passenger

As shown in Figure 5.3, the detour ( $D$ ) is equal to  $\overline{OB} + \overline{BA} - \overline{OA}$ , where  $\overline{OA}$  and  $\overline{OB}$  are the distances from station  $O$  to passengers' home or final destination and parcel delivery point, respectively. It is assumed  $D = \alpha \overline{OB}$ , where  $\alpha$  is unknown. The value of  $\overline{BA}$  can be calculated by the law of cosines, where the angle between  $\overline{OA}$  and  $\overline{OB}$  is  $\theta$ . Accordingly, using Equation (5.26),  $\alpha$  can be calculated.

$$\begin{aligned} \alpha \overline{OB} &= \overline{OB} + \sqrt{\overline{OA}^2 + \overline{OB}^2 - 2\overline{OA}\overline{OB}\cos\theta} - \overline{OA} \rightarrow \alpha \\ &= \frac{\overline{OB} + \sqrt{\overline{OA}^2 + \overline{OB}^2 - 2\overline{OA}\overline{OB}\cos\theta} - \overline{OA}}{\overline{OB}} \end{aligned} \quad (5.26)$$

The angle between  $\overline{OA}$  and  $\overline{OB}$  ( $\theta$ ) can change from  $-180$  to  $+180$  with respect to a specific distribution function. Since,  $\cos\theta = \cos-\theta$ , the absolute value of  $\theta$  varies from  $0$  to  $180$ . To avoid unnecessary complications, we assume  $\theta$  has a uniform distribution. Therefore,  $E(\theta) = \int_0^\pi \theta f(\theta)d\theta = \frac{\pi}{2}$  and  $E(\alpha) = \frac{\overline{OB} + \sqrt{\overline{OA}^2 + \overline{OB}^2} - \overline{OA}}{\overline{OB}}$ . Moreover,  $E(\overline{OA}) = \gamma$  can be replaced with  $\overline{OA}$ . As the result,  $E(D) = E(\alpha)\overline{OB} = \overline{OB} + \sqrt{\gamma^2 + \overline{OB}^2} - \gamma$ . Later, in Section 5.5,  $E(\overline{OA})$  or  $\gamma$  is appropriately set for the real case explored in this study. Following the adjustments, the revised version of Equations (5.10) to (5.12) are as follows:

$$g_{ij}^k = \alpha + \beta_1 \omega^k + \beta_2 I^k + \beta_3 \left( d_j^k + \sqrt{\gamma^2 + (d_j^k)^2} - \gamma \right) \quad \forall i, j \in N, k \in K \quad (5.27)$$

$$f_{ij}^k = \frac{1}{1 + e^{-g_{ij}^k}} \quad \forall i, j \in N, k \in K \quad (5.28)$$

$$P_{ij}^k = 1 - (1 - f_{ij}^k)^{h'_{ij}} \quad \forall i, j \in N, k \in K \quad (5.29)$$

Accordingly, index  $m$  is removed from (5.10) and (5.11), resulting in (5.27) and (5.28), respectively. By removing index  $m$  from (5.10) and (5.11), Equation (5.12) will be converted to Equation (5.29). In fact,  $\prod_{m \in M_{ij}} (1 - f_{ij}^{km})$  will convert to  $(1 - f_{ij}^{km})^{|M_{ij}|} = (1 - f_{ij}^{km})^{h'_{ij}}$  since the probabilities of accepting CS task  $k$  by the entire passenger pool travelling from  $i$  to  $j$  are now identical.

The incentive offered to PT passengers for carrying CS tasks is a decision variable in the model. Existing compensation schemes in the CS literature do not arbitrarily set the prices, instead, they follow different compensation values (Mohri et al., 2023). For example, in CS systems with occasional drivers, the compensation depends usually on parcel travel distance, weight, and type. In a relevant field of research, interregional freight transport, pricing on shipping freights is made in accordance with the ton-kilometres of shipments (Mohri and Thompson, 2022). Inspired by these studies, we assume the CS incentive is a function of weight and detour, as shown by Equation (5.30).

$$I^k = \delta \omega^k \left( d_j'^k + \sqrt{\gamma^2 + (d_j'^k)^2} - \gamma \right) \quad \forall k \in K \quad (5.30)$$

Where  $\delta$  determines how much incentive should be paid for moving one unit of package weight over one unit of detour distance. Varying  $\delta$  results in different compensation values. Now, to simplify the model,  $I^k$  is set in the model according to a compensation value, which has a specific  $\delta$ . Sensitivity analyses are then performed to find the best compensation value and  $\delta$ . Therefore,  $g_{ij}^k$  and subsequently  $f_{ij}^k$  and  $P_{ij}^k$  will become parameters and we can take out Equations (5.10) to (5.12) from the mathematical model. Given the proposed adjustments, the model's objective function and constraints are as follows:

- **Objective function:** (5.5)
- **Equation and constraints:** (5.6-5.9), (5.13-5.25), and (5.27-5.29)

A 9-step heuristic algorithm is proposed to solve the adjusted model for large-sized cases. The algorithm, named 'PT-based CS,' iteratively applies both the basic and a modified version of the Clarke and Wright (CW) saving algorithm, along with repetitive cost estimations. This

approach optimises the allocation of demand points between the CS system and traditional vehicle delivery, while identifying the optimal pricing strategy for parcels allocated to the CS system and optimising delivery routes. A high-level pseudocode of the PT-based CS algorithm is presented below to illustrate its execution steps, while the detailed pseudocode with detailed description of steps is provided in Appendix A1.

---

**Algorithm 1: PT-based CS**

---

**Step 1: Initialisation**

- Read inputs: demand points, vehicle capacities, parcel data, cost parameters, initial compensation values, etc.

**Step 2: Solving CW Algorithm Without CS Delivery**

- Apply the basic CW algorithm to determine the optimal routing for direct vehicle delivery (without CS delivery).
- Store the total routing costs.

**Step 3: Estimating Routing Cost for Each Parcel**

- For each parcel in the routing plan, calculate the average routing cost.
- Store the routing cost for further analysis.

**Step 4: Forming a Loop to Optimise Compensation Values for CS Delivery**

- Assign initial (or updated) compensation values for parcels that could be allocated to the CS system
- Repeat Steps 5-8 until optimal compensation values are found.

**Step 5: Estimating Total Expected CS Costs**

- For each parcel, estimate the total expected costs if delivered through the CS system.

**Step 6: Solving Modified CW Algorithm**

- Apply the modified CW algorithm to allocate parcels to direct vehicle delivery or CS delivery based on cost estimates.

**Step 7: Allocating Parcels in CS System to PT Hub Stations and Updating Total Routing Costs**

- Identify the optimal PT station for dropping off CS-allocated parcels to be outsourced to PT passengers.
- Update the demand at PT stations, considering high-volume delivery points for vehicles.
- Re-solve the basic CS algorithm with updated demand and allocation data.
- Update total vehicle routing costs in the system

**Step 8: Calculate Total Expected Costs**

- Compute the total expected costs of the CS-integrated delivery system, including both direct vehicle delivery and CS delivery costs.

**End Repeat Loop**

**Step 9: identifying optimal compensation values**

- Assess the effectiveness of compensation values
  - Find the optimal compensation values leading to the lowest expected delivery costs in the CS-integrated system
- 

The algorithm operates as follows: in Step 1, the algorithm initialises with the values of all parameters defined in the model. Subsequently, Step 2 assumes the absence of CS delivery and calculates the total delivery costs by solving a VRP using the basic CW savings algorithm, supplemented by local search improvement heuristics. The integration of CS should enhance the solution by reducing costs for the carrier, otherwise, it would not be economically viable for the carrier to implement the CS system. In Step 3, the algorithm estimates the routing cost per delivery point. This estimation is crucial for assessing the additional costs the carrier would incur if a parcel initially allocated for CS delivery is rejected by PT passengers and must be retrieved from lockers and delivered the following day via direct vehicle delivery. Essentially, this step initialises the parameter  $\bar{c}_k$  used in calculating  $C_5$ , as referenced in Equation (5.9). In

Step 4, a loop is initiated to test different levels of parcel delivery compensation and identify the optimal one. During this step, different compensation values are iteratively assigned to delivery points, and Steps 5 through 8 are executed to estimate the total expected delivery costs within the CS-integrated delivery system. Accordingly, in Step 5, using the compensation values and other parameters,  $c_{ij}^k$  is calculated. The value  $c_{ij}^k$  represents the expected CS delivery cost for delivery point  $k$  using passengers traveling from PT station  $i$  to  $j$ . This is a disaggregated CS delivery cost for each delivery point.

In Step 6, the modified CW algorithm is executed. The detailed introduction of this algorithm and its corresponding pseudocode are provided in Appendix A1. Unlike the basic CW algorithm, the modified version may result in some delivery points being unmet. These are the points assigned to the CS system that will not be directly visited by delivery vehicles. A new condition is incorporated into the modified CW algorithm, enabling it to identify and exclude certain delivery points from vehicle delivery routes. These are the points where the delivery cost through the CS system is expected to be lower compared to the direct vehicle delivery system. In Step 7, the unassigned delivery points are optimally allocated to existing lockers within the CS system, which are situated at different PT stations. By doing so, the locker locations to which these delivery points are assigned are treated as virtual delivery points, with their parcel delivery volumes ( $\omega_k$ ) and service times ( $s_k$ ) being updated accordingly. Subsequently, the basic CW algorithm is solved again to estimate the total routing costs ( $C_1 + C_2$ ) for visiting both real and virtual delivery points (i.e., locker points). In Step 8, the total expected costs within the CS system ( $C_3 + C_4 + C_5$ ) are estimated and added to  $C_1 + C_2$  to determine the total expected costs in the CS-integrated delivery system. This total cost represents the value of the model's objective function under the compensation values set in Step 4. Finally, in Step 9, the algorithm evaluates the effectiveness of all compensation values set in Step 4 and identifies the optimal values as those resulting in the minimum total system cost.

To evaluate the speed and accuracy of the proposed solution algorithm, its performance is compared with some simple greedy solution algorithms, which successively optimise allocation and routing decisions until no more significant improvement in the model's solution is achieved. In Appendix A2, these algorithms are introduced and by testing them on hypothetical cases, their performance versus the proposed algorithm (Algorithm 1) are presented. Results show that the proposed algorithm outperforms others in terms of speed and accuracy.

## 5.5 Case Study

We consider parcel delivery to the Eastern suburbs of GS, Australia as the case study (Figure 5.4). To prepare the model for testing on this case, several parameters should be set. The parameters are categorised into four groups of parcel delivery network, PT system, CS behavioural models, and other parameters, which are explained in the following.

**Parcel delivery network:** The region has 5,206 Mesh Blocks, the smallest geographical area defined by the Australian Bureau of Statistics (2016). The region has 172,565 dwellings with a population of around 355 thousand persons. The monthly expected number of deliveries to each dwelling is 1.236 parcels in Australia, which was estimated recently in the study of Mohri et al. (2024c). Therefore, every day around 7,110 parcels are delivered to this region by all carriers. The majority of Australian carriers (90% of carriers) have a market share in range of 1% to 5% of the total number of parcel deliveries (Mohri et al., 2024c). Accordingly, a carrier with a market share in this range is targeted, resulting in a daily delivery number of 240 parcels. These parcels are distributed proportionally to the number of dwellings in the mesh blocks inside this region. The local warehouses of carriers are mostly located in the south of the region, in the proximity of the Sydney Airport and Port Botany. Hence, as shown in Figure 5.4, the carrier's depot is positioned in this region. Statistics show nearly 17% of parcels are heavy with more than 3 kgs weight (Mohri et al., 2024c). Accordingly, we randomly set the weight of 40 out of 240 parcels in the range of 3kgs to 30kgs. For the light parcels, the weights vary in the range of 0.2 kgs to 2.9 kgs. Overall, five scenarios for modelling the parcel delivery network are generated by changing the spatial distribution patterns of parcels and their weights. Figure 5.4 shows one scenario of the spatial distribution patterns.

