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Cebeci, M.S.

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BEHAVIOUR OF PROSUMERS IN LAST-MILE LOGISTICS:

THE CASE OF CROWDSHIPPING

Behaviour of Prosumers in Last-mile Logistics: The Case of Crowdshipping

Merve Seher CEBECI

Delft University of Technology

Behaviour of Prosumers in Last-mile Logistics: The Case of Crowdshipping

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by

Merve Seher CEBECI

Delft University of Technology
Master of Science in Transportation, Infrastructure and Logistics
Delft University of Technology, the Netherlands
born in Istanbul, Türkiye

This dissertation has been approved by the promotors.

Composition of the doctoral committee:

Rector Magnificus	Chairperson
Prof.dr.ir. L.A. Tavasszy	Delft University of Technology, promotor
Dr.ir. M. de Bok	Delft University of Technology, copromotor

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To those who strive for wisdom and those who build knowledge.

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Merve Seher Cebeci,
Delft, September 2025.

Contents

Summary

This dissertation addresses consumer decisions in last-mile logistics, with a particular focus on the emerging concept of crowdshipping. By conceptualising consumers as both users and service providers of logistics services referred to as ”prosumers”, this research examines how their dual role influences the efficiency and sustainability of last-mile delivery systems. Through a combination of defining a conceptual framework, empirical analyses, and a simulation study, this work investigates key aspects of crowdshipping and the role of prosumers in supply and demand perspectives.

The dissertation is structured around a main research question: How does prosumer decision-making within crowdshipping impact the performance and sustainability of last-mile delivery systems? To answer this overarching question, the research investigates several key aspects of consumer behaviour, specifically focusing on how consumers make decisions within hyperconnected delivery networks and their evolving role as active participants in crowdshipping.

The research concerned four major steps.

First, we **map citizen's decisions** about connected last-mile services, either as users or as logistics service suppliers. To do this, we conduct a comprehensive literature review to examine the evolving role of consumers in last-mile logistics. We frame consumer behaviour by identifying the key decisions made around last-mile parcel delivery. We introduce the concept of ”prosumers” where individuals not only receive services but also actively participate in logistics through crowdshipping. The study categorises consumer decisions into three main areas: shopping channel selection, delivery method choice, and willingness to act as occasional carriers. By placing these decisions within the broader context of urban logistics, we propose a conceptual framework that links consumer behaviour to the overall understanding of last-mile delivery systems. This study establishes the theoretical foundation for the thesis by providing insights into consumer behaviour in the context of crowdshipping. The review of the literature leads to the identification of several research opportunities, including (1) the role of trust in occasional carriers in the choice for delivery services, (2) the willingness of a non-travelling occasional carrier to accept an assignment and (3) the potential volume of crowdshipping markets as resulting from outlier parcels of professional service providers.

Second, we explore **the role of trust in crowdshipping adoption** from the perspective of service users, in other words, the demand for the service. Using a Stated Preference (SP) experiment combined with a Hybrid Choice Model (HCM), we examine how trust influences consumer preferences for delivery options. Recognising trust as a critical determinant of the acceptability of non-professional delivery services, we model trust as a latent variable and

examine its mediating effects on consumer preferences for last-mile delivery options. The analysis reveals that trust has a partially and, for some features, fully mediating effect towards the crowdshipping service choice. While the delivery company's reputation and the possibility of damage are fully mediated by trust, interestingly, same-day delivery was found to have a direct positive effect on adoption, independent of trust. Finally, trust has a partially mediating affect on the remaining attributes. This literature review highlights the importance of designing a crowdshipping business model that incorporates trust-related features to address consumer concerns and improve adoption rates.

Third, we shift our focus to the supply side of crowdshipping by analysing **the willingness of occasional carriers to bring parcels**. The sub-research question addresses the willingness of occasional carriers to accept a delivery request, even if the delivery operation generates a new trip. By employing a SP experiment and a Latent Class Choice Model (LCCM), this study investigates two scenarios: commute-based deliveries that align with existing trips and home-based deliveries that generate new trips. The findings show that while commute-based crowdshipping minimises additional travel demand, home-based deliveries might generate new trips and increase urban congestion and emissions. The study also highlights the influence of income levels, with lower-income individuals being more likely to accept crowdshipping tasks due to their lower value of time. Moreover, the study emphasises the need for pricing strategies and operational models that promote sustainable crowdshipping practices.

Finally, we dive deeper into **the potential market share of crowdshipping** by integrating supply and demand perspectives into a simulation-based analysis. This study introduces a cost-based outlier parcel identification mechanism to target high-cost parcels for outsourcing parcel delivery to crowdshipping. The results indicate that only a small proportion (around 1%) of total parcel demand qualifies as high-cost outliers suitable for crowdshipping. While this highlights the limited scalability of crowdshipping for traditional logistics, the findings suggest its viability for specific use cases, such as customer-to-customer deliveries and time-sensitive shipments. This study provides practical insights into the operational dynamics of crowdshipping and its role as a supplementary last-mile delivery model by considering demand and supply mechanisms.

The research identifies several opportunities for future exploration, including investigating the impact of social networks on crowdshipping adoption, extending the study to different geographical contexts, and further exploring the environmental impacts of crowdshipping, especially in relation to new trip generation. Additionally, integrating crowdshipping with other urban logistics innovations, such as parcel lockers and hyperconnected logistics networks, presents another avenue for enhancing its operational profitability and sustainability.

Overall, this thesis explores the feasibility of crowdshipping as an innovative solution for last-mile delivery logistics. By incorporating both demand- and supply-side decisions, we develop a framework to analyse consumer choices and assess their impact on system performance in conjunction with the traditional courier market. The results highlight that crowdshipping, while promising as a supplementary delivery model, faces considerable challenges due to the complex interaction between demand and supply factors. Trust, compensation, and the type of delivery task are central to its adoption and success. For

economically and environmentally sustainable implementation, crowdshipping platforms must prioritise a deep understanding of consumer behaviour. We argue that overlooking stakeholder behaviour when developing crowdshipping systems can lead to misjudgements and misleading conclusions regarding their effectiveness and potential. Hence, practitioners in crowdshipping should prioritise consumer-centric business models, focusing on building trust to support user adoption and loyalty. By offering tailored compensation strategies and targeting niche segments such as time-sensitive or high-cost parcels, platforms might optimise resources and ensure sustainability.

Samenvatting[1]

Deze dissertatie behandelt consumentbeslissingen in stedelijke last-mile pakketbezorging, met een specifieke focus op het opkomende concept van crowdshipping, ofwel incidentele bezorging door burgers. Door consumenten te conceptualiseren als zowel gebruikers als aanbieders van logistieke diensten, aangeduid als prosumers, wordt onderzocht hoe deze dubbele rol de efficiëntie en duurzaamheid van last-mile bezorgsystemen beïnvloedt. Door een combinatie van een conceptueel kader, empirische analyses van keuzegedrag en een simulatiestudie draagt het werk bij tot een beter begrip van het fenomeen crowdshipping, in het bijzonder wat betreft de integratie van vraag- en aanbodaspecten.

De dissertatie is gestructureerd rond de centrale onderzoeksvraag: Hoe beïnvloedt de besluitvorming van prosumers binnen crowdshipping de prestaties en duurzaamheid van last-mile bezorgsystemen? Om deze overkoepelende vraag te beantwoorden, wordt de nadruk gelegd op beslissingen van burgers in sterk verbonden (hyperconnected) bezorgnetwerken, en hun evoluerende rol als actieve deelnemers aan de crowdshipping-markt.

Het onderzoek omvat vier delen.

Allereerst brengen we de **beslissingen van burgers in kaart** als gebruikers en als leveranciers van logistieke diensten. Dit doen we door middel van een systematische literatuurstudie, waarin de veranderende rol van consumenten in last-mile logistiek wordt geanalyseerd. We kaderen consumentengedrag in door de belangrijkste beslissingen rondom pakketbezorging te identificeren. We introduceren het concept van prosumers, waarbij individuen niet alleen diensten afnemen, maar ook actief logistieke diensten uitvoeren via crowdshipping. Het onderzoek categoriseert consumentbeslissingen in drie hoofdgebieden: de keuze van het aankoopkanaal, de keuze van de bezorgmethode en de bereidheid om als incidentele bezorger op te treden. Door deze beslissingen binnen de bredere context van stedelijke logistiek te plaatsen, stellen we een conceptueel kader voor dat consumentengedrag koppelt aan het algemene begrip van last-mile bezorgsystemen. Deze studie vormt de theoretische basis van de dissertatie. De literatuurstudie leidt tot de identificatie van verschillende kansen voor wetenschappelijk onderzoek, waaronder (1) de rol van vertrouwen in incidentele bezorgers bij de keuze voor bezorgdiensten, (2) de bereidheid van een niet-reizende incidentele bezorger om een bezorgtaak te accepteren en alsnog een reis te starten (3) het potentiële volume van de crowdshipping-markt, voortkomend uit qua bezorgkosten relatief ongunstige pakketten van professionele dienstverleners, de zogenaamde outliers.