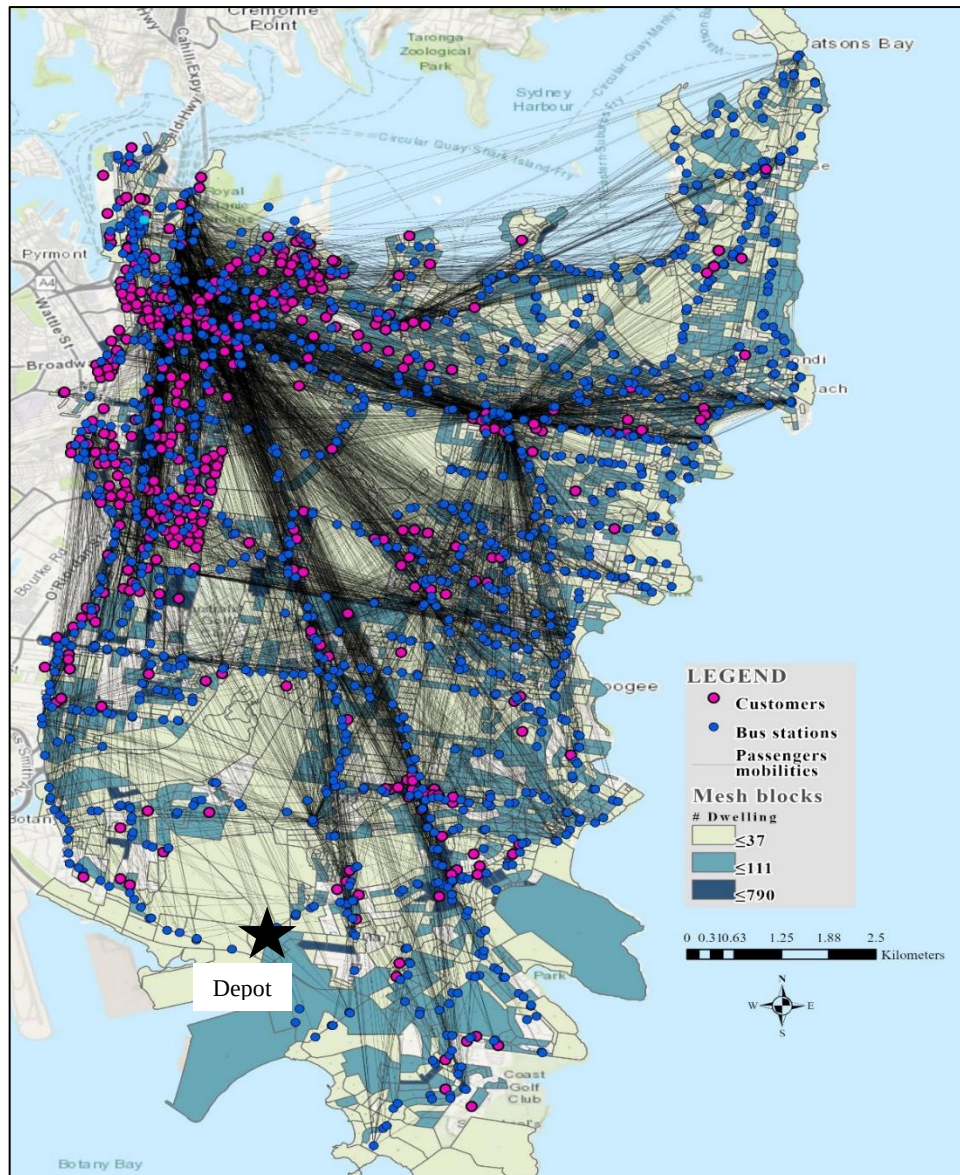


Figure 5.4 The GS case study

**PT system:** Train and bus are the dominant PT modes in Sydney, where on average 53% (420 million passenger trips) and 41% (324 million passenger trips) of annual PT ridership (before COVID-19) were made by train and bus, respectively (TfNSW, 2022). In the Eastern suburbs, 12 train stations and 1,291 bus stations are located. Given the geographical dispersion of the bus network, in this study we only focus on bus stations and associated ridership. The expected daily passenger movement between bus stations are extracted from Sydney public transport fare card data (called Opal data). The data covers all bus trips in the region from 1<sup>st</sup> February 2022 to 1<sup>st</sup> March 2022. Figure 5.4 shows the bus stations in the region and the trajectories of passenger movements between the stations. Also, Figure 5.13 in Appendix A3 illustrates the histogram of daily movements between the stations.

**CS behavioural models:** The intention of PT passengers to participate in a CS initiative, as well as the probability of accepting CS tasks, are the main behavioural equations integrated into the proposed mathematical model. The parameters of these equations are set up based on the earlier studies (Mohri et al. (2024a;(2024b). Accordingly, the participation ratio ( $P_{rate}$ ) is set at 0.60 (Mohri et al., 2024a). The MNL model designed in the study of Mohri et al. (2024b) is borrowed to set up Equation (5.27). Accordingly, the values of  $\alpha$ ,  $\beta_1$ ,  $\beta_2$ , and  $\beta_3$  are set at 2.2, -0.205, 0.178, and -1.95, respectively. Another parameter used in this equation is  $E(\overline{OA})$  or  $\gamma$ , which is the expected passengers waking distance from bus stations in the targeted region to their homes and vice versa. Daniel and Mully (2013) study the distribution of walking distances to PT stations in the GS area. They found that the distribution of walking distance to bus stations varies from zero to 2000 meters, following a triangular distribution with a mean equal to 454 meters for inner parts of the area (Figure 5.14). Accordingly,  $E(\overline{OA})$  is set at 454 meters.

**Other parameters:** In Table 5.1, other parameters, which are needed to solve the model are listed and their initial values, as well as references used for calibration, are presented.

Table 5.1 Setting up model's parameters.

| Symbol                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                            | Short definition                                                          | Value / Reference                                                                                                                                                                          |
|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| $\overline{OC}$                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                   | Hourly operating cost of delivery vehicles                                | AU\$ 80 (without including external costs)<br>AU\$ 110 (including external costs)/ <b>Refer to Comment 1</b>                                                                               |
| $\omega_{max}$                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                    | Maximum parcel weight for CS                                              | 3 kgs/ Mohri et al., (2024b)                                                                                                                                                               |
| $Q$                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                               | Capacity of delivery vehicles                                             | 500 kgs/ <b>Refer to Comment 2</b>                                                                                                                                                         |
| $b_{n+1}$                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                         | Maximum duration of routes                                                | 8 hours/ Mohri et al., (2024a)                                                                                                                                                             |
| $t_{kk'}$                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                         | Travel time from $k$ to $k'$ by delivery vehicles                         | The average travel speed is set at 35 km/h. using the speed and travel distance between customers, $t_{kk'}$ is calculated. The travel distance is calculated using the OpenStreetMap API. |
| $s_k$                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                             | Service time on delivery $k \in K_1$                                      | 5 minutes/ Mohri et al., (2024c)                                                                                                                                                           |
| $\mu$                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                             | The percentage of service time that is reduced because of locker delivery | 50%/ Mohri et al., (2024c)                                                                                                                                                                 |
| # Hubs                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                            | The number of hubs in the system                                          | Varies from 2 to 18 bus stations with the step size of 1                                                                                                                                   |
| $\delta$                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                          | The incentive for moving a 1 kg parcel over a 1 km detour distance        | Varies from AU\$ 3 to AU\$ 8 with the step size of AU\$ 0.50.<br><b>Refer to Comment 3</b>                                                                                                 |
| $F_{rate}$                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                        | Familiarity rate with CS                                                  | Varies from 0.05 to 0.75 with the step size of 0.05                                                                                                                                        |
| <b>Comments:</b> <ol style="list-style-type: none"> <li>1. The average hourly operating cost of delivery vehicles (vans) in Australia is around A\$80/hour (Mohri et al., 2024c). These trips are subject to additional external costs imposed to the transport systems, which is around 0.78 AU\$/km (Gössling et al., 2022; Lemp and Kockelman, 2008; Mohri et al., 2024c). Accordingly, considering an average speed of 35 km/h, every operating hour of the vehicles costs AU\$ 27.3. Therefore, the hourly operating cost of delivery vehicles including external costs is set at AU\$ 110.</li> <li>2. Medium-sized vans have a payload of around 750 kgs (Vansdirect, 2023), but due to space limitations and low-dense packages, usually, this payload is hard to achieve. Therefore, it is adjusted to 500 kgs in this study.</li> </ol> |                                                                           |                                                                                                                                                                                            |

3. The minimum hourly wage in Australia is approximately AU\$24 (Mohri et al., 2024a, and 2024b). Given that the average walking speed is 5 km/h, walking 1 kilometre would take around 12 minutes. To compensate passengers for this walking time, they should receive approximately AU\$4.80 per trip. Therefore, values of  $\delta$  are adopted around this figure.

## 5.6 Results and Discussion

In this section, we present the results of numerical experiments. As shown in Table 5.1, the parameters with varying ranges include; (1) the number of hubs (ranging from 2 to 18 with the step size of 1, resulting in a total of 17 scenarios), (2)  $F_{rate}$ : from 0.05 to 0.75 with the step size of 0.05, resulting to 15 scenarios, (3)  $\delta$ : from AU\$ 3 to AU\$ 8 with the step size of AU\$ 0.50, resulting to 11 scenarios and (4)  $\overline{OC}$ : AU\$ 80 or AU\$ 110. We also consider five scenarios based on the spatial distribution of delivery points over the studied region. Accordingly, the model is solved 22,440 times and the outputs (i.e., the average of outputs by running the model for the five spatial distribution scenarios) are used to perform sensitivity analysis. We first present the results related to cost savings, followed by optimal compensation value, allocation patterns, and the carrier's market share. Cost savings are computed through the comparison of total delivery costs between a delivery system with and without CS. Mathematically, it is represented as the difference between delivery costs in a system without CS and those with CS, divided by the delivery costs in a system without CS.

### 5.6.1 Cost saving by CS integration

Incentive is a decision variable in the proposed model. However, for simplicity, it is treated as a parameter and its value is set by a compensation value (please refer to Section 5.4). Hence, to find the optimal compensation value ( $\delta$ ), we iteratively solve the model for different  $\delta$  that results in the minimum total delivery system cost. In this section, the performance of the CS-integrated delivery system based on the optimal compensation values is compared with the conventional vehicle delivery system. The CS delivery systems tested are different with respect to the number of PT hub stations ( $\# Hubs$ ) and the CS initiative familiarity rate ( $F_{rate}$ ). Accordingly, Table 5.2 is presented, where the rows and columns demonstrate the scenarios for  $\# Hubs$  and  $F_{rate}$ . The cell values show the total cost savings (in percent) by integrating CS. Data in this table is set based on  $\overline{OC} = AU\$ 80$ , which accounts only for operational cost savings. Operational and external cost savings (i.e., where  $\overline{OC} = AU\$ 110$ ) for the scenarios are presented in Table 5.4 in Appendix A3.