[1] The Dutch abstract was initially translated with the assistance of ChatGPT, and its substantive correctness was verified by the promotor.

Ten tweede onderzoeken we **de rol van vertrouwen bij de adoptie van crowdshipping** vanuit het perspectief van dienstgebruikers, oftewel de vraag naar de dienst. Door middel van een Stated Preference (SP)-experiment, gecombineerd met een Hybrid Choice Model (HCM), analyseren we hoe vertrouwen consumentvoorkeuren voor bezorgopties beïnvloedt. Vertrouwen wordt erkend als een mogelijk relevante determinant voor de acceptatie van niet-professionele bezorgdiensten. Daarom modelleren we vertrouwen als een latente variabele en analyseren we het mediërende effecten ervan op consumentvoorkeuren op basis van een steekproef. De kwantitatieve analyse toont aan dat vertrouwen inderdaad een significante invloed heeft op belangrijke dienstkenmerken, zoals bezorgkosten, bedrijfsreputatie en het risico op schade. Opmerkelijk is dat bezorging op dezelfde dag een directe positieve invloed heeft op de adoptie, onafhankelijk van vertrouwen. Deze resultaten benadrukken het belang van een crowdshipping-bedrijfsmodel dat vertrouwen-gerelateerde functies integreert om consumentenzorgen aan te pakken en adoptiepercentages te verbeteren.

Ten derde verschuiven we de focus naar de aanbodzijde van crowdshipping door de **bereidheid van incidentele bezorgers om pakketten mee te nemen** te analyseren. Deze onderzoeksvraag richt zich op de bereidheid van burgers om een bezorgverzoek te accepteren, zelfs als de bezorging een nieuwe reis genereert. Met behulp van een SP-experiment en een Latent Class Choice Model (LCCM) onderzoeken we twee scenario's: woon-werkbezorgingen die samenvallen met bestaande reizen en thuis-gebaseerde bezorgingen die nieuwe reizen genereren. Terwijl woon-werk-crowdshipping een minimale extra vervoersvraag genereert, leiden thuis-gebaseerde bezorgingen tot het risico stedelijke congestie en emissies te verhogen. De resultaten laten zien dat beide typen voorkomen afhankelijk van de omstandigheden. Het onderzoek benadrukt de invloed van inkomensniveaus: individuen met een lager inkomen zijn eerder geneigd om crowdshipping-taken te accepteren, vanwege hun lagere tijdwaardering. Hiermee onderstreept het onderzoek de noodzaak van incentives zoals prijsstrategieën en operationele logistieke modellen die duurzame crowdshipping-praktijken bevorderen.

Tot slot onderzoeken we hoe het **potentiële marktaandeel van crowdshipping** kan worden bepaald door de vraag- en aanbodperspectieven te integreren in een simulatie-gebaseerde analyse. Deze studie introduceert een kosten-gebaseerd mechanisme voor het identificeren van uitschieters qua bezorgkosten, waarvan professionele bezorgdiensten geneigd zullen zijn deze te uit te besteden. Van het uit te besteden volume komt een deel terecht bij de markt voor crowdshipping. Voor de case van de provincie Zuid-Holland blijkt dat het uiteindelijke volume dat op deze manier bezorgd wordt een kleine fractie is van alle zendingen, ongeveer 1 procent. Deze deelstudie toont aan dat bij realistische bedrijfseconomische en logistieke aannamen het potentieel van crowdshipping beperkt is. De dissertatie identificeert verschillende kansen voor nieuw onderzoek, waaronder de invloed van sociale netwerken op de adoptie van crowdshipping, het uitbreiden van de studie naar verschillende geografische contexten en een verdere verkenning van de milieu-impact van crowdshipping, vooral met betrekking tot de generatie van nieuwe ritten. Daarnaast biedt de integratie van crowdshipping met andere stedelijke logistieke innovaties, zoals pakketkluizen en hyperconnected logistieke netwerken nieuwe mogelijkheden om de operationele winstgevendheid en duurzaamheid van stedelijke bezorging te verbeteren.

Samengevat onderzoekt deze dissertatie de haalbaarheid van crowdshipping als een innovatieve oplossing voor last-mile bezorging. Door zowel vraag- als aanbodbeslissingen te integreren, ontwikkelen we een kader om consumentkeuzes te analyseren en hun impact op de systeemprestaties te beoordelen in combinatie met de traditionele koeriersmarkt. De resultaten tonen aan dat crowdshipping, hoewel veelbelovend als aanvullend bezorgmodel, aanzienlijke uitdagingen kent door de complexe interactie tussen vraag- en aanbodfactoren. Vertrouwen, vergoeding en het type bezorgtaak zijn cruciaal voor de adoptie en het succes van crowdshipping. Voor een economisch en ecologisch duurzame implementatie moeten crowdshipping-platforms een diepgaand begrip van consumentengedrag ontwikkelen. Het negeren van dit gedrag bij het evalueren van crowdshipping-systemen kan leiden tot verkeerde interpretaties en conclusies over hun effectiviteit en potentieel. Onze aanbeveling aan crowdshipping-initiatieven is dat zij zich richten op consumentgerichte bedrijfsmodellen, waarbij vertrouwen centraal staat om gebruikersacceptatie en loyaliteit te bevorderen. Door bijvoorbeeld op maat gemaakte vergoedingsstrategieën aan te bieden en zich te richten op niche-segmenten zoals tijdgevoelige of dure pakketten, kunnen platforms efficiënter en duurzamer opereren.

Özet

Bu tez, son kilometre lojistiğinde tüketici kararlarını ele almakta ve özellikle öne çıkan bir kavram olan kitle kaynaklı taşımacılığa odaklanmaktadır. Tüketicilerin hem lojistik hizmetlerinin kullanıcısı hem de sağlayıcısı olarak "üretici-tüketici" başka bir ifadeyle "profesyonel tüketici" rolünü üstlenmesi çerçevesinde, bu araştırma, söz konusu çift yönlü rolün son kilometre teslimat sistemlerinin verimliliği ve sürdürülebilirliği üzerindeki etkilerini incelemektedir. Kavramsal bir analiz, deneysel model analizleri ve simülasyon tabanlı bir değerlendirme yöntemi kullanılarak, kitle kaynaklı taşımacılığın temel bileşenleri ve arz-talep dinamiklerinin entegrasyonu araştırılmaktadır.

Tez, şu temel araştırma sorusu etrafında yapılandırılmıştır: Üretici-tüketicilerin kitle kaynaklı taşımacılık bağlamında aldığı kararlar, son kilometre teslimat sistemlerinin performansını ve sürdürülebilirliğini nasıl etkilemektedir? Bu temel soruya yanıt bulmak amacıyla araştırma, tüketici davranışının çeşitli yönlerini incelemekte ve özellikle birbiri ile bağlantılı teslimat ağları içinde tüketicilerin nasıl karar aldıklarına ve kitle kaynaklı taşımacılığa aktif katılımlarına odaklanmaktadır. Çalışma dört temel aşamadan oluşmaktadır.

İlk olarak, **tüketicilerin son kilometre hizmetleriyle ilgili karar alma süreçleri** incelenmiştir. Tüketicilerin, hem hizmet kullanıcısı hem de lojistik hizmet sağlayıcısı olarak rol üstlenmesine dair kapsamlı bir literatür taraması gerçekleştirilmiş, son kilometre lojistiğinde değişen tüketici rolü analiz edilmiştir. Tüketici davranışı, kargo teslimatı bağlamında alınan temel kararlar üzerinde çerçevelendirilmiş ve bireylerin yalnızca hizmet alıcısı değil, aynı zamanda kitle kaynaklı taşımacılık aracılığıyla lojistik süreçlerine aktif olarak katıldığı "üretici-tüketici" kavramı detaylandırılmıştır. Çalışma, tüketici kararlarını üç ana başlık altında sınıflandırmaktadır: alışveriş kanalı seçimi, teslimat yöntemi tercihi ve kitle taşımacılığına katılmaya yönelik isteklilik. Bu kararlar, kentsel lojistik bağlamında ele alınarak, tüketici davranışının son kilometre teslimat sistemlerinin genel yapısı ile ilişkisini ortaya koyan bir kavramsal çerçeve geliştirilmiştir. Literatür taraması, üç temel araştırma boşluğunu öne sürmüştür: (1) tüketicilerin kitle taşıyıcılarına duyduğu güvenin teslimat hizmetleri tercihi üzerindeki etkisi, (2) halihazırda seyahat etmeyen bireylerin teslimat görevlerini kitle taşıyıcısı olarak kabul etme istekliliği ve (3) yüksek maliyetli kargoların kitle kaynaklı taşımacılık yoluyla taşınma potansiyeli.