Table 5.2 Operational cost savings after introducing CS with  $\overline{OC} = AU\$ 80$ .

| Familiarity<br>rate | # Hubs       |              |              |              |              |              |              |              |               |               |               |               |               |               |               |               |               |               |               |  |
|---------------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|---------------|---------------|---------------|---------------|---------------|---------------|---------------|---------------|---------------|---------------|---------------|--|
|                     | # Hubs<br>=2 | # Hubs<br>=3 | # Hubs<br>=4 | # Hubs<br>=5 | # Hubs<br>=6 | # Hubs<br>=7 | # Hubs<br>=8 | # Hubs<br>=9 | # Hubs<br>=10 | # Hubs<br>=11 | # Hubs<br>=12 | # Hubs<br>=13 | # Hubs<br>=14 | # Hubs<br>=15 | # Hubs<br>=16 | # Hubs<br>=17 | # Hubs<br>=18 | # Hubs<br>=19 | # Hubs<br>=20 |  |
| 0.05                | 3.1          | 3.2          | 3.2          | 3.4          | 3.4          | 3.4          | 4.3          | 4.7          | 4.7           | 10.3          | 11.9          | 13.6          | 13.6          | 13.6          | 13.6          | 14.6          | 14.6          | 15.5          | 15.5          |  |
| 0.1                 | 2.9          | 2.9          | 2.9          | 3.9          | 3.9          | 4.0          | 4.2          | 4.9          | 4.9           | 13.6          | 15.8          | 19.0          | 19.1          | 19.1          | 19.1          | 19.9          | 19.9          | 21.3          | 21.3          |  |
| 0.15                | 3.3          | 4.0          | 4.0          | 6.2          | 6.2          | 6.3          | 6.5          | 7.5          | 7.5           | 15.1          | 17.4          | 21.5          | 21.6          | 21.6          | 21.6          | 22.6          | 22.6          | 24.6          | 24.6          |  |
| 0.2                 | 3.8          | 4.4          | 4.4          | 7.1          | 7.1          | 7.2          | 7.6          | 8.7          | 8.7           | 16.0          | 18.5          | 23.1          | 24.6          | 24.6          | 24.6          | 25.9          | 25.9          | 28.1          | 28.1          |  |
| 0.25                | 4.6          | 4.7          | 4.7          | 9.2          | 9.2          | 9.3          | 8.6          | 9.9          | 9.9           | 16.9          | 19.6          | 25.0          | 26.1          | 26.1          | 26.1          | 27.2          | 27.2          | 29.6          | 29.6          |  |
| 0.3                 | 5.0          | 5.3          | 5.3          | 9.8          | 9.8          | 9.9          | 10.5         | 11.8         | 11.8          | 17.9          | 20.6          | 26.5          | 27.3          | 27.3          | 27.3          | 28.3          | 28.3          | 30.7          | 30.7          |  |
| 0.35                | 5.0          | 5.1          | 5.1          | 10.4         | 10.4         | 10.4         | 11.0         | 12.4         | 12.4          | 18.0          | 20.8          | 27.3          | 28.0          | 28.0          | 28.0          | 29.1          | 29.1          | 31.4          | 31.4          |  |
| 0.4                 | 5.0          | 5.4          | 5.4          | 11.1         | 11.1         | 11.2         | 11.9         | 13.3         | 13.3          | 18.3          | 21.2          | 28.1          | 28.7          | 28.7          | 28.7          | 29.7          | 29.7          | 32.1          | 32.1          |  |
| 0.45                | 5.1          | 5.8          | 5.8          | 11.6         | 11.6         | 11.7         | 12.3         | 13.8         | 13.8          | 18.7          | 21.6          | 28.7          | 29.3          | 29.3          | 29.3          | 30.3          | 30.3          | 32.9          | 32.9          |  |
| 0.5                 | 5.1          | 5.9          | 5.9          | 11.5         | 11.5         | 11.6         | 12.2         | 13.6         | 13.6          | 19.5          | 22.3          | 29.5          | 29.7          | 29.7          | 29.7          | 30.8          | 30.8          | 33.3          | 33.3          |  |
| 0.55                | 5.2          | 6.2          | 6.2          | 11.9         | 11.9         | 11.9         | 12.5         | 14.0         | 14.0          | 19.7          | 22.6          | 29.9          | 30.2          | 30.2          | 30.2          | 31.2          | 31.2          | 33.7          | 33.7          |  |
| 0.6                 | 6.1          | 6.4          | 6.4          | 12.1         | 12.1         | 12.2         | 12.7         | 14.2         | 14.2          | 19.9          | 22.9          | 30.6          | 30.8          | 30.8          | 30.8          | 31.8          | 31.8          | 34.1          | 34.1          |  |
| 0.65                | 6.3          | 7.0          | 7.0          | 12.3         | 12.4         | 12.5         | 12.6         | 14.3         | 14.3          | 20.2          | 23.1          | 31.0          | 31.1          | 31.1          | 31.1          | 32.1          | 32.1          | 34.4          | 34.4          |  |
| 0.7                 | 6.5          | 7.3          | 7.3          | 12.6         | 12.7         | 12.7         | 12.9         | 14.6         | 14.6          | 20.4          | 23.4          | 31.3          | 31.5          | 31.5          | 31.5          | 32.4          | 32.4          | 34.6          | 34.6          |  |
| 0.75                | 6.0          | 8.7          | 8.7          | 12.8         | 12.8         | 12.9         | 13.0         | 15.0         | 15.0          | 20.5          | 23.6          | 31.6          | 31.7          | 31.7          | 31.7          | 32.7          | 32.7          | 34.9          | 34.9          |  |



CS with a Small PL network



CS with a Medium PL network



CS with a Large PL network

As shown in Table 5.2, by increasing the number of PT stations equipped with PLs and improvement in familiarity rate, the carrier's cost saving increases. However, the trend is not linear. By fixing the familiarity rate and gradually increasing the number of hubs, three levels of cost savings are revealed, which are shown in Figure 5.5.

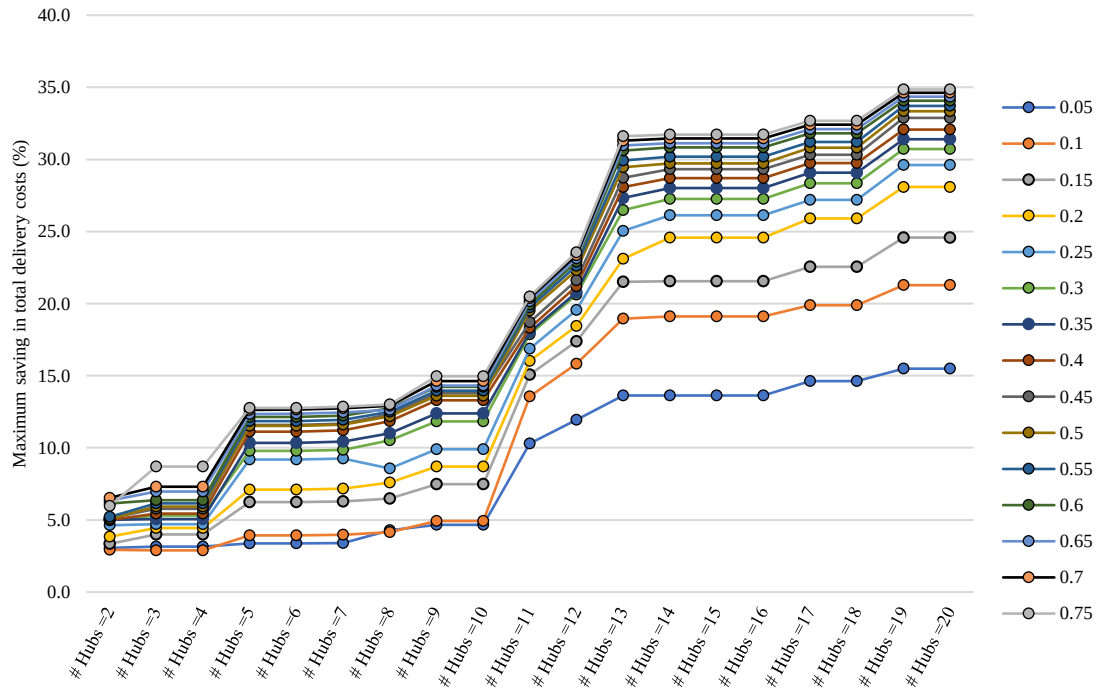


Figure 5.5 Maximum delivery cost savings after implementing the PT-based CS system.

The first level represents a CS system with two to four hubs. We call this configuration ‘CS with a small PL network’, demonstrating a cost saving between 3% to 9% for the carriers. The second level includes CS systems with five to ten hubs, which is called ‘CS with a medium PL network’. In this level, carrier can save up to 15%. In the third level, a CS system with more than twelve hubs is conceptualised, which is named ‘CS with a large PL network’. This setting could lead to a cost saving between 13% to 36%, depending on the rate of familiarity. This observation emphasises on the importance of optimal PL location selection in the PT stations. Specifically, it appears a decentralised locker network outperforms a centralised configuration. However, lowering the degree of centrality would not be always cost-effective. For example, for the studied case, deploying more than 13 hubs will not lead to exponentially higher cost saving. In the following, instead of considering 18 scenarios for the number of PT hub stations, only three scenarios are considered, which are attributed to CS systems with small, medium, and large PL networks. Increasing the familiarity rate with CS leads to greater saving for the carrier, however, the growth depends on the size of the PL network. In Figure 5.6, we also present the outputs corresponding to  $\overline{OC} = AU\$ 110$ . As shown, by increasing  $F_{rate}$  in small- and medium-sized PL networks, carrier’s cost saving grows linearly, while a logarithmical trend is observed for the large PL network. However, if the carrier decides to deploy a medium-sized PL network, it is recommended to improve the familiarity rate, for example through

advertisement or promotional initiatives in the community. Furthermore, adjusting  $\overline{OC}$  from AU\$ 80 to AU\$ 110 increases the expected cost saving by 2%, 3%, and 4% for small, medium, and large PL networks, respectively, with a CS familiarity rate larger than 0.50. As shown in Figure 5.7, vehicle routing costs ( $C_1 + C_2$ ), calculated by Equation (5.6), is also reduced between 35% to 70% after utilising the CS system. While the growth patterns for the savings in the vehicle routing costs are similar to those observed in total system cost saving, in the large-sized PL networks, the pattern is more logarithmic.

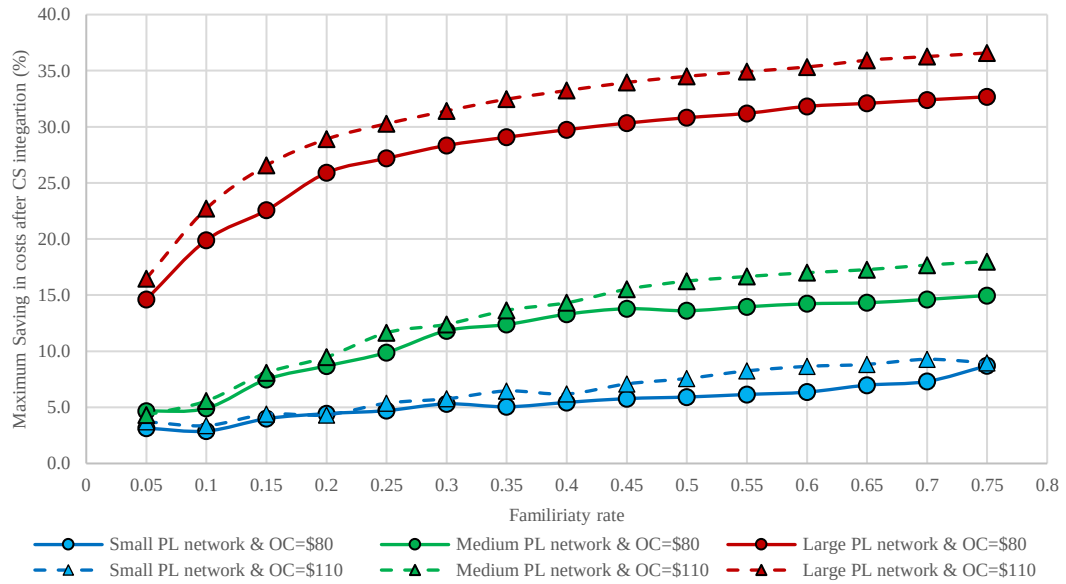


Figure 5.6 Maximum savings in the delivery costs after implementing the CS system with different PL network sizes

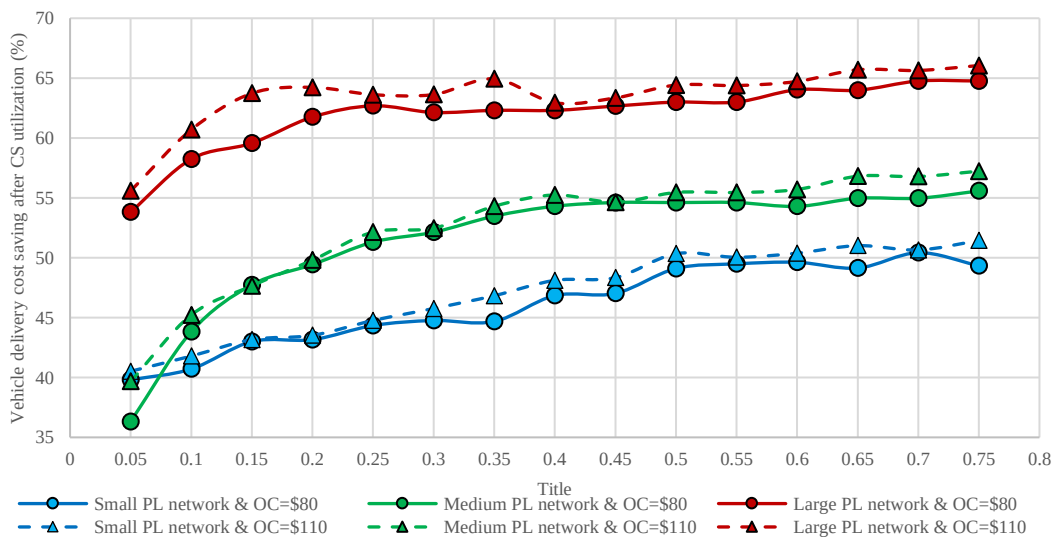


Figure 5.7 The cost-saving percentages in vehicle delivery costs after the integration of CS