İkinci aşamada, **kitle kaynaklı taşımacılığın benimsenmesinde güvenin rolü, hizmet kullanıcıları (talep) açısından ele alınmıştır**. Belirtilmis Tercih yöntemi ile Hibrit Seçim Modeli kullanılarak, güvenin tüketicilerin teslimat seçeneklerine yönelik tercihleri üzerindeki etkisi incelenmiştir. Güven, profesyonel olmayan kitle taşıyıcılarının kabul edilebilirliğini belirleyen kritik bir unsur olarak değerlendirilmiştir. Bu nedenle, güven gizli değişken olarak modellenmiş ve son kilometre teslimat seçenekleri üzerindeki aracı rolü ve etkileri

analiz edilmiştir. Araştırma sonuçları, güvenin teslimat maliyeti, hizmet sağlayıcının itibarı ve hasar riski gibi temel hizmet nitelikleri üzerinde önemli bir etkiye sahip olduğunu göstermektedir. Ayrıca, aynı gün teslimat seçeneğinin, güven düzeyinden bağımsız olarak doğrudan olumlu bir etkisi olduğu belirlenmiştir. Çalışma, kitle kaynaklı taşımacılık iş modellerinin, güvenle ilişkili unsurları içerecek şekilde tasarlanmasının, tüketici endişelerinin giderilmesi ve hizmetin benimsenme oranlarının artırılması açısından kritik bir öneme sahip olduğunu ortaya koymaktadır.

Üçüncü aşamada, kitle kaynaklı taşımacılığın arz yönüne odaklanılmış ve **kitle taşıyıcılarının teslimat görevlerini kabul etme istekliliği analiz edilmiştir**. Bu aşamada araştırma sorusu, bireylerin kitle kaynaklı taşımacılık çerçevesinde bir teslimat talebini kabul etme eğilimini ve bu eğilimin ek yolculuk ortaya çıkarıp çıkarmayacağı incelenmiştir. Belirtilmis Tercih deneyi ve Örtük Sınıf Analizi kullanılarak iki senaryo analiz edilmiştir: mevcut yolculuklarla uyumlu gerçekleştirilen kitle taşımacılığı ve yeni yolculuk ortaya çıkaran kitle taşımacılığı. Bulgular, mevcut yolculuk temelli kitle kaynaklı taşımacılık uygulamalarının ek ulaşım talebini en aza indirirken, yeni yolculuk meydana getiren kitle taşımacılığın trafik sıkışıklığı ve karbon emisyonlarını artırma riski taşıdığını göstermektedir. Ayrıca, düşük gelir düzeyine sahip bireylerin zaman değerinin daha düşük olması nedeniyle kitle kaynaklı taşımacılık görevlerini kabul etme olasılıklarının daha yüksek olduğu belirlenmiştir. Bu doğrultuda, sürdürülebilir kitle kaynaklı taşımacılık uygulamalarının teşvik edilmesi için fiyatlandırma stratejileri ve operasyonel modellerin geliştirilmesi gerektiği vurgulanmaktadır.

Son aşamada, **kitle kaynaklı taşımacılığın potansiyel pazar payının nasıl şekillendiği**, arz ve talep perspektiflerinin simülasyon tabanlı bir analiz yoluyla entegre edilmesiyle incelenmiştir. Çalışmada, yüksek maliyetli paketler tespit edilmiş ve kitle kaynaklı taşımacılığın lojistik hizmet sağlayıcıları tarafından dış kaynak olarak kullanım olasılığı değerlendirilmiştir. Sonuçlar, toplam paket talebinin yalnızca küçük bir kısmının (%1 civarında) kitle kaynaklı taşımacılığa uygun yüksek maliyetli olarak tanımlanabileceğini göstermektedir. Bu bulgular, kitle kaynaklı taşımacılığın geleneksel lojistik operasyonları açısından sınırlı ölçeklenebilirliğe sahip olduğunu vurgulamakla birlikte, tüketiciden bir diğer tüketiciye gönderilen teslimatlar ve zaman açısından hassas gönderimler gibi belirli kullanım senaryoları için uygun olduğunu ortaya koymaktadır. Çalışma, kitle kaynaklı taşımacılığın operasyonel dinamikleri ve talep-arz mekanizmaları dikkate alındığında son kilometre teslimat modeli olarak oynayabileceği rol hakkında pratik öngörüler sunmaktadır.

Bu tez, kitle kaynaklı taşımacılığın son kilometre lojistiğinde yenilikçi bir çözüm olarak uygulanabilirliğini incelemektedir. Hem talep hem de arz kararlarını bütüncül bir yaklaşımla ele alarak, tüketici tercihlerinin analiz edilmesi ve bu tercihler ile geleneksel kurye pazarının etkileşiminin değerlendirilmesi için bir çerçeve geliştirilmiştir. Bulgular, kitle kaynaklı taşımacılığın tamamlayıcı bir teslimat modeli olarak umut vadettiğini ancak arz ve talep faktörleri arasındaki karmaşık etkileşim nedeniyle önemli zorluklarla karşı karşıya olduğunu göstermektedir. Güven, teşvik mekanizmaları ve teslimat türü, benimsenme sürecinde belirleyici unsurlar olarak öne çıkmaktadır. Ekonomik ve çevresel açıdan sürdürülebilir bir uygulama için, kitle kaynaklı taşımacılık platformlarının tüketici davranışlarını derinlemesine anlamaya odaklanması gerekmektedir.

Chapter 1

Introduction

1.1 Background

Last-mile logistics is a critical phase of the supply chain, representing the final and one of the most complex links between businesses and consumers (Lim et al., 2018). This stage, driven by the rapid growth of e-commerce and technological advancements, involves not only the transportation of parcels from distribution centres to consumers' doorsteps but also the need to meet increasing customer demand in many aspects such as speed, cost-efficiency, and reliability. The rise of omnichannel retailing further complicates the current urban freight environment, as consumers no longer play a passive role but increasingly become active participants or prosumers within the logistics network through various activities, such as picking up or dropping off their parcels. Consumers expect a seamless experience across multiple channels, from in-store pickups to home deliveries and same-day services. This shift demands a more dynamic and flexible last-mile logistics strategy, capable of integrating different distribution channels and online platforms into a delivery network.

Moreover, as cities expand and urbanisation accelerates, growing on-demand consumer requests lead to pressure on the limited urban space available. Consequently, challenges such as traffic congestion, negative environmental impacts, and inefficiencies in last-mile delivery become more evident (Lim et al., 2018; Mangiaracina et al., 2019). Addressing these interconnected challenges requires rethinking how urban freight deliveries can be made more sustainable to mitigate their negative impacts while meeting the evolving needs of consumers.

In response, researchers and urban planners explore approaches to create more sustainable and efficient urban freight transportation systems. One such approach is the vision of hyperconnected logistics, embodied in the Physical Internet (PI) (Crainic & Montreuil, 2016; Ballot et al., 2021). Introduced by Montreuil (2011), the PI envisions a globally hyperconnected network that applies the principles of the digital Internet to the physical flow of goods. This framework promotes the seamless, efficient movement of freight through shared, open, and interconnected logistics network, with the goal of reducing the environmental footprint and inefficiencies of traditional freight systems. While the PI comprises many components ranging from modularisation of containers to routing protocols (Montreuil, 2011; Marcucci et al., 2023) and variety of application areas from manufacturing (Zhong et al., 2017) to circular supply chains (Wu et al., 2023), this thesis focuses specifically on urban freight service solutions (Pan et al., 2017; Crainic et al., 2023). In particular, it explores crowdshipping—a service closely aligned with PI principles through its use of connectivity, technology, and collaborative logistics (Buldeo Rai et al., 2017; Marcucci et al., 2017; Rougès & Montreuil, 2014; Di Febbraro et al., 2018)— as well as the evolving behaviour of consumers within this landscape.