## 5.6.2 Optimal compensation value

In this subsection, we reflect on the findings related to optimal incentivisation. Based on different familiarity rates and PL network sizes, we solve the model 11 times with varying compensation values ( $\delta$ ), ranging from AU\$3 to AU\$8 for carrying one kilogram parcel over one kilometre walking detour. The employed range of compensation values is based on the findings of previous behavioural models, including the participation rates and acceptance probability (Mohri et al., (2024a;2024b)). Specifically, we differentiate the total delivery cost between the conventional vehicle-only and CS-integrated systems based on different compensation values. The results are presented for small, medium, and large PL network sizes in Figures 5.8, 5.9, and 5.10.

| Familiarity rate | Incentive = \$3 | Incentive = \$3.5 | Incentive = \$4 | Incentive = \$4.5 | Incentive = \$5 | Incentive = \$5.5 | Incentive = \$6 | Incentive = \$6.5 | Incentive = \$7 | Incentive = \$7.5 | Incentive = \$8 |
|------------------|-----------------|-------------------|-----------------|-------------------|-----------------|-------------------|-----------------|-------------------|-----------------|-------------------|-----------------|
| 0.05             | 3.06            | 3.05              | 3.09            | 3.07              | 3.15            | 3.1               | 3.09            | 3.08              | 3.09            | 3.1               | 3.12            |
| 0.1              | 2.63            | 2.55              | 2.69            | 2.82              | 2.89            | 2.86              | 2.76            | 2.65              | 2.77            | 2.84              | 2.79            |
| 0.15             | 3.63            | 3.9               | 3.84            | 3.77              | 3.99            | 3.72              | 3.68            | 2.88              | 2.85            | 2.83              | 2.81            |
| 0.2              | 3.95            | 4.4               | 4.44            | 4.06              | 4               | 3.94              | 3.87            | 3.18              | 3.14            | 3.11              | 2.59            |
| 0.25             | 4.62            | 4.55              | 4.71            | 4.39              | 4.18            | 4.1               | 4.02            | 3.77              | 3.74            | 3.7               | 3.22            |
| 0.3              | 5.27            | 5.31              | 5.13            | 4.82              | 4.72            | 4.62              | 4.61            | 4.28              | 3.74            | 3.94              | 3.9             |
| 0.35             | 5.05            | 4.72              | 4.65            | 4.63              | 4.88            | 4.73              | 4.35            | 4.08              | 3.97            | 4.13              | 4.07            |
| 0.4              | 5.44            | 5.09              | 4.94            | 5.01              | 5.04            | 5                 | 4.89            | 4.41              | 4.35            | 4.3               | 4.24            |
| 0.45             | 5.78            | 5.66              | 5.45            | 5.37              | 5.33            | 5.27              | 5.14            | 4.64              | 4.58            | 4.52              | 4.45            |
| 0.5              | 5.92            | 5.82              | 5.74            | 5.58              | 5.41            | 5.24              | 5.2             | 4.84              | 4.78            | 4.71              | 4.64            |
| 0.55             | 6.15            | 5.94              | 5.49            | 5.41              | 5.43            | 5.24              | 5.21            | 5.04              | 4.96            | 4.88              | 4.82            |
| 0.6              | 6.36            | 6.25              | 5.77            | 5.62              | 5.67            | 5.46              | 5.29            | 5.11              | 5               | 5.06              | 4.98            |
| 0.65             | 6.98            | 6.52              | 6.04            | 5.87              | 5.93            | 5.7               | 5.5             | 5.46              | 5.19            | 5.31              | 5.13            |
| 0.7              | 7.31            | 7.01              | 6.46            | 6.48              | 6.44            | 5.95              | 5.7             | 5.66              | 5.35            | 5.5               | 5.54            |
| 0.75             | 8.71            | 8.01              | 7.26            | 6.87              | 6.47            | 6                 | 5.84            | 5.68              | 5.47            | 5.33              | 5.56            |

Figure 5.8 The effect of the incentive value on total delivery cost saving (in %) in small PL networks

Figure 5.8 indicates that for small PL networks, the carrier should offer higher incentives to crowdshippers, particularly with a familiarity rate lower than 50% ( $F_{rate} \leq 0.50$ ). Specifically, the incentive must be set at AU\$8 (maximum amount) and AU\$6 when  $F_{rate} \leq 0.10$  and  $0.10 \leq F_{rate} \leq 0.50$ , respectively. These incentive values will not only guarantee the required delivery workforce size (# active crowdshippers in the CS system) and improve  $F_{rate}$  over time, but also no significant reduction in carrier's net profit occurs. By following

this compensation strategy, only 3% to 5% of the carrier's total delivery costs will be declined in the initial phases of running the CS system. However, as time passes and the familiarity rate grows, the carrier experiences a cost saving of up to 9%. This requires the carrier to gradually decline the incentive value to their lowest amount (AU\$3) after reaching  $F_{rate} = 0.50$ . The same compensation program is advised when the carrier designs a medium or large PL network. For a medium-sized PL network, after reaching  $F_{rate} = 0.20$  and reducing the incentives, a cost saving between 9% to 15% is estimated. With a large PL network,  $F_{rate} = 0.15$  justifies the reduction in incentive with expected cost saving between 22% and 32%.

| Familiarity rate | Incentive = \$3 | Incentive = \$3.5 | Incentive = \$4 | Incentive = \$4.5 | Incentive = \$5 | Incentive = \$5.5 | Incentive = \$6 | Incentive = \$6.5 | Incentive = \$7 | Incentive = \$7.5 | Incentive = \$8 |
|------------------|-----------------|-------------------|-----------------|-------------------|-----------------|-------------------|-----------------|-------------------|-----------------|-------------------|-----------------|
| 0.05             | 4.28            | 4.27              | 4.25            | 4.24              | 4.02            | 3.87              | 3.84            | 3.82              | 4.56            | 4.66              | 4.65            |
| 0.1              | 4.5             | 4.55              | 4.92            | 4.81              | 4.69            | 3.26              | 3.17            | 3.61              | 3.49            | 4.66              | 3.75            |
| 0.15             | 7.49            | 7.28              | 7               | 6.28              | 6.2             | 7.14              | 6.98            | 4.98              | 4.68            | 4.52              | 4.42            |
| 0.2              | 8.67            | 8.69              | 8.45            | 8.19              | 7.92            | 7.64              | 7.93            | 6.32              | 5.84            | 5.63              | 5.31            |
| 0.25             | 9.69            | 9.51              | 9.26            | 8.86              | 8.49            | 8.09              | 8.33            | 6.67              | 6.32            | 5.99              | 5.46            |
| 0.3              | 11.8            | 11.1              | 9.78            | 10.1              | 9.73            | 9.16              | 9.04            | 7.34              | 6.95            | 6.58              | 6.26            |
| 0.35             | 12.4            | 11.9              | 10.5            | 10.7              | 10.2            | 9.72              | 9.3             | 7.84              | 7.42            | 7.05              | 6.71            |
| 0.4              | 13.3            | 12.5              | 11.1            | 11                | 10.7            | 10.2              | 9.75            | 9.15              | 8.7             | 7.85              | 7.5             |
| 0.45             | 13.8            | 13.2              | 11.5            | 11.4              | 10.8            | 10.3              | 10.1            | 9.48              | 9.04            | 8.64              | 7.8             |
| 0.5              | 13.6            | 13.4              | 11.9            | 11.8              | 11.2            | 10.6              | 10.1            | 9.76              | 9.31            | 8.9               | 8.06            |
| 0.55             | 14              | 13.7              | 12.2            | 12.1              | 11.5            | 10.9              | 10.4            | 9.92              | 9.53            | 9.11              | 8.71            |
| 0.6              | 14.2            | 14.1              | 12.5            | 12.3              | 11.9            | 11.4              | 10.6            | 10.1              | 9.64            | 9.28              | 8.88            |
| 0.65             | 14.3            | 13.4              | 12.8            | 12.7              | 12.2            | 11.6              | 10.8            | 10.3              | 9.84            | 9.39              | 9.05            |
| 0.7              | 14.6            | 13.6              | 13.1            | 12.9              | 12.3            | 11.8              | 11              | 10.5              | 10              | 9.55              | 9.19            |
| 0.75             | 15              | 14                | 13              | 12.8              | 12.1            | 12.4              | 11.6            | 10.6              | 10.1            | 9.66              | 9.32            |

Figure 5.9 The effect of the incentive value on total delivery cost saving (in %) in medium PL networks

| Familiarity rate | Incentive = \$3 | Incentive = \$3.5 | Incentive = \$4 | Incentive = \$4.5 | Incentive = \$5 | Incentive = \$5.5 | Incentive = \$6 | Incentive = \$6.5 | Incentive = \$7 | Incentive = \$7.5 | Incentive = \$8 |
|------------------|-----------------|-------------------|-----------------|-------------------|-----------------|-------------------|-----------------|-------------------|-----------------|-------------------|-----------------|
| 0.05             | 14.6            | 13.9              | 13.3            | 12.8              | 12.2            | 12.2              | 11.9            | 10.7              | 10.3            | 10                | 8.74            |
| 0.1              | 19.9            | 18.8              | 18.1            | 17.2              | 16.4            | 16.2              | 15.5            | 13.9              | 13.3            | 12.7              | 12.3            |
| 0.15             | 22.6            | 21.5              | 20.5            | 19.8              | 18.7            | 18.4              | 17.6            | 16.1              | 15.2            | 14.6              | 13.9            |
| 0.2              | 25.9            | 23.5              | 22.2            | 21.3              | 20.2            | 19.2              | 18.5            | 17.3              | 16.3            | 15.7              | 15              |
| 0.25             | 27.2            | 24.3              | 23.2            | 22.1              | 21.1            | 20.3              | 19.9            | 18.6              | 17.1            | 16.4              | 15.7            |
| 0.3              | 28.3            | 26.8              | 24.1            | 23.3              | 21.6            | 20.5              | 20.2            | 19                | 18              | 16.8              | 16.1            |
| 0.35             | 29.1            | 27.5              | 25.2            | 23.7              | 22.8            | 21.7              | 20.6            | 19.4              | 18.4            | 17.2              | 16.5            |
| 0.4              | 29.7            | 28.2              | 25.8            | 24.4              | 23.4            | 22.2              | 21.5            | 20                | 18.7            | 17.6              | 16.8            |
| 0.45             | 30.3            | 28.7              | 26.2            | 24.6              | 23.8            | 22.6              | 22.1            | 20.4              | 19.2            | 18.2              | 17.1            |
| 0.5              | 30.8            | 29.1              | 26.7            | 25                | 24              | 22.9              | 22.4            | 20.6              | 19.5            | 18.7              | 17.3            |
| 0.55             | 31.2            | 29.5              | 27.3            | 25.3              | 24.3            | 23.1              | 22.6            | 20.9              | 19.7            | 18.9              | 17.9            |
| 0.6              | 31.8            | 29.9              | 27.6            | 25.6              | 24.6            | 23.3              | 22.9            | 21.1              | 19.9            | 19.1              | 18.3            |
| 0.65             | 32.1            | 30.1              | 27.8            | 25.8              | 24.8            | 23.5              | 23.1            | 21.3              | 20.1            | 19.3              | 18.5            |
| 0.7              | 32.4            | 30.4              | 28              | 26                | 25              | 23.7              | 23.3            | 21.5              | 20.2            | 19.4              | 18.6            |
| 0.75             | 32.7            | 30.6              | 28.4            | 26.2              | 25.4            | 23.9              | 23.4            | 21.6              | 20.4            | 19.5              | 18.7            |

Figure 5.10 The effect of the incentive value on total delivery cost saving (in %) in large PL networks

### 5.6.3 Task allocation patterns

To optimally design PT-based CS systems, the trade-off between familiarity rate and crowdshipper supply must be assessed. Knowing this and other PT network variables such as ridership and seasonality, carriers are able to reconfigure their PLs, and eventually, maximise profit. Figure 5.11 shows the relationship between familiarity rate and the percentage of customers considered for CS delivery work, according to different PL network sizes.

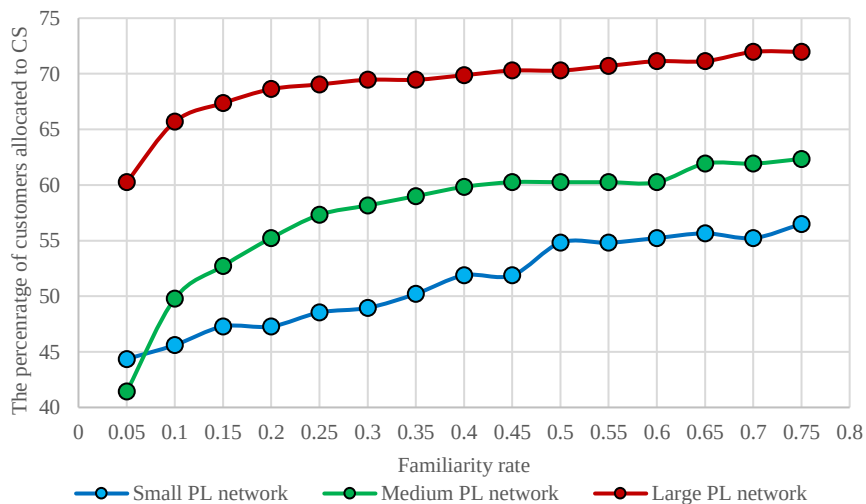


Figure 5.11 The percentage of customers allocated to the PT-based CS system.

As shown in Figure 5.11, even in the small PL network size, the system allocates 45% to 55% of the available work to PT passengers, depending on the rate of familiarity. In medium-sized PL networks, this allocation starts at around 40% and rises to 62% when the majority of passengers are familiar with the CS initiative. For large-scale PL networks, even at the lowest familiarity rate, it is optimal to outsource delivery work to more than 60% of customers. With large PL networks, up to 72% of available delivery work could be outsourced to CS. Notably, 17% out of the remaining 28% of tasks performed by the carrier involve heavy parcels, which cannot be delivered by the CS system. Therefore, it can be interpreted that almost 87% of light parcel delivery volume can be outsourced to CS in a large PL network. Similarly, by excluding heavy parcels, our results show that with any rate of familiarity and PL network size, at least 50% of light parcels can be outsourced to CS. In the previous subsection, it was observed that when the familiarity rate is small, the model suggests increasing the incentive and allocating parcels to the CS system. Such observation is also aligned with the results presented in Figure 5.11, suggesting higher incentives improve job acceptance with low number of PT passengers.

#### 5.6.4 Carrier's Market Share

The preceding analysis was conducted using a carrier with 240 daily deliveries, as depicted in Figure 5.4. In this subsection, we analyse the impact of carrier size as the function of daily delivery volume. Specifically, to evaluate the performance of PT-based CS in terms of cost saving, we consider a delivery volume in the range of 100 to 400. For this analysis, we consider a familiarity rate of 50% ( $F_{rate} = 0.50$ ), hourly operational cost of  $\overline{OC} = 80$  for vehicles, PL network size of large with 15 PT hub stations, and compensation value of AU\$3 for carrying one kilogram parcel over one-kilometre walking detour ( $\delta = 3$ ). Daily deliveries are increased from 100 to 400 with a step size of 20 and for different daily delivery volumes, 20 random scenarios are generated. Figure 5.12 illustrates the cost savings based on daily delivery volume.

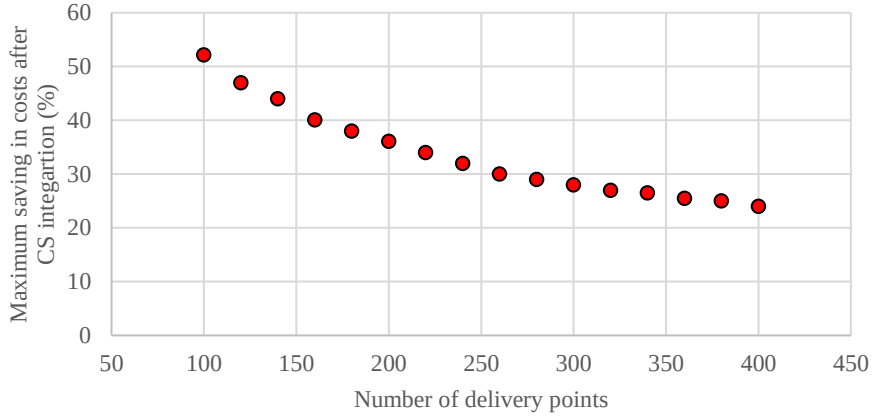


Figure 5.12 Maximum cost savings by implementing the CS system with different daily delivery volumes

As depicted in Figure 5.12, CS cost saving declines as delivery volume increases. The reduction in the potential cost savings can be associated with the expansion of the carrier's distribution network, as a result of required delivery for heavy parcels. As the carrier's market share grows, the number of delivery points with heavy parcels also increases. Since heavy parcels cannot be delivered through the PT-based CS system, the carrier must establish dedicated vehicle delivery routes to service these points. Consequently, these routes would cover a larger portion of the region compared to scenarios where the carrier has a lower market share. As a result, the marginal cost of adding delivery points with light parcels to these routes would decrease, which could explain the lower benefits of PT-based CS in such scenarios. However, it is important to note that although the percentage of cost savings decreases, the absolute magnitude of savings remains significant for large networks. Moreover, with a distribution network involving PLs, carriers would be able to provide more flexible services and expand their geographical coverage at marginal cost. Furthermore, PL-enabled networks allow two or more carrier(s) to collaborate in joint delivery services.

## 5.7 Conclusion

This study develops a PT-based CS system at an operational planning level. At this level, the carrier participating in the CS system aims to optimally assign parcels either to dedicated vehicles or lockers established in PT stations, after which, the delivery is outsourced to commuters. Consequently, the system's goal is to minimise the total cost, including both the incentives paid to PT passengers and the operational costs of dedicated delivery vehicles. To optimise the operational decisions, we propose a mathematical model, in which the probability of accepting CS tasks by PT passengers is characterised using an MNL approach that is sensitive to the weight of parcel, detour, and incentive. Accordingly, the incentive for each CS

task is determined using a set of compensation values. To simplify the problem, we relax the compensation value as a parametric equation in the model and its parameters' optimal values are found by iteratively solving the model. We then evaluate the model using a real-world case study from the GS area in Australia. A heuristic solution algorithm is also proposed to solve the model for medium to large case studies. We conclude our work by summarising the following key learnings:

- Numerical results indicate that increasing the number of PT hub stations could lead to lowered operational cost for carriers. However, the reduction is not always linear. For example, in the case study of the GS area, it was observed that changing the number of hubs from 2 to 4, 5 to 10, or 13 to 20 would not lead to substantial cost savings. Therefore, to implement a PL network, three different sizes of small, medium, and large are suggested, which resulted to cost savings of up to 9%, 15%, and 36%, respectively. In these networks, the delivery costs by carrier's dedicated vehicles were reduced by 50%, 56%, and 65%, respectively.
- Increasing the familiarity rate of CS initiatives was noticed to have major cost-saving potential. In small or medium PL network, increasing the rate would linearly increase the saving, while in a large PL network, a logarithmic growth was observed. Furthermore, by incorporating externalities in the cost of delivery vehicle operations and higher hourly operating cost, greater savings could be achieved.
- Our findings suggest that it is more effective for carriers to offer higher incentive values to PT passengers during the initial stages of introducing CS. As the familiarity rate increases, the carrier can gradually decrease the incentive to reduce operational costs. In small PL networks, carriers can drop incentives once familiarity rate reaches 0.5, while this rate for medium and large PL network are 0.25 and 0.15, respectively.

The present study comes with limitations, which provide directions for future research. First, we suggest future work to incorporate locational decisions for placing PLs within PT network into the model. Since our work focused on operational level, this decision was excluded. However, PL locational decision is essential during the planning phase. Second, to address uncertainty surrounding CS task acceptance, alternative techniques could focus on exploring different uncertainty management approaches. For example, the applications of chance constraint techniques could complement the expected cost minimisation approach.

Using this approach, expected costs would be computed for cases that satisfy the probabilistic constraint, while only direct van delivery would be considered for those that do not. Third, advanced solution algorithms could facilitate testing the model in expanded spatial scales and for carriers with larger market share. Fourth, simulation techniques such as agent-based approaches could be employed to incorporate more realistic assumptions such as traffic level, varying socio-economic factors, and weather conditions. Lastly, our work focused on bus stations. Future research could consider other modes of PT such as rail, tram, and their hybrid configurations with a focus on decisions related to optimisation of network, task assignment, and pricing.

## Appendix A1

This section introduces the solution algorithm presented in Section 5.4 in detail. It provides the algorithm's pseudo-code in a technical format and thoroughly explains each step.

**Step 1 (setting initial parameters):** by taking this step, the following model parameters are set up:

- List of PT hub stations and their coordinates ( $\forall i \in N_1$ ),
- All PT stations and their coordinates ( $\forall i \in N$ ),
- Coordinates, weights, and service time of final parcel delivery points ( $\omega_k, s_k \forall k \in K_1$ ),
- Carrier's depot location ( $(0, \pi)$ ),
- Capacity of carrier's vehicles ( $Q$ ),
- Maximum weight of a parcel which can be carried by crowdshippers ( $\omega_{max}$ ),
- Coefficients of the acceptance utility function ( $\alpha, \beta_1=weigh, \beta_2=incentive, and \beta_3=detour$ ),
- The expected distance between PT passenger destinations and neighbouring PT stations ( $\gamma$ ),
- Maximum duration that vehicles can travel ( $b_{n+1}$ ),
- Familiarity and participation rates with the CS program ( $F_{rate}, P_{rate}$ ),
- The daily expected number of PT trips between every pair of PT stations ( $h_{ij}$ ),
- Travel time between all delivery points and depot ( $t_{kk'} \forall k, k' \in K \cup \{0\}$ ),
- Travel distance from PT stations to final parcel delivery points ( $d_j^k \forall j \in N, k \in K_1$ ).

Although the location of PT hub stations is an input for the operational model, they are the nodes with the maximum Node Redundancy Coefficients (NRCs). NRC for PT station  $i$  is equal to the division of outflows from  $i$  per total outflows from all PT stations. Depending on the defined number of PT hub stations, the stations having the largest NRCs are chosen as the hubs.

---

**Algorithm 1: PT-based CS**

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- 1 **Step 1: Input** initial demand information and model parameters
  - 2 **Output** best solution (routing, allocating, and incentivising decisions) and the minimum objective function ( $Min C_1 + C_2 + C_3 + C_4 + C_5$ )
  - 3 **Step 2: Assign** all demand points to delivery services by the carrier's vehicles
  - 4 **Run** the basic CW algorithm
  - 5 **Apply** local search heuristics to the CW algorithm's solution and extract total routing costs ( $C_1 + C_2$ )
  - 6 **Step 3: Distribute** the total routing costs between demand points and calculate  $\bar{c}_k$
  - 7 **Step 4: Define** a set of compensation values for  $\delta$
  - 8 **For every**  $\delta$  **do**
  - 9 **Step 5:** **Calculate incentive**  $I^k$  ( $I^k = \delta \omega^k \left( d_{ij}^k + \sqrt{\gamma^2 + (d_{ij}^k)^2} - \gamma \right) \quad \forall k \in K$ )
  - 10 **Calculate utilities and probabilities**,  $g_{ij}^k$ ,  $f_{ij}^k$  and  $P_{ij}^k$  with Equations (5.27-5.29)
  - 11 **Calculate cost**  $c_{ij}^k$  ( $c_{ij}^k = P_{ij}^k I^k + (1 - P_{ij}^k)(\mu s_k \bar{OC} + \bar{c}_k)$ )
  - 12 **Step 6:** **Run Algorithm 2** (modified CW algorithm) and find demand points allocated to CS
  - 13 **Update**  $\omega_k$  and  $s_k$  for PT hub stations based on volume and number of demand points assigned to the stations for CS
  - 14 **Step 7:** **Run** the basic CW algorithm
  - 15 **Apply** local search heuristics to the CW algorithm's solution and extract total routing costs ( $C_1 + C_2$ )
  - 16 **Step 8:** **Enumerate the** objective function value ( $C_1 + C_2 + C_3 + C_4 + C_5$ )
  - 17 **End**
  - 18 **Step 9: Find** the optimal compensation value ( $\delta$ ) resulted in the minimum  $C_1 + C_2 + C_3 + C_4 + C_5$
- 

**Step 2 (vehicle-only delivery cost):** All delivery points are considered for the carrier's vehicles and the basic version of the CW algorithm is run. After finding the solution, local search improvement heuristics are applied sequentially to enhance the solution quality. These heuristics are performed sequentially as follows: Move, Swap, 2-opt, and 2-opt\*. Since these heuristics are very well recognized, for more information, readers are referred to the literature (Hemmelmayr et al., 2012).