Crowdshipping integrates last-mile delivery with everyday travel, using citizens travelling for their private purposes, who are willing to add parcel delivery to their existing activity schedule; also referred to as occasional carriers (Rougès & Montreuil, 2014). Through digital platforms, shippers of parcels are matched with these travellers, allowing parcels to be delivered without dedicated freight vehicles. This approach not only promises to reduce delivery cost and time but also offers the potential to cut down on emissions and diminish urban congestion by making use of existing passenger trips (Rougès & Montreuil, 2014; Di Febbraro et al., 2018). However, as the service scales up, there is a possibility that it could exacerbate negative externalities, highlighting the need for further research to understand its impacts and feasibility. This is the starting point of this thesis.

1.2 Knowledge gaps

In the literature, there are various studies focusing on the role of consumer behaviour and innovative last-mile logistics services. However, significant research gaps remain, particularly in the context of crowdshipping. This thesis addresses several knowledge gaps by focusing on four key areas: the framing of consumer decisions in hyperconnected last-mile logistics, operationalising trust in crowdshipping, the trip-generating potential of crowdshipping service, and the market dynamics between crowdshipping and traditional courier services. All in all, the perspective of consumer behaviour is the common aspect between these areas.

1.2.1 Decentralised consumer decision-making

Decision-making in logistics is either centralised, maximising system-wide performance, or decentralised, optimising the utility of individual actors. Most last-mile logistics research assumes centralised decision-making, often overlooking the independent decisions of consumers (Meyer et al., 2019). This thesis focuses on decentralised decision-making, specifically how individual consumers' choices affect logistics services in hyperconnected urban freight. Consumers, by placing orders, initiate freight demand, often prioritising short delivery times and low costs (Stathopoulos et al., 2011). Their decisions, from delivery location to preferred delivery time, can lead to higher costs and inefficiencies.

In the current last-mile era, consumers are offered customised products and services, which contribute to an increase in production and delivery costs. As shown in Figure 1.1, traditional shopping trips decline, leading to a shift where they are now complemented by multiple delivery options—such as shop pick-up, home deliveries, and locker pick-up all of which rely on the integration of online platforms. This transformation introduces new complexities, as consumer decisions now directly influence logistics chains.

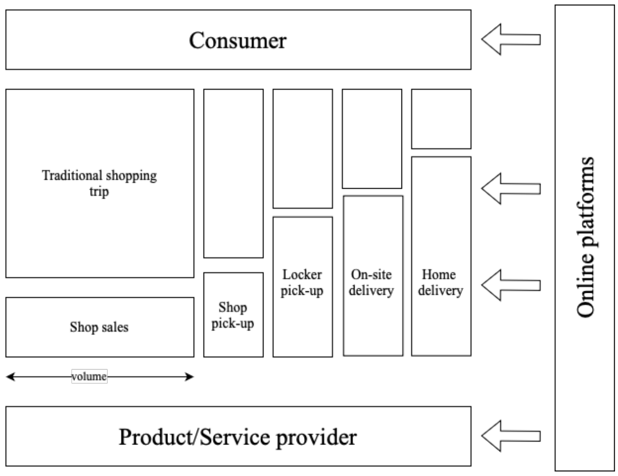


Figure 1.1: Omnichannel retailing revolution

Similar transitions are also viable in the context of hyperconnected urban freight. Hyperconnected logistics rely on the seamless integration of various actors—such as consumers, service providers, and technology platforms into a highly interconnected network. This system enables real-time data exchange between stakeholders, for example, from one logistics service provider (LSP) to another or from a shipper to an LSP. Moreover, coordination across multiple stakeholders becomes feasible that allows logistics operations to respond dynamically to consumer preferences in delivery service choice, as well as delivery characteristics such as time and cost. Understanding consumer decision-making is key to formulating policies that promote sustainable last-mile logistics. While crowdshipping and other shared-economy models are promising in terms of their economical and environmental sustainability, they require a deeper understanding of how consumers' participation affects demand-supply balance and efficiency. This understanding is key to formulating effective policies that can support the future of last-mile logistics.

Knowledge gap 1: framing consumer decisions in hyperconnected last-mile logistics.

1.2.2 Trust in crowdshipping

Research focuses on different aspects of crowdshipping ranging from operational efficiencies, routing strategies, compensation schemes, reverse logistics and combination potential of crowdshipping with other services. Behavioural studies examining user acceptance highlight factors such as delivery time, cost, and sustainability, which are crucial in determining whether potential users are willing to adopt the service (Rougès & Montreuil, 2014; Punel et al., 2018b). Research suggests that users prefer crowdshipping when it offers faster or more flexible delivery options at a lower cost compared to traditional methods (Punel & Stathopoulos, 2017; Le et al., 2019). Moreover, the growing focus on sustainability in urban freight logistics indicates that consumers are more likely to choose crowdshipping if it is perceived to reduce emissions and urban congestion (Wicaksono et al., 2022; Mohri et al., 2024).

Trust is an important determinant for the successful adoption of crowdshipping, as building trust addresses the uncertainties of relying on non-professional couriers for last-mile deliveries. Unlike traditional LSPs, crowdshipping involves occasional carriers, which introduces risks concerning package safety, privacy, and reliability compared to traditional delivery. While studies explore factors such as delivery time and cost, little research has examined how platforms can build and operationalise trust for the service users. Establishing trust in this context involves multiple dimensions, not only the perceived economic attributes but also factors such as reliability and risk. Users are more likely to trust platforms that offer transparent processes, such as real-time tracking. Additionally, rating systems, user reviews, and insurance policies help mitigate risks associated with package loss or damage and might impact the level of trust in crowdshipping. This highlights a significant gap in the current literature for empirical research to better understand and operationalise trust from the perspective of service users.

Knowledge gap 2: operationalisation of trust from the perspective of the users of crowdshipping services.

1.2.3 Trip-generating potential of crowdshipping

Theoretically, crowdshipping is a service where deliveries are made part of an existing passenger trip. However, the potential for crowdshipping to generate new trips raises important questions about its environmental and logistical impact. Although crowdshipping is often promoted as a sustainable solution by leveraging trips that travellers make, there is a risk that individuals acting as couriers may accept longer detour trips or start a new trip to deliver parcels. Such behaviours can offset the foreseen benefits of crowdshipping, such as reduced emissions and congestion, by increasing vehicle kilometres travelled (VKT) and leading to urban traffic inefficiencies. The assumption that crowdshipping reduces the reliance on dedicated freight delivery vehicles requires the need for further evaluations.

Knowledge gap 3: crowdshipping acceptance from the perspective of occasional carriers and the impact on trip generation for crowdshipping services.

1.2.4 Market dynamics of crowdshipping

The market dynamics of crowdshipping present both opportunities and challenges, particularly when considering its scalability and long-term viability. Despite its growing prominence, limited research has explored the barriers to scaling crowdshipping services, especially in light of lessons learned from the first wave of crowdshipping companies, such as Nimber (n.d., 2012a). These early experiences reveal challenges related to operational sustainability, service adoption and competition with LSPs. Understanding these barriers is crucial for accurately predicting the potential market size and viability of crowdshipping.

The identification of a feasible market for crowdshipping remains a significant gap in the literature. This is particularly true in contexts where deliveries are outsourced to independent couriers or platforms, raising questions about cost-effectiveness and the ability to maintain service quality at scale. Factors such as trust, compensation schemes, and user demographics influence the practicality and attractiveness of crowdshipping as a last-mile solution. Hence, exploring which types of parcels are suitable for crowdshipping is essential for providing actionable insights to urban logistics stakeholders, including policymakers, platform operators, and logistics service providers. Such an analysis could guide the design of crowdshipping systems that are economically sustainable, environmentally friendly, and capable of meeting the growing demands of urban freight.

Knowledge gap 4: the potential market of parcel deliveries for crowdshipping service from the perspective of couriers.

1.3 Main research question

Following the knowledge gaps in understanding the decision-making of prosumers and developing models to capture both their consumer and supplier roles in hyperconnected last-mile delivery services and these decisions impact the market share of crowdshipping, we propose the main research question:

How does prosumer decision-making within crowdshipping impact the performance and sustainability of last-mile delivery?

1.4 Sub-research questions

To address the overarching main research question, this study explores four sub-questions that investigate key dimensions of consumer decision-making in hyperconnected networks and the impact of these decisions on the performance of crowdshipping. Each sub-question examines a unique aspect of the problem, focusing on the decentralised decision-making of consumers and their evolving roles as prosumers in the crowdshipping service. By incorporating both the demand side, where consumers choose a delivery service, and the supply side, where consumers can act as suppliers of the delivery service, these questions provide valuable insights into the broader implications of crowdshipping for urban logistics and the behaviour of prosumers.