**Step 3 (estimating  $\bar{c}_k$ ):**  $\bar{c}_k$  is the additional delivery cost incurred to visit (failed) parcel delivery point  $k$  in next day. These parcel deliveries are those that were unsuccessfully fulfilled in the CS system. Accordingly,  $\bar{c}_k$  is set heterogeneously (e.g., a penalty cost) for every  $k$ . To set  $\bar{c}_k$  for every  $k$ , we estimate the carrier's total daily delivery cost, which is calculated in Step 2. Hence, the total cost can be distributed between delivery points ( $\forall k \in K$ ) proportional to their distances from the carrier's depot since deliveries located far from the depot impose higher delivery costs.

**Step 4 (compensation values):** To find the best compensation value, a set of pre-identified values for  $\delta$  are considered. Accordingly, for each value, the following steps are taken, and the best objective results are considered. This set is defined based on a combination of empirical data, expert judgment, and preliminary analysis (Mohri et al., 2024a and 2024b). We aim to cover a limited range of reasonable values. This ensures that the iterative process explores a comprehensive set of possibilities without overwhelming computational effort. Further details on how the values are determined can be found in Table 5.1.

**Step 5 (CS parameters and costs):** By substituting the initial values of the parameters into the behavioural equations related to parcel CS acceptance probability, the CS-related equations are adjusted. Accordingly, Equation (5.30) calculates  $I^k \forall k \in K_1$  and then Equations (5.27) to (5.29) compute  $g_{ij}^k$ ,  $f_{ij}^k$  and  $P_{ij}^k$ . For every possible combination of  $(i, j, k)$ ,  $i \in N_1$ ,  $j \in N$ ,  $k \in K_1$  and using  $g_{ij}^k$ ,  $f_{ij}^k$  and  $P_{ij}^k$ , the CS cost per each task, which is indicated by  $c_{ij}^k$ , is estimated. According to (7-9),  $c_{ij}^k$  is equal to  $P_{ij}^k I^k + (1 - P_{ij}^k)(\mu s_k \overline{OC} + \bar{c}_k)$ , where  $\mu s_k \overline{OC}$  is the additional service cost imposed on the carrier for managing failed parcels in the CS system.

| Algorithm 2: The modified Clarke and Wright (CW) algorithm |                                                                                                                                         |
|------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------|
| 1                                                          | <b>Input</b> $\omega_k, s_k \forall k \in K_1, Q, \omega_{max}, c_{ij}^k, t_{kk'}$                                                      |
| 2                                                          | <b>Output</b> $C_1 + C_2$                                                                                                               |
| 3                                                          | <b>Calculate</b> pair saving for $\forall k \in K_1$ and make a saving list                                                             |
| 4                                                          | <b>Sort</b> the savings list in descending order and construct the initial routes                                                       |
| 5                                                          | $r = 1$ ( $r$ is the index in the savings list, where $r = 1$ is the top element with the maximum saving)                               |
| 6                                                          | $V = 0$ ( $V$ shows the total volume of parcel deliveries assigned to the under-construction route)                                     |
| 7                                                          | $T = 0$ ( $T$ shows the total duration of the under-construction route)                                                                 |
| 8                                                          | <b>While</b> the saving list is not empty <b>do</b> :                                                                                   |
| 9                                                          | <b>If</b> $r =$ index of last element in saving list <b>then</b>                                                                        |
| 10                                                         | Break (while loop)                                                                                                                      |
| 11                                                         | <b>Else</b>                                                                                                                             |
| 12                                                         | Merge routes based on saving in row $r = 1$ in the saving list                                                                          |
| 13                                                         | Remove the element with index $r = 1$ in the saving list                                                                                |
| 14                                                         | Update $V$ and $T$ based on $\omega_k$ and $s_k$ of parcel $k$ added to the route                                                       |
| 15                                                         | Update route travel cost                                                                                                                |
| 16                                                         | <b>End</b>                                                                                                                              |
| 17                                                         | <b>While</b> $V \leq Q$ and $T \leq b_{n+1}$ and $r \neq$ index of last element in saving list <b>do</b>                                |
| 18                                                         | <b>If</b> the route merging conditions in the basic CW algorithms are passed, <b>then</b>                                               |
| 19                                                         | <b>If</b> with this merge, the additional cost is less than the $\min_{i,j} c_{ij}^k$ and if $\omega_k \leq \omega_{max}$ <b>then</b> : |
| 20                                                         | Merge routes and update $V$ and $T$                                                                                                     |
| 21                                                         | $r = 1$                                                                                                                                 |
| 22                                                         | <b>Else</b>                                                                                                                             |
| 23                                                         | $r = r + 1$ (go to the next element in the saving list)                                                                                 |
| 24                                                         | <b>End</b>                                                                                                                              |
| 25                                                         | <b>Elseif</b> both starting and ending points of $r$ have been visited in the extended routes <b>then</b> :                             |
| 26                                                         | Remove the element with index $r$ in the saving list                                                                                    |
| 27                                                         | $r = r + 1$ (go to the next element in the saving list)                                                                                 |
| 28                                                         | <b>Else</b>                                                                                                                             |
| 29                                                         | $r = r + 1$ (go to the next element in the saving list)                                                                                 |

|    |                                                                                                       |                                                          |
|----|-------------------------------------------------------------------------------------------------------|----------------------------------------------------------|
| 30 |                                                                                                       | End                                                      |
| 31 |                                                                                                       | End                                                      |
| 32 |                                                                                                       | Add the constructed route to a list of completed routes. |
| 33 |                                                                                                       | $V = 0$ and $T = 0$                                      |
| 33 | End                                                                                                   |                                                          |
| 34 | Return $C_1 + C_2 =$ total costs of constructed routes, vehicles routes, and customers assigned to CS |                                                          |

**Step 6 (route construction & CS allocation):** In this step, a modified version of the CW algorithm is proposed to select certain delivery points for direct vehicle delivery and optimise the routes for visiting them. Unlike the basic CW algorithm, the modified version may conclude with some delivery points still unmet. These unmet points are passed to delivery by the CS system.

Similar to the CW saving algorithm, in this method the saving list is formed for every pair of delivery points and ordered in a non-increasing fashion. Then, routes are merged and extended by testing savings options in the list from top to down. Our proposed algorithm adds a new condition for merging and extending routes, that is the extension is accepted (i.e., adding a new  $k$  to the under-construction route), only if the  $(\min_{i,j} c_{ij}^k)$  is greater than the additional cost imposed to the route after adding  $k$ , or if  $k$  is a delivery point with a heavy parcel. With this condition, the algorithm determines the series of points to be transferred to the CS system. This is because these delivery points will incur lower costs for the system if they are delivered through CS rather than by direct vehicle delivery.

It is worth noting that the proposed algorithm does not remove savings that do not pass the new condition. The savings are kept because with the development of the route, they would be used to extend the route with costs less than their corresponding CS costs. The algorithm stops when no feasible route extension exists and the delivery points which are not accommodated into the routes are assigned to CS delivery.

**Step 7 (route re-construction):** For every unassigned delivery point ( $k$ ) in Step 4, the PT hub station ( $i$ ) with  $\min_{i,j} c_{ij}^k$  is identified. Then  $\omega_k$  and  $s_k$  of the final delivery point ( $k$ ) are added to the  $\omega_k$  and  $s_k$  of the virtual delivery point ( $k'$ ), where  $O(k') = i$ . Next, we apply the basic CW algorithm, and find delivery routes.

**Step 8 (Calculating total costs of running the system):** Given the identified routes from Step 7,  $C_1 + C_2$  is calculated, which is pertinent to the operation of vans in the system. Also,  $\sum_{k \in K_1} \min_{i,j} x_{ij}^k c_{ij}^k$  calculates expected costs in the CS systems ( $C_3 + C_4 + C_5$ ). The summation of  $C_1 + C_2$  and  $C_3 + C_4 + C_5$  will result in the total cost of running the delivery system with both vehicle delivery and CS under compensation value  $\delta$ .

After testing all compensation values, the value resulted in the minimum  $C_1 + C_2 + C_3 + C_4 + C_5$  is then introduced as the best option for incentivising CS tasks.

## Appendix A2

**Greedy Algorithms:** Four simple greedy algorithms are proposed for solving the model. These algorithms are used as a baseline for assessing the quality of solutions generated by the proposed solution algorithm in Section 5.4. These algorithms are an integration of a greedy algorithm for allocation decisions and the CW algorithm for routing decisions. All have four steps, where their differences are in Step 2, as follows:

**Step 1:** All customers are assigned to vehicle delivery and CW algorithm plus local search algorithms are applied to find the total cost of the delivery system.

**Step 2:** In this step, first, a subset of customers is moved to the CS delivery system, and their parcels are placed on PT hubs, leading to the lowest expected CS cost. In the following, the process of subset selection is explained. The size of the subset is selected randomly in the range of 1% to 15% of total customers. Then, the costs of CS and vehicle delivery are calculated again. If the total delivery system cost is reduced, then the solution is accepted and the list of customers assigned to vehicle delivery is updated, otherwise, the process is repeated by choosing another subset of customers with a different size.

The subset is selected based on four different approaches, which differentiate the greedy algorithms (4 approaches) from one another. Before taking the approaches, first a list of customers with light parcels (i.e., less than 3 kgs) eligible to be serviced by CS formed. Then, according to each approach, customers are ranked in a list. The subset is selected from the customers at the top of the list.

*Approach 1:* The expected CS cost for every customer in the list is calculated and then customers are sorted based on the cost from low to high.

*Approach 2:* The lowest travel distance from each customer in the list to the customers having heavy parcels (more than 3 kgs weights) are identified and then customers are sorted based on the distance from high to low.

*Approach 3:* The density of customers with heavy parcels around other customers in the list is calculated (i.e., in an area with a 500-meter radius) and then the customers in the list are sorted based on the density from low to high.

**Approach 4:** The density of all parcels around each customer in the list is calculated (i.e., in an area with a 500-meter radius) and then the customers are sorted based on the density from low to high.

**Step 3:** If after 20 times repeating Step 2, no improvement is achieved, the algorithm is stopped and running time and the best identified objective function are reported.

**Hypothetical Cases:** The hypothetical cases are extensions of the real case introduced in Section 5.5. The values of all parameters are set similarly to those of the real case. The only difference is the number of customers in the system. Accordingly, cases with 50, 100, 150, 200, and 250 customers are generated. The locations of customers are set randomly inside the region, with 17% of them are marked as heavy parcels. Then, the weight of customers' parcels is set similarly to the approach taken for the real case. The Manhattan distance function is also applied to calculate travel distance between customers. In Table 5.1, defined parameters in different are also adjusted for each case and solved by the four simple greedy algorithms and proposed PT-based solution algorithm.

**Compute System:** MATLAB software is used to code the heuristics by a computer system with the following specifications: Intel(R) Core(TM) i7 CPU @2.3 GHz and 16 GB of RAM with Windows 7 (64 bit).

**Comparative Results:** Results show that the proposed algorithm performs considerably better than the simple greedy algorithms, particularly in terms of computational time (Table 5.4). Also, the greedy algorithm is not able to find a good solution over the time. Furthermore, a gap is observed in the range of 3% to 15% from the best solution found by the proposed algorithm.