Understanding consumer decision-making in last-mile logistics requires identifying how consumers evaluate and choose among delivery services such as home delivery, parcel locker delivery or crowdshipping. Here, consumers can be either prospective users or suppliers of last-mile logistics services. Traditional centralised decision-making approaches, while effective for maximising operational efficiency, can struggle to accommodate the diverse demand of prosumers. Existing review studies have primarily focused on the demand side of consumer decision-making, specifically on consumer choices related to delivery services when ordering goods online. Therefore, our research objective is to provide a systematic review of existing research, contributing to the literature on the PI, last-mile delivery, and consumer decision-making. To achieve this objective, we focus our exploration on the following main question: *How do consumers make decisions about hyperconnected last-mile services, either as users or as suppliers, in the context of omnichannel retailing?* **[Chapter 2]**

To explore the adoption of crowdshipping, trust is an indispensable factor especially for a service that is new or relatively unfamiliar to consumers (Akhmedova et al., 2021). Trust can shape consumers' perceptions of reliability and safety, making it a decisive factor in their willingness to choose crowdshipping over traditional delivery methods. This thesis, therefore, seeks to understand how trust impacts crowdshipping adoption through the following sub-question: *What is the role of trust in crowdshipping service choice?* **[Chapter 3]**

After investigating the effect of trust on consumers' choice behaviour as users, it is also essential to examine their behaviour as potential service suppliers, particularly in terms of the trip generation potential of crowdshipping. Understanding the conditions under which consumers are willing to act as occasional carriers not only sheds light on the supply-side dynamics but also allows us to assess how crowdshipping may influence urban mobility patterns through the generation of additional trips. To address these aspects, we pose the following research question: *When are occasional carriers willing to accept a delivery request, even if the delivery operation generates a new trip?* **[Chapter 4]**

Once the decision-making processes of consumers as users and as suppliers of last-mile delivery are captured, the next step is to assess the potential scale and viability of crowdshipping within the current delivery market. The last sub-research question, therefore, seeks to define the demand for crowdshipping to clarify its capacity to act as a supplement to traditional delivery services: *How can the potential demand for crowdshipping be defined?* **[Chapter 5]**

1.5 Research approach

To address the research questions described in Section 1.4, we propose specific methodologies for each research question, as illustrated in Figure 1.2. The methodologies span both theoretical and empirical approaches, ranging from conceptual model development to empirical choice and simulation models.

In Chapter 2, a literature review is conducted to identify key stakeholders and explore the factors that influence consumer decisions. Consequently, a conceptual model of the problem is developed, which maps the decision-making pathways, roles, and choices consumers face in hyperconnected last-mile delivery. The model serves as a fundamental step for understanding how consumers perceive and engage with last-mile services. The conceptual framework is used as a guidance of the empirical investigations in the following chapters.

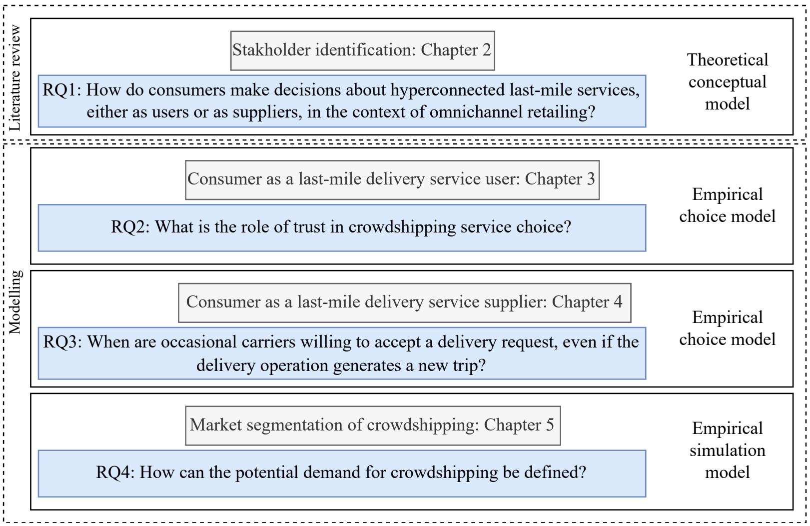


Figure 1.2: Research approach flow

After developing the conceptual framework, crowdshipping is used as a running case to explore the dual role of consumers: (1) as a last-mile delivery service user and (2) as a last-mile delivery service provider. In RQ2, to investigate how trust influences consumer adoption of crowdshipping services, an empirical choice model is estimated. Specifically, a Stated Preference (SP) experiment is designed to collect data on how consumers weigh different attributes of crowdshipping services, including trust-related factors. These attribute weights are then incorporated into a Hybrid Choice Model (HCM), which combines traditional discrete choice modeling with latent variables (trust).

Next, RQ3 focuses on the supply side of crowdshipping, specifically on the willingness of occasional carriers to take on delivery tasks. An empirical choice model is employed to examine the conditions under which occasional carriers agree to accept delivery requests, particularly if fulfilling the request requires them to generate a new trip, as opposed to delivering en route during an already planned journey. Data is collected from a SP experiment that presents occasional carriers with various delivery scenarios, varying compensation levels, travel distance, and time. By employing a Latent Class Choice Model (LCCM), we identify different groups of occasional carriers who may have varying preferences and behaviours towards becoming an occasional carrier.

Lastly, in RQ4, a simulation model is developed to integrate the demand-side insights from RQ2 and the supply-side factors from RQ3. The simulation model allows us to assess how different variables (e.g., compensation and trust levels) interact within an urban freight environment. By simulating different market scenarios, this model helps identify potential demand segments for crowdshipping and provide insights into how the service can be scaled efficiently.

1.6 Thesis contributions

Given the knowledge gaps identified in this dissertation, as outlined in Section 1.2, this research provides several contributions that are important to both the scientific community and broader societal applications, as described below.

1.6.1 Scientific contributions

This thesis contributes to the existing literature by addressing several knowledge gaps in consumer decision-making for last-mile logistics and crowdshipping.

In Chapter 2, the conceptual model for consumer decision-making introduces new insights into how independent actors—such as consumers, occasional carriers, and courier companies—interact within a complex urban logistics environment. While much of the research in last-mile logistics focuses on centralised decision- making models (Meyer et al., 2019), this study shifts the focus toward decentralised decision-making at the individual actor level, which represents a key contribution of this work. In this context, the consuming and producing roles that citizens can take are combined under the term ”prosumer.”

In Chapters 3 and 4, we focus on novel behavioural models to examine the decision-making processes of consumers for crowdshipping services. Chapter 3 explores demand-side behaviour in depth, particularly how consumer decisions— whether as users or service providers—shape the overall performance of crowdshipping. The incorporation of social elements, particularly trust, in the same chapter is another novel aspect of this work. Trust plays a critical role in crowdshipping, an emerging solution for last-mile delivery. By modelling the impact of trust on service adoption and participation, this thesis highlights a key factor that has been largely overlooked in the literature. In doing so, it provides insights into how trust can be operationalised to achieve the market acceptance of crowdshipping.

In Chapter 4, the thesis focuses on the supply-side decisions for crowdshipping and investigates an often neglected aspect of crowdshipping: the possibility of it generating new passenger trips. The study examines the willingness of individuals to undertake shipments through newly generated home-based trips and compares their choices to those of occasional carriers who integrate parcel deliveries into their routine home-to-work commutes. By modelling these interactions, we provide insights into the value of time for occasional carriers and the impact of sociodemographics on their decision to become suppliers in the urban delivery system.

In Chapter 5, this thesis bridges the gap between the macro-level challenges such as sustainability and the micro-level decisions made by individuals in a simulation environment to evaluate the use of crowdshipping for delivering high negative impact parcels. By investigating both sides—demand and supply—the research provides a more holistic view of how crowdshipping can be implemented in practice. This integrated approach helps to create a more accurate model of last-mile logistics, offering valuable insights not only for academics but also for policymakers and practitioners in the urban freight sector.

1.6.2 Societal contributions

Last-mile deliveries account for up to 53% of the total logistics costs Statista (2024). With urban transport responsible for 8% of global CO_2 emissions, cities worldwide needs to implement effective solutions to meet ambitious climate goals (IPCC, 2022). For instance, the European Union has committed to reducing transport emissions by 90% by 2050, which requires innovations that can achieve substantial environmental impact (Fetting & Office, 2020). To this end, this thesis addresses a critical gap in last-mile logistics by evaluating the feasibility of crowdshipping as a sustainable delivery solution. The rising demand for last-mile delivery is not solely an operational challenge since it has a societal implications with widespread impacts on urban congestion, air quality, and public infrastructure.

This thesis evaluates the feasibility and impacts of crowdshipping as a sustainable delivery solution. While crowdshipping has been proposed as a sustainable alternative for last-mile delivery, this research shows that its societal impact may be limited due to the challenges in aligning demand and supply mechanisms. The effectiveness of crowdshipping depends heavily on matching the availability of occasional carriers with the delivery needs of consumers, which can be difficult to achieve consistently in real-world settings.

Despite the optimistic projections for crowdshipping's ability to reduce traffic congestion and emissions, this study reveals that markets are more complex than studied so far. The demand for crowdshipping services often fluctuates, and the willingness of individuals to participate as carriers depends on various factors such as compensation, convenience, and trust. The concern that crowdshipping might generate new trips needs to be validated as well. As a result, crowdshipping may not always lead to substantial reductions in vehicle kilometres travelled or CO_2 emissions, and possibly even increases.

This thesis also highlights the conditions under which crowdshipping could be more impactful. By identifying specific niches—such as time-sensitive deliveries or customer-to-customer delivery demand—this research suggests that crowdshipping could still play a valuable role in certain segments of the market. Moreover, the insights gained from this study can guide policymakers and businesses in developing more targeted strategies to optimise the conditions for crowdshipping to function effectively. These strategies could include dynamic pricing models or incentive structures designed to better align supply and demand.

1.7 Outline of the thesis

Figure 1.3 shows an overview of the thesis, that is based on journal articles that are published or are under review at the time of writing the thesis. Thus, chapters 2 to 5 are identical to the published work. The thesis first starts with the review of consumer decision-making in the current last-mile delivery era (Chapter 2). We then investigate consumers' preferences and the perceived level of trust as service users of crowdshipping (Chapters 3). Chapter 4 explores willingness to become occasional carriers as service providers of crowdshipping. In Chapter 5, the market potential of crowdshipping is explored. Lastly, Chapter 6 concludes the thesis with conclusions and recommendations for research, practice and policymaking.

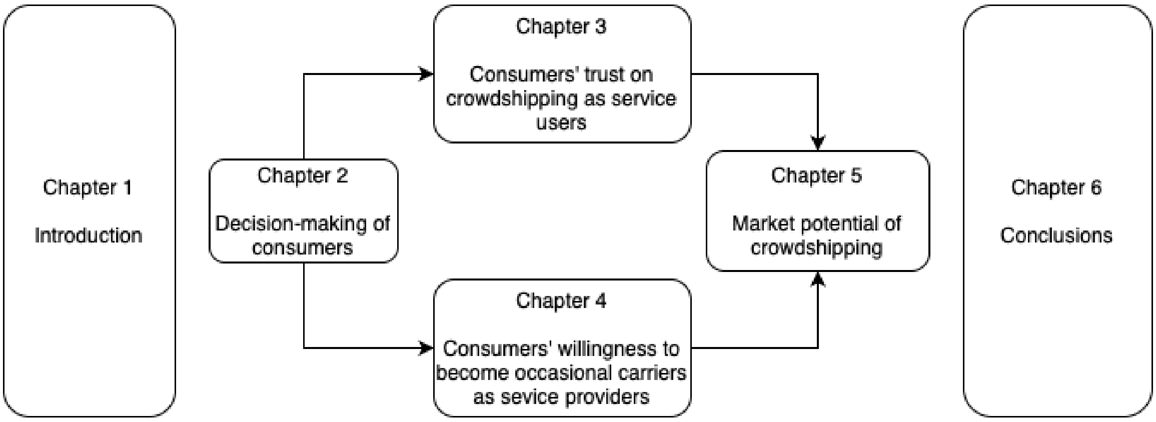


Figure 1.3: Organisation of the dissertation

Chapter 2

Decision-making characteristics of consumers

This chapter focuses on consumer decision-making in emerging last-mile delivery services. It addresses challenges and opportunities arising from e-commerce growth and emphasises the need for seamless integration in urban logistics.

By analysing consumers' roles as both users and providers of last-mile logistics, this chapter aims to address the knowledge gaps in current literature. It offers a comprehensive review and proposes a framework to understand key factors influencing consumer decisions and their impact on urban transport policies.

This chapter is based on the following journal paper: Cebeci, M., de Bok, M., & Tavasszy, L. (2023). The changing role and behaviour of consumers in last-mile logistics services: A review. Journal of Supply Chain Management Science, 4(3-4), 114–138. DOI: https://doi.org/10.59490/jscms.2023.7265

2.1 Introduction

The evolution of omnichannel retailing with its on-demand and customised deliveries has strongly affected the way last-mile delivery operations take place. In recent years, online purchases have increased rapidly, and consumers expect faster deliveries and more control over their ordered products. Considering some of the biggest retail markets, such as China, Germany, and the United States, last-mile delivery of parcels accounts for 40% of the market (Joerss et al., 2016). Additionally, the last-mile delivery market is projected to grow by 78% globally by 2030 (World Economic Forum, 2020). Emerging challenges for the ecosystem include emissions and congestion in urban areas, which are expected to increase by 32% and 21% by 2030, respectively (World Economic Forum, 2020).

Following the expanse of e-commerce, omnichannel retailing is replacing it as the new overarching retail strategy (Risberg, 2023). Omnichannel retailing offers diverse delivery channels to enhance product distribution across all possible consumer touchpoints (Risberg, 2023). This trend is primarily evident in the growth of e-commerce sales, resulting in increased pressure on service providers and the fragmentation of urban freight patterns, implying negative impacts on urban areas. In response, urban planners are actively seeking alternative solutions and working towards creating sustainable and cost-efficient urban freight transport methods (Holguín-Veras et al., 2020). If sufficiently integrated into logistics systems, technological advancements like parcel lockers and collaboration among last-mile service platforms could relieve problems (Pisoni et al., 2022).

As part of the ongoing omnichannel revolution, end-users in last-mile logistics are experiencing a significant transition from their traditional role as mere recipients of services, towards one of active carriers. They participate in the delivery process by picking up, handling, and transporting products not only for themselves but also for others (X. Wang et al., 2023, 2022). We argue that in order to develop effective policies for future last-mile logistics, it is crucial to comprehend the decision-making processes of consumers. This includes understanding their transportation demands as well as their involvement in the supply chain as service providers.

The Physical Internet (PI) offers a contextual vision for innovations in city logistics (Crainic & Montreuil, 2016; Crainic et al., 2023). The PI envisions a future logistics system that integrates various elements mentioned above, enabling asset sharing and flow consolidation through standardised packaging, modularisation, protocols, and interfaces (Montreuil, 2020). A central tenet of the PI vision is hyperconnectivity, implying the full interconnection of services to create an open, dense network of delivery services. While existing research on the PI has predominantly concentrated on designing this system, there is a notable gap in addressing consumer decisions within the PI. The only study we have found addressing this aspect is by Bidoni & Montreuil (2021), which mentions the positive impact of consumer satisfaction on the adoption of new services. We are not aware of any other research explicitly addressing this decision-making behaviour within the PI framework.

Existing review studies have examined various partial aspects of consumer decision-making, concerning inbound and outbound logistics (Monnot et al., 2023) and omnichannel retailing (Mishra et al., 2021; Lafkihi et al., 2019), within the context of smart and sustainable deliveries (Pan et al., 2021). These studies focus on the demand side, mainly on consumer choices related to delivery services when ordering goods online. Recent reviews by Ma et al. (2022), X. Wang et al. (2023) and Yusoff et al. (2023) touch upon consumer behaviour and last-mile delivery but with limited mention of consumer participation. Another study by Risberg (2023) proposes a decision framework for omnichannel retailers, highlighting logistics activities but overlooking consumer decision-making. Empirical studies have explored consumer decision-making in the last-mile, considering factors such as delivery service (Merkert et al., 2022; Cai et al., 2021) and personal attributes (X. Wang et al., 2018). However, also here, there is a gap in understanding consumer behaviour towards third-party last-mile services, such as crowdshipping.

Common limitations in the literature include cultural bias due to region-specific case studies and limited sample sizes that constrain the generalisability of findings. Moreover, many studies lack an integrated view that considers both the demand and supply perspectives or fail to consider the role of consumers as active participants in the logistics chain. These limitations emphasise the need for a broader, more integrative review to contextualise and address these research gaps. Therefore, our research objective is to provide a comprehensive review that contributes to the literature on PI, on last-mile delivery and consumer decision-making. To achieve this objective, we focus our exploration on the following main question:

How do consumers make decisions about hyperconnected last-mile services, either as users or as suppliers, in the context of omnichannel retailing?

To answer our main research question, we investigate the choices consumers make when engaging with hyperconnected last-mile services, both as users benefiting from the services and as potential suppliers involved in last-mile logistics. Our approach involves exploring user decision-making characteristics and satisfaction, considering the integration of these services within omnichannel retail experiences. Simultaneously, we consider consumers' willingness to become suppliers, also examining the role of crowdshipping. The question of decision making applies to all forms of modern shipping solutions. From this inventory, we create a conceptual model that can guide research into the various aspects of the main question. Finally, we provide related recommendations for research.