Table 5.3 Computational results by solving the model with different heuristics

| # Customers | # Cases | The proposed PT-based CS algorithm | Greedy algorithm with Approach 1 |      | Greedy algorithm with Approach 2 |       | Greedy algorithm with Approach 3 |      | Greedy algorithm with Approach 4 |      |
|-------------|---------|------------------------------------|----------------------------------|------|----------------------------------|-------|----------------------------------|------|----------------------------------|------|
|             |         | Time (seconds)                     | Avg of gap                       | Time | Avg of gap                       | Time  | Avg of gap                       | Time | Avg of gap                       | Time |
| 50          | 10      | 1.23                               | 3.4%                             | 7.83 | 4.6%                             | 9.10  | 9.7%                             | 22.6 | 8.3%                             | 31.6 |
| 100         | 10      | 1.47                               | 4.8%                             | 23.6 | 6.1%                             | 43.8  | 14.3%                            | 134  | 13.5%                            | 97.3 |
| 150         | 10      | 2.65                               | 7.8%                             | 76.1 | 5.8%                             | 198.7 | 15.2%                            | 345  | 16.1%                            | 265  |
| 200         | 10      | 2.51                               | 7.4%                             | 112  | 8.8%                             | 363.5 | 12.0%                            | 852  | 14.7%                            | 780  |
| 250         | 10      | 2.79                               | 7.1%                             | 167  | 11.7%                            | 446.5 | 17.1%                            | 976  | 15.4%                            | 1100 |

Avg of gap: the percentage of gap between the best solutions found by the proposed algorithm and the greedy algorithm.

## Appendix A3

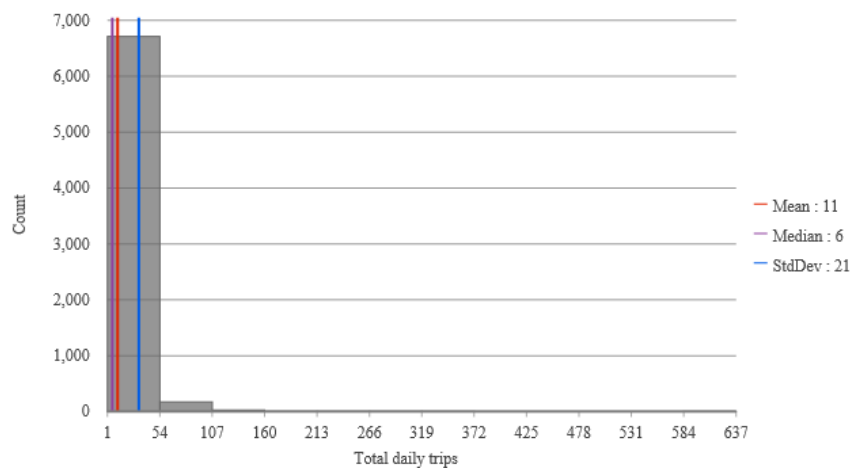


Figure 5.13 The histogram of volume of movements between all pairs of bus stations in the studied region

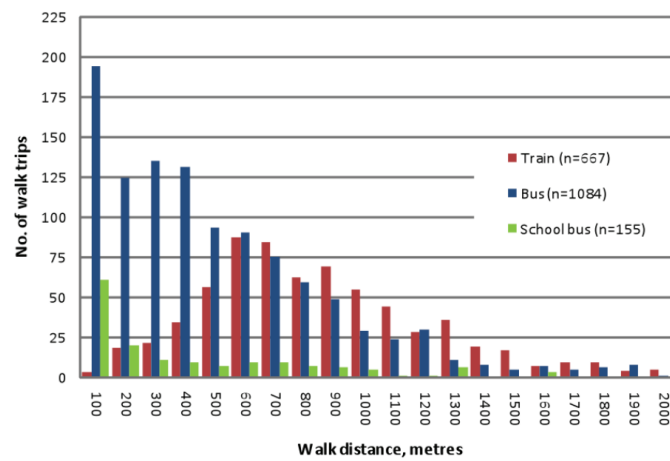


Figure 5.14 The distribution of walking distance to PT stations in the GS area (Daniel and Mully, 2013)

Table 5.4 Operational cost savings after introducing CS into parcel delivery systems with  $\overline{OC} = AU\$ 110$

| Familiarity<br>rate | # Hubs       |              |              |              |              |              |              |              |               |               |               |               |               |               |               |               |               |               |               |  |
|---------------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|---------------|---------------|---------------|---------------|---------------|---------------|---------------|---------------|---------------|---------------|---------------|--|
|                     | # Hubs<br>=2 | # Hubs<br>=3 | # Hubs<br>=4 | # Hubs<br>=5 | # Hubs<br>=6 | # Hubs<br>=7 | # Hubs<br>=8 | # Hubs<br>=9 | # Hubs<br>=10 | # Hubs<br>=11 | # Hubs<br>=12 | # Hubs<br>=13 | # Hubs<br>=14 | # Hubs<br>=15 | # Hubs<br>=16 | # Hubs<br>=17 | # Hubs<br>=18 | # Hubs<br>=19 | # Hubs<br>=20 |  |
| 0.05                | 4.0          | 3.7          | 3.7          | 4.1          | 4.1          | 4.2          | 3.8          | 4.3          | 4.3           | 11.8          | 13.5          | 15.4          | 15.4          | 15.4          | 15.4          | 16.5          | 16.5          | 17.5          | 17.5          |  |
| 0.1                 | 2.9          | 3.4          | 3.4          | 4.2          | 4.5          | 4.6          | 4.8          | 5.6          | 5.6           | 15.7          | 17.7          | 21.1          | 21.7          | 21.7          | 21.7          | 22.7          | 22.7          | 24.4          | 24.4          |  |
| 0.15                | 3.8          | 4.4          | 4.4          | 6.7          | 6.7          | 6.7          | 7.0          | 8.1          | 8.1           | 17.1          | 19.6          | 24.1          | 25.1          | 25.1          | 25.1          | 26.6          | 26.6          | 28.7          | 28.7          |  |
| 0.2                 | 3.7          | 4.3          | 4.3          | 7.6          | 7.6          | 7.6          | 8.2          | 9.5          | 9.5           | 19.0          | 21.5          | 26.9          | 27.4          | 27.4          | 27.4          | 28.9          | 28.9          | 31.1          | 31.1          |  |
| 0.25                | 4.9          | 5.4          | 5.4          | 9.6          | 9.6          | 9.7          | 10.3         | 11.7         | 11.7          | 19.8          | 22.3          | 28.4          | 29.1          | 29.1          | 29.1          | 30.3          | 30.3          | 32.8          | 32.8          |  |
| 0.3                 | 5.1          | 5.8          | 5.8          | 10.4         | 10.4         | 10.5         | 11.0         | 12.4         | 12.4          | 20.4          | 23.0          | 29.6          | 30.3          | 30.3          | 30.3          | 31.4          | 31.4          | 34.0          | 34.0          |  |
| 0.35                | 5.2          | 6.5          | 6.5          | 11.5         | 11.5         | 11.6         | 12.1         | 13.7         | 13.7          | 20.5          | 23.5          | 30.8          | 31.2          | 31.2          | 31.2          | 32.5          | 32.5          | 35.1          | 35.1          |  |
| 0.4                 | 5.4          | 6.2          | 6.2          | 12.4         | 12.4         | 12.5         | 12.8         | 14.3         | 14.3          | 21.0          | 23.9          | 31.6          | 32.0          | 32.0          | 32.0          | 33.2          | 33.2          | 35.8          | 35.8          |  |
| 0.45                | 6.1          | 7.1          | 7.1          | 13.5         | 13.5         | 13.6         | 13.9         | 15.5         | 15.5          | 21.8          | 24.5          | 32.3          | 32.6          | 32.6          | 32.6          | 34.0          | 34.0          | 36.3          | 36.3          |  |
| 0.5                 | 6.9          | 7.6          | 7.6          | 14.2         | 14.2         | 14.3         | 14.5         | 16.3         | 16.3          | 22.1          | 24.7          | 32.9          | 33.2          | 33.2          | 33.2          | 34.5          | 34.5          | 37.1          | 37.1          |  |
| 0.55                | 7.2          | 8.3          | 8.3          | 14.6         | 14.6         | 14.7         | 14.9         | 16.7         | 16.7          | 22.4          | 25.1          | 33.4          | 33.7          | 33.7          | 33.7          | 34.9          | 34.9          | 37.5          | 37.5          |  |
| 0.6                 | 6.8          | 8.7          | 8.7          | 14.9         | 14.9         | 15.0         | 15.2         | 17.0         | 17.0          | 22.7          | 25.3          | 33.9          | 34.1          | 34.1          | 34.1          | 35.3          | 35.3          | 37.9          | 37.9          |  |
| 0.65                | 7.0          | 8.8          | 8.8          | 15.1         | 15.1         | 15.2         | 15.4         | 17.3         | 17.3          | 22.9          | 25.6          | 34.3          | 34.5          | 34.5          | 34.5          | 35.9          | 35.9          | 38.2          | 38.2          |  |
| 0.7                 | 7.3          | 9.3          | 9.3          | 15.5         | 15.5         | 15.6         | 15.8         | 17.7         | 17.7          | 23.1          | 25.8          | 34.7          | 34.8          | 34.8          | 34.8          | 36.3          | 36.3          | 38.5          | 38.5          |  |
| 0.75                | 7.4          | 9.0          | 9.0          | 15.8         | 15.8         | 15.9         | 16.1         | 18.0         | 18.0          | 23.5          | 26.2          | 35.1          | 35.2          | 35.2          | 35.2          | 36.6          | 36.6          | 38.7          | 38.7          |  |

## **CHAPTER 6**

# **CONCLUSIONS AND FUTURE DIRECTIONS**

## **6 Conclusions and Future Directions**

### **6.1 Introduction**

This doctoral research endeavours to overcome challenges hindering the implementation of an effective CS system by PT passengers. Through rigorous analyses, valuable insights have been extracted. This section encapsulates a comprehensive summary of the entire research, organized into the following subsections. Subsection 6.2 elucidates the objectives and their corresponding resolutions. Subsection 6.3 highlights the significant contributions made. The limitations encountered during the research process are summarized in Subsection 6.3, and the section concludes with Subsection 6.4, offering suggestions for future research endeavours.

### **6.2 How Objectives Were Addressed**

The overarching aim of this research was to explore and develop CS initiatives within PT systems, focusing on three distinct objectives. The first objective involved creating a crowdshipper model to understand and model the intention of PT passengers to participate in PT-based CS initiatives as well as the probability of accepting CS tasks by participated passengers. Modelling the intention to participate was achieved by designing a survey, collecting responses, and developing a binary logit model to identify key factors influencing participation. Moreover, a LC choice model was developed to understand the CS task acceptance probability by passengers with heterogenous characteristics. The second objective aimed at providing a comprehensive evaluation system for measuring the performance of a designed CS system. The system's inputs, operational and tactical decisions, and outputs were considered to evaluate its economic, environmental, and social performance. Lastly, the third objective focused on delivering a decision support system for making strategic decisions regarding PL locations and capacities. The decision support system was integrated into the evaluation system to facilitate optimal deployment planning.

### **6.3 Contributions**

The main contributions of the research are as follows:

- The proposed PT-based CS system introduced a novel locker-to-home delivery structure, addressing potential ecological concerns associated with occasional drivers in traditional CS systems.
- The study on PT passengers' intention to participate in CS initiatives revealed significant insights. The behavioural model identified various demographic and socio-economic factors influencing participation likelihood. Prohibiting factors were categorized, and the study provided recommendations for CS managers to balance demand and supply, tailor advertising strategies, and consider personalized marketing approaches.
- The LC choice model identified three distinct classes of PT passengers with different preferences for accepting CS tasks. Policy implications were derived, emphasizing bundle delivery and partial delivery policies to optimize system performance.
- The operational planning level of PT-based CS systems was addressed, with a mathematical model optimizing parcel assignment, vehicle routing, and incentive allocation. Insights from a real-world case study demonstrated the impact of PL network size, familiarity rate, and hourly operating costs on delivery costs. The study provided practical recommendations for carriers, including the suggestion of optimal PL network sizes for cost savings.

## 6.4 Empirical findings and policies

***Policy implications from behavioural models:*** Behavioural research regarding the adoption of the proposed CS initiative by PT passengers has yielded valuable findings and insights. The results from the binomial logit model, utilized to examine the inclination towards participation in the CS system, indicate several demographic and behavioural factors associated with the likelihood of participation. Factors such as gender (female), age (senior adult), income level (low), employment status (full-time or retired), frequency of PT trips (high), and monthly delivery volume (medium or high) are linked to a reduced probability of CS participation. Conversely, factors including youth, residence in larger households, environmental sustainability concerns in freight delivery, and previous experience or preference for parcel lockers correlate with an increased likelihood of participation. Elasticity estimates derived from the model suggest that while medium- and high-volume delivery exhibit the largest negative elasticities, prior experience with parcel lockers or a preference for them, coupled with an interest in sustainable freight delivery systems, demonstrate the largest positive elasticities.