The paper is structured as follows: Section 2.2 explains the literature review approach. It is followed by an explanation of the review results in Section 2.3. Section 2.4 discusses the various emerging research directions. Section 2.5 concludes with a summary of the findings and recommendations.

2.2 Review Approach

The research followed the Systematic Literature Review (SLR) approach (Wee & Banister, 2016; Xiao & Watson, 2019). The review is initiated by formulating the research problem. In a second stage, a coding scheme is created where the aim is to identify the synthesis of studies concerning the journals, research context, and methodological approaches. A screening of literature is done for relevance, and, after subsequent searches, a final set of papers is selected, followed by data extraction and analysis. Finally, the main findings of the review are synthesised and reported.

Figure 2.1 shows the main streams of literature considered in this review: (1) the omnichannel retailing literature, where the emphasis is on consumer behaviour in the final leg of omnichannel retail operations; (2) the last-mile logistics literature, which explains innovative last-mile delivery services; (3) decision-making literature, which primarily focuses on consumers' behaviour and decisions. Moreover, by adding the component of hyperconnectivity to these research streams, we aim to extend our literature review by considering the vision of the PI and providing an overview of studies conducted in this area. Vice versa, the older and larger streams of omnichannel retailing, last-mile logistics, and decision-making literature contain several important insights that, positioned within the PI literature, enrich the PI framework.

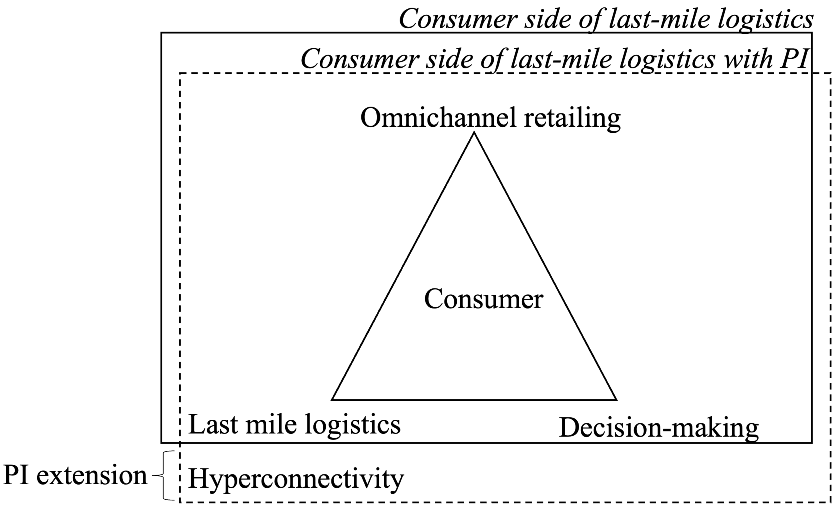


Figure 2.1: Main research streams considered in the review

In Figure 2.2 below, the process of our literature review study is illustrated. We construct the main body of literature using specific keywords. To do this, we conduct our searches on Scopus. In our exploration of consumer-focused studies, our queries include terms such as "consumer," "decision," and "behaviour," particularly in the context of the "last-mile" and "omnichannel." Additionally, we use variations of "crowdshipping," including "crowd-shipping" and "crowdsourcing," as keywords to explicitly incorporate studies in this area, considering crowdshipping enables consumers to act as service providers for deliveries. Moreover, we extend our search to cover the physical internet, hyperconnectivity, and consumer engagement in the last-mile logistics. By applying a diverse range of keywords such as "physical internet," "hyperconnect*," "decision," "omnichannel," and "last-mile," we ensure a comprehensive exploration of both consumer-centric and PI-related literature.

Our search terms are specified in British English, aligning with Scopus' standards. Notably, we avoid hyphens in terms such as "omni channel" and "last-mile," as Scopus recognises both British and American English variations without requiring hyphenation. Specifically, we search for omnichannel in two ways: (1) "omnichannel" and (2) "omni channel," resulting in different numbers of search results. Additionally, we include the term 'consumer' in our search queries.

However, this specific inclusion did not yield a significant number of eligible papers.

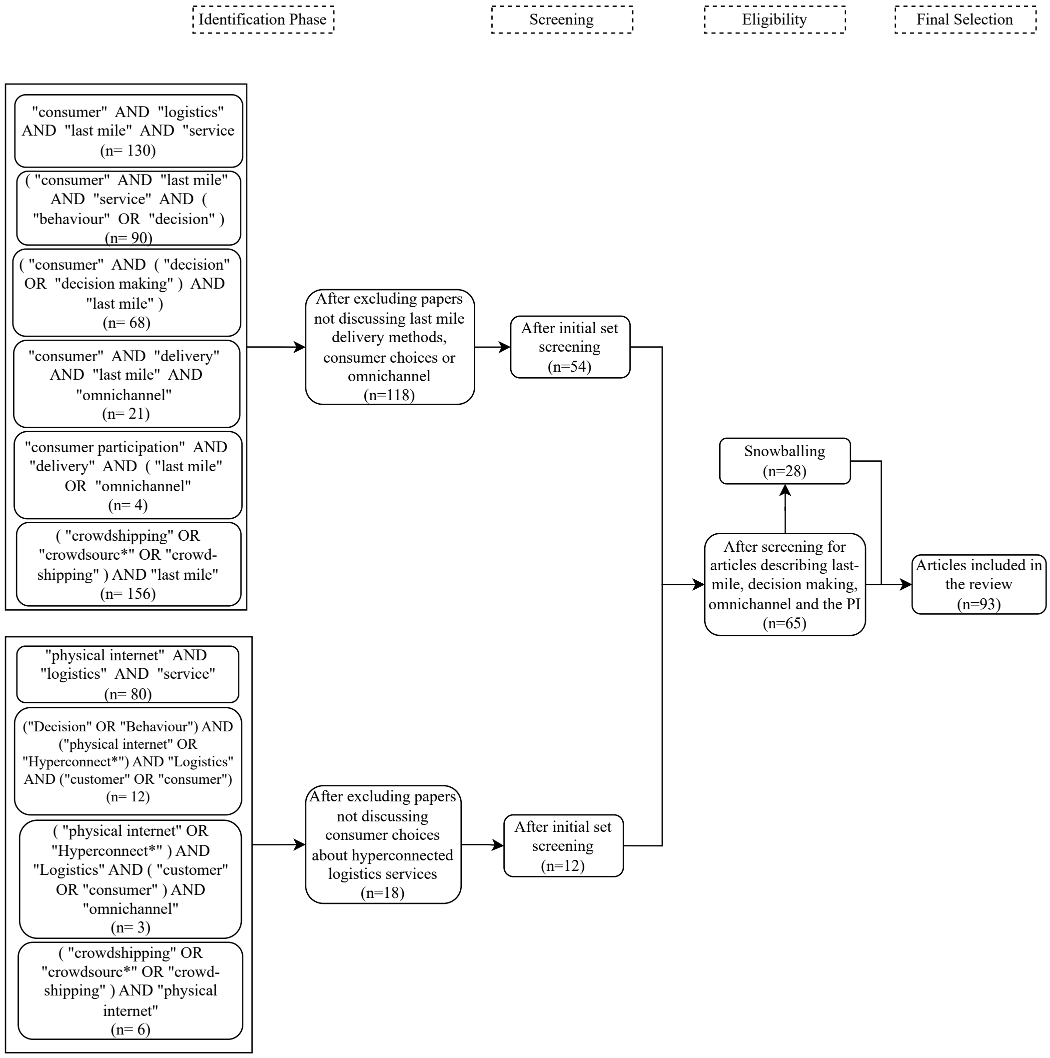


Figure 2.2: Paper selection process (date of search: 28 November 2023)

We searched Scopus and Web of Science using specific strings, as shown in Figure 2.2, applied to the title, abstract, and keywords. No time constraints were applied, and articles had to be in English and published in indexed journals or proceedings. For cross-referencing and validation, we confirmed that the same search strings yielded similar results in both databases. After the initial search, we removed duplicates and irrelevant publications. Finally, we applied snowballing techniques to the remaining papers, resulting in 93 unique papers included in this review.