Inductive thematic analysis reveals nine major categories of factors hindering PT passengers from participating in CS: time constraints, physical or mental limitations, compensation concerns, perceived responsibility, safety and security apprehensions, social or labour-related considerations, convenience factors, infrequent PT usage, and lack of interest. Notably, insufficient time and irregular schedules, infrequent PT utilization, physical limitations, and expectations of higher compensation emerge as primary reasons for non-participation. Other factors include fear of assuming responsibility, safety concerns, displacement of traditional labour roles in the delivery market, and apprehensions about becoming recipients of CS packages. The study further explores how individual characteristics intersect with prohibiting factors, indicating varying degrees of sensitivity across different demographic and socioeconomic profiles. For instance, physical health concerns disproportionately affect the participation likelihood of women, low-income individuals, and those residing in smaller households.

Maintaining a balanced supply and demand within CS systems, particularly during the initial stages, is crucial to market efficiency. Addressing oversupply or overdemand situations is paramount to prevent deadweight losses. Recommendations include targeted advertising strategies to attract PT passengers with a higher probability of participation, such as young males with frequent PT trips and prior parcel locker experience. Personalized marketing approaches, particularly addressing safety concerns for women and job security for existing delivery employees, are suggested to enhance participation rates among specific demographic groups, such as full-time employees.

The LC model, developed to analyse the acceptance of CS tasks among participating passengers, identifies three distinct classes within the target population, each exhibiting unique preferences. Through an examination of significant variables utilized in class-specific choice and class membership models, these classes are categorized as follows: leisurely users (19% of the population), avid users (53% of the population), and sceptical users (28% of the population). Leisurely users, typically older employees with infrequent PT trips, demonstrate a modest willingness to undertake CS tasks if not overly burdensome. Avid users, primarily young PT passengers, display lower sensitivity to task attributes and may accept tasks with minimal incentives. Sceptical users, often with high PT trip frequency and good income, are reluctant to accept CS tasks without adequate compensation.

Key policy implications emerge from the empirical findings of the acceptance model. The LC model highlights that PT passengers prioritize detours over package weight. Given that a significant portion of urban package deliveries are lightweight, it is recommended to offer

passengers bundles of deliveries or allow them to customize bundles based on their preferences, enabling multiple deliveries to neighbouring locations without significant detours.

Implementing a partial delivery policy is another viable strategy, where delivery paths are segmented and CS tasks are outsourced to individual crowdshippers for each segment. By defining segments such as station-to-station and station-to-home, managers can leverage the observed behavioural heterogeneities among crowdshippers. Additionally, access to basic socio-economic characteristics of participating individuals allows managers to estimate market size across behavioural classes.

Detour magnitude, a significant factor in the LC model, varies depending on passenger destinations. Managers can estimate detours by analysing walking distance distributions from PT stations, facilitating the calculation of anticipated detours for parcel deliveries near PT stations. Considering that Classes 1 and 3, comprising nearly half of the population, exhibit high sensitivity to detours, it is advisable to deploy Class 1-2 users on Segment 1 (station-to-station) where no detour is necessary. Conversely, Class 2 (Avid) users, who are more likely to accept tasks even with detours, may be deployed on Segment 2 (station-to-home), thereby expediting package delivery and potentially encouraging recipients to collect packages from nearby PT stations.

The outcomes of the LC model indicate that even with more demanding CS tasks and the exclusion of lockers around destination points, PT passengers exhibit a propensity to engage with and accept CS tasks. This underscores the importance of evaluating the performance of PT-based CS systems and optimizing their design accordingly.

***Policy implications from behavioural models:*** An optimization model is devised to design PT-based CS systems and make decisions at both operational and strategic planning levels. This model aims to optimize operational decisions (such as parcel assignment to lockers/passengers, vehicle routing, and incentive amounts) and strategic decisions (including the number of PT hub stations) by probabilistically modelling the probability of PT passengers accepting CS tasks as crowdshippers. Through testing the model on a case study from the GS area and conducting various sensitivity analyses, several insights emerge, the main ones of which are summarized below.

Increasing the number of PT hub stations (i.e., the size of the PL network) enables carriers to reduce their total daily delivery costs, although this reduction is not always linear. For instance, altering the number of hubs from 2 to 4, 5 to 10, or 13 to 20 does not necessarily yield significant cost savings in the GS area case study. Therefore, it is suggested to implement PL

networks of small, medium, and large sizes, offering cost savings of up to 9%, 15%, and 36%, respectively, with corresponding reductions in delivery costs by carrier's dedicated vehicles.

Enhancing the familiarity rate ( $F_{rate}$ ) of CS initiatives contributes to cost savings for carriers, contingent upon the size of the PL network. In smaller or medium PL networks, increasing  $F_{rate}$  leads to linear cost savings, whereas in larger PL networks, a logarithmic growth pattern is observed. Additionally, higher hourly operating costs of delivery vehicles correlate with improved cost savings.

Our findings indicate that it is more effective for carriers to provide greater incentives to PT passengers during the initial stages of CS introduction. As the familiarity rate increases, carriers can gradually reduce incentives to mitigate operational costs. In small PL networks, incentives can be phased out once the familiarity rate reaches 0.5, while for medium and large PL networks, this threshold decreases to 0.25 and 0.15, respectively.

## **6.5 Limitations and Future Research**

The exploration, despite its depth and breadth, is not without limitations. The main limitations in this research as well as their corresponding future research suggestions are listed in the following.

- The research incorporated behavioural modelling for crowdshippers in CS systems and integrated these models into planning frameworks. While understanding the behaviours of crowdshippers is crucial, successfully launching CS initiatives requires comprehending the behavioural aspects of all involved stakeholders in the system. Parcel receivers and senders are among the other stakeholders, and without knowing their willingness to participate in CS systems, accurately predicting the performance of a CS system before implementation becomes challenging. Therefore, we propose extending behavioural explorations and modelling to other stakeholders and integrating all the models into the evaluation and planning systems.
- In this research, an open-ended question was employed to investigate the factors hindering the participation of PT passengers in the CS system. Future research endeavours should delve deeper into the factors influencing participation rates in CS initiatives. While our current study has illuminated the constraining factors, we recognize the importance of comprehending the effective motivations and potential incentives that can encourage individuals to actively participate. This study has

demonstrated that compensation alone may not be a significant deterrent, necessitating a more nuanced exploration. To address this, we propose the adoption of robust data collection techniques, such as in-depth interviews, to capture qualitative insights into the economic aspects and other factors shaping individuals' decisions to engage in crowd shipping activities. This qualitative approach will offer a more comprehensive understanding of the intricacies involved and contribute to the development of more reliable and effective CS initiatives. By expanding our focus beyond the constraining factors and delving into the motivations for participation, future research can furnish CS managers with a comprehensive toolkit for designing and implementing crowd-driven services. This holistic approach will not only bolster the reliability of CS initiatives but also advance the broader understanding of crowd participation dynamics in the evolving landscape of CS management

- Given the fixed nature of the case study, the assessment of factors like the level of accessibility within the PT network on participation rates was not possible. Subsequent studies could explore these influences by collecting data from diverse cases globally and examining whether characteristics of PT systems, such as accessibility, can indeed have an impact on participation rates
- Many CS systems typically allocate individual tasks to their crowdshippers, anticipating binary responses (accept or reject). Although single-alternative questions are consistent with post-implementation choices and can mitigate hypothetical bias in choice modelling, incorporating multiple-alternative questions can enhance the robustness of statistical models. As certain CS platforms feature task menus (Ausseil et al., 2022), employing multiple-alternative questions aligns with the characteristics of such systems. Future research endeavours should investigate task acceptance in menu-based CS systems using this approach.
- In this study, only three attributes—namely incentive, weight, and detour—are considered for CS tasks. While the insights from consultations and pilot studies have guided the research towards these three primary attributes, it is essential to acknowledge that there could be additional factors influencing the decision-making process of crowdshippers when accepting or declining a CS task. For example, findings from the pilot study have highlighted concerns among PT passengers related to safety (e.g., handling unknown products or interacting with unfamiliar receivers), security (e.g., CS platform or receiver tracking), and liability (e.g., costs borne by crowdshippers in cases

of product theft or damage) (Mohri et al., 2023a). Additionally, the purpose of the trip and time pressure experienced by PT passengers may impact their decisions regarding CS delivery tasks. Consequently, we recommend that future research investigates the impact of other attributes, such as traceability, delivery insurance, level of complexity, as well as the size, quantity, type, and value of CS tasks, on the acceptance decision. Recognizing that some of these variables may encompass attitudinal aspects, it is imperative to appropriately define them using latent variables to accurately capture their underlying unobservable nature.

- In the proposed PT-based CS system, the assumption is that passengers collect packages from a locker at a specific PT station, proceed to another PT station, exit the PT system, and deliver packages to their destinations on their way home. An alternative system could involve excluding the station-to-station movement of packages from crowdshippers' tasks and instead relocating lockers between stations. This alternative approach would mean that in-vehicle crowding in certain segments of PT lines would not impact the acceptance decision. Additionally, while this research concentrates on the behavioural aspects of the initiatives in evaluating the performance of PT-based CS systems, designing them can be a subject for future studies
- It is crucial to acknowledge that PT-based CS systems cannot entirely substitute traditional carrier delivery systems due to their limited operational capacity, primarily handling small and lightweight packages. Therefore, it is essential to explore the cost-effectiveness of incorporating CS systems from the carriers' standpoint. Gaining insights into the economic implications and feasibility of integrating CS within the current carrier networks would offer valuable information for decision-making processes.
- The delegation of package deliveries to PT passengers requires the establishment of intermediary points, commonly known as transfer or TPs. Previous research (Marcucci et al., 2017; Serafini et al., 2018; Gatta et al., 2019a; Gatta et al., 2019b; Fessler et al., 2022; Mohri et al., 2023a) has advocated for PLs as optimal relay points for this purpose. However, the implementation of PLs comes with substantial costs. While this study introduces a novel approach to a PT-based CS system operating between lockers and recipients' homes, necessitating a reduced number of PLs located at or near PT stations, the financial demands of such an initiative could still surpass a carrier's budget capacity. Therefore, forthcoming studies could leverage cost-benefit analyses and

revenue models to identify potential stakeholders responsible for providing the required PLs. In this context, local or national governments, as well as TPL entities, can play a crucial role, reminiscent of the Singaporean "Locker Alliance" program, where the government supports the establishment of an extensive PL delivery network (Lin et al., 2020).

- The current operational planning model did not consider delivery time windows. It is recommended that the mathematical model in Chapter 5 be extended to include time windows, particularly focusing on x-hour delivery concepts, such as 24-hour or 48-hour delivery. Time windows are crucial for ensuring timely and efficient service, especially with the growing demand for same-day and next-day delivery. Incorporating time-specific constraints would improve the model's practicality, providing more accurate solutions for urgent deliveries while maintaining operational efficiency.
- While the current study identified time-specific delivery solutions as a limitation, future research could address this by developing models that optimize delivery routes and parcel assignments while ensuring deliveries are completed within defined time windows. This extension would not only improve customer satisfaction but also align with evolving industry trends where rapid and precise delivery is a key competitive advantage. By accounting for time windows and x-hour delivery requirements, future studies could explore balancing the operational costs with the need for speed and reliability, thus enhancing the model's relevance to real-world applications.
- In this study, the optimization of the planning system at the strategic level involved conducting sensitivity analysis for the location of PLs in the evaluation model. We recommend that future research incorporates location decisions for placing PLs within the PT network into the model. This is a crucial step during the planning phase of PT-based CS initiatives to foster further synergy and enhance decision-making. However, the addition of these new decisions will increase the complexity of the model. Therefore, advanced solution algorithms should be proposed to facilitate testing the model on expanded spatial scales and for carriers with larger market share. Moreover, simulation techniques, such as agent-based approaches, can be integrated with optimization to incorporate more realistic assumptions, including traffic levels, varying socio-economic factors, and weather conditions. Lastly, future investigations could explore time-specific delivery solutions by PT passengers to understand how PT-based CS systems can contribute to achieving fast delivery goals.

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