2.3 Review results

2.3.1 Bibliometric overview

As can be seen in Table 2.1, the set of 93 papers has a varied background from the mentioned areas of literature. In addition to seventy-seven journal articles, we also include eleven conference papers and five book chapters. Our analysis shows that the research interest in the topic increases after 2015. The distribution of research contributions among different countries shows a broad landscape of scholarly engagement. The United States, Singapore, China, South Korea, and France lead with 14, 13, 12, 12 and 10 contributions respectively. The publications listed in the table exhibit a wide array of focuses, ranging from transportation and retail to marketing and consumer services. These journals cover a broad spectrum of topics, including transportation research, logistics and distribution management, retailing, and consumer behaviour. The publications cover different types of research including review papers, qualitative and – predominantly – quantitative modelling.

Table 2.1: Bibliometric scope of the selected papers

Years	2005 (2); 2006-2008 (0); 2009 (1); 2010 (0); 2011 (1); 2012 (2); 2013-2014 (0); 2015 (1); 2016 (5); 2017 (6); 2018 (11); 2019 (11); 2020 (12); 2021 (12); 2022 (15); 2023 (13); 2024 (1)
Authors	Wang,X. (12); Yuen,K.F. (12); Wong,Y.D. (9); Gatta,V. (6); Marcucci,E. (6); Montreuil,B. (5); Teo,C.C. (5); Ballot,E. (3); Koh,L.Y. (3); Buldeo Rai,H.(2); Others (30)
Countries	USA (14); Singapore (13); China (12); South Korea (12); France (10); Others (32)
Sources	Journal of Retailing and Consumer Services (7); Transportation Research Part E (8); Logistics and Transportation Review (5); Transportation Research Procedia (5); Sustainability (4); Cities (2); IFAC Proceedings Volumes, IFAC Papers online (2); Industrial Management and Data Systems (2); International Journal of Logistics Management (2); International Journal of Physical Distribution And Logistics Management (2); IFAC Proceedings Volumes, IFAC Papers online (2); Industrial Management and Data Systems (2); International Journal of Logistics Management (2); Others (56)
Approach	Quantitative modelling (76); Review studies (13); Qualitative modelling (4)

Table 2.2 below provides an overview of the main research methods and modelling techniques used in the corpus of this review study. A detailed overview is provided in Appendix A.

Table 2.2: An overview of the methods used

	Author(s)
Factor Analysis	Tang et al., (2021); Wang et al., (2020)
Regression	Millioti et al. (2020); Tang et al., (2021); Felch et al. (2019); Hagen, & Scheel-Kopeinig, (2021); Yuen et al. (2018); Meuter et al. (2005); Wang et al. (2023); Chatterjee and Kumar (2017); Marcucci et al. (2017)

Structural Equation Modelling (SEM)	Wang et al. (2021c); Chen et al. (2018); Giglio and Maio (2022); Zhou et al. (2020); Edrisi and Ganjipour (2022); Cai et al., (2021); Kapser & Abdelrahman, (2020); Koh et al. (2023); Koh et al. (2023b); Wang et al. (2018); Tsai and Tiwasing (2021); Yuen et al. (2019); Titiyal et al. (2022); Aziz et al. (2021); Upadhyay et al. (2022)
Stated Preference Experiment (SPE)	Gatta et al. (2021); Gatta et al. (2018); Wicaksono et al. (2022); Cebeci et al. (2023); Cebeci et al., (2023b); Merkert et al. (2022); Polydoropoulou et al., (2022); Marcucci et al. (2021); Hsiao (2019); Maltese et al. (2021); Le and Ukkusuri (2019); Serafini et al. (2018); Miller et al. (2017); Mohri et al. (2024)
Revealed Preference Experiment (RPE)	Bjerkan et al. (2020); Cauwelier et al. (2023); Rossolov et al. (2021); Wieland (2021)
Optimisation studies	Raviv and Tenzer (2018); Di Febbraro et al. (2018); Zhang et al. (2023); Faugère and Montreuil, (2020); Orenstein and Raviv, (2022); Pan et al. (2021)
Descriptive analysis	Mahdi Zarei et al. (2020); Rai et al. (2021)
Conjoint analysis	Rai et al. (2018); Nguyen et al. (2019)
Cluster analysis	Schaefer and Figliozzi (2021); Rai et al. (2021); Nguyen et al. (2019)
Latent Class Analysis	Wang et al., (2020); Mohri et al. (2024)
Simulation	Bidoni and Montreuil (2021); Devari et al. (2017); Akeb et al. (2018); Chen et al., (2017)
System dynamics	Melkonyan et al. (2020); De La Torre et al. (2019)
Multi-criteria analysis	Melkonyan et al. (2020)
Focus group	Vakulenko et al. (2018)
Interviews	Madlberger and Sester (2005); Haridasan and Fernando (2018)

A notable finding from the review study is that a significant portion of the studies employ survey techniques for collecting data. While a subset of the studies applies stated preference experiments (SPEs), where respondents are asked to choose from several alternatives, a considerable number of studies rely on structural equation modelling (SEM) techniques in which person-level indicators are used to estimate the dependent variable. Moreover, regression and factor analysis, as well as discrete choice models in SPEs, are applied in most of the studies. As noted by Mishra et al. (2021) and Monnot et al. (2023) focus on individual decisions may oversimplify the linkages among consumer choices, resulting in limited understandings of consumer decision-making.

To represent the heterogeneity in choice preferences, a few studies employ cluster and latent class analysis. Cluster analysis focuses on finding natural patterns or structures in the data based on the similarity of observations (Blashfield & Aldenderfer, 1978), while latent class analysis aims to identify unobserved latent classes that generate the observed response patterns (Boxall & Adamowicz, 2002). Although these methods are straightforward and easy to interpret, their generalisability and applicability in policymaking is challenging due to the complexity of identifying target groups. Clusters that emerge from a mathematical grouping of individuals are often difficult to identify or address in practice.

The reviewed studies reveal a scarcity of use of simulation techniques, the predominant focus is on optimisation. The small set of studies employing simulation in the realm of consumer decision-making focuses on crowdshipping. These studies explore crowdshipping as a collaborative last-mile delivery solution (Akeb et al., 2018), examine consumer acceptance of this service in relation to their social network (Devari et al., 2017), assess the sustainability of last-mile delivery services (Melkonyan et al., 2020) and consumer behaviour and the market dynamics (De La Torre et al., 2019).

Lastly, our review study shows a lack of research applying qualitative modelling techniques. The representation of social sciences and management sciences in this body of literature is low, compared to operations research and industrial engineering scholars. Nevertheless, qualitative modelling techniques can be a valid methodology to explore and understand the dynamics of a delivery service and to specify the assumptions for complex quantitative models. Moreover, the outcome of the qualitative research can provide transferable knowledge.

2.3.2 A conceptual model for consumers' logistics decisions

This section outlines the conceptual framework, which is built on the studies found, organized around the typical consumer decisions observed in the literature. We first define a skeleton framework of consumer decisions and next discuss the different components of the model.

One of the first studies on logistics decision-making, by Bowersox et al. (1974), identified five logistics components that form the industrial logistical system: facility location, inventory, transportation, handling and storage, and communication. Granzin & Bahn (1989) identified ten decision areas in consumer logistics and linked these to Bowersox's five functional subsystems. The decisions considered ranged from type of residence and vehicle type to post-trip communication, such as communicating with other households regarding the trip and the quality of the service (Granzin & Bahn, 1989). We take this framing as a starting point, noting that here the roles and choices associated with consumers were purely seen as for their own consumption purposes (Bahn et al., 2015), the final leg of the delivery being handled by the consumer. We enrich this framework with the supply-side choices involving consumer participation as a carrier or handler of products for others.

According to (Granzin & Bahn, 1989), facility location represents the point of consumption, while inventory is defined as the availability of a specific product for consumption at a desired place and time. Next, when it comes to transportation, the main consideration is the choice of transportation mode. In an omnichannel environment, consumers are provided with diverse shopping options, including online and in-store shopping, as well as hybrid choices like searching online and buying in-store, or vice versa. Each option triggers different logistics processes (Madlberger & Sester, 2005). Depending on the shopping channel decision, consumers make a delivery method choice. In the context of an omnichannel retailing, e-retailers provide consumers with various delivery methods, such as collection points, in-store pickup, parcel lockers, click-and-collect, crowdshipping, and home delivery (Risberg, 2023). These delivery options will also impact consumers' decisions regarding transportation as well as handling, and storage. Lastly, communication refers to the flow of information during the (post-) shopping process (Granzin & Bahn, 1989). While communication could be about the choice of shopping options or the delivery method, it could also be about the evaluation and feedback concerning the choices made.

The conceptual framework presented in Figure 2.3 can serve as a basis for modelling urban freight systems, including with statistical analysis using for example SEM, or more comprehensive behavioural urban freight models, using for example agent-based simulation.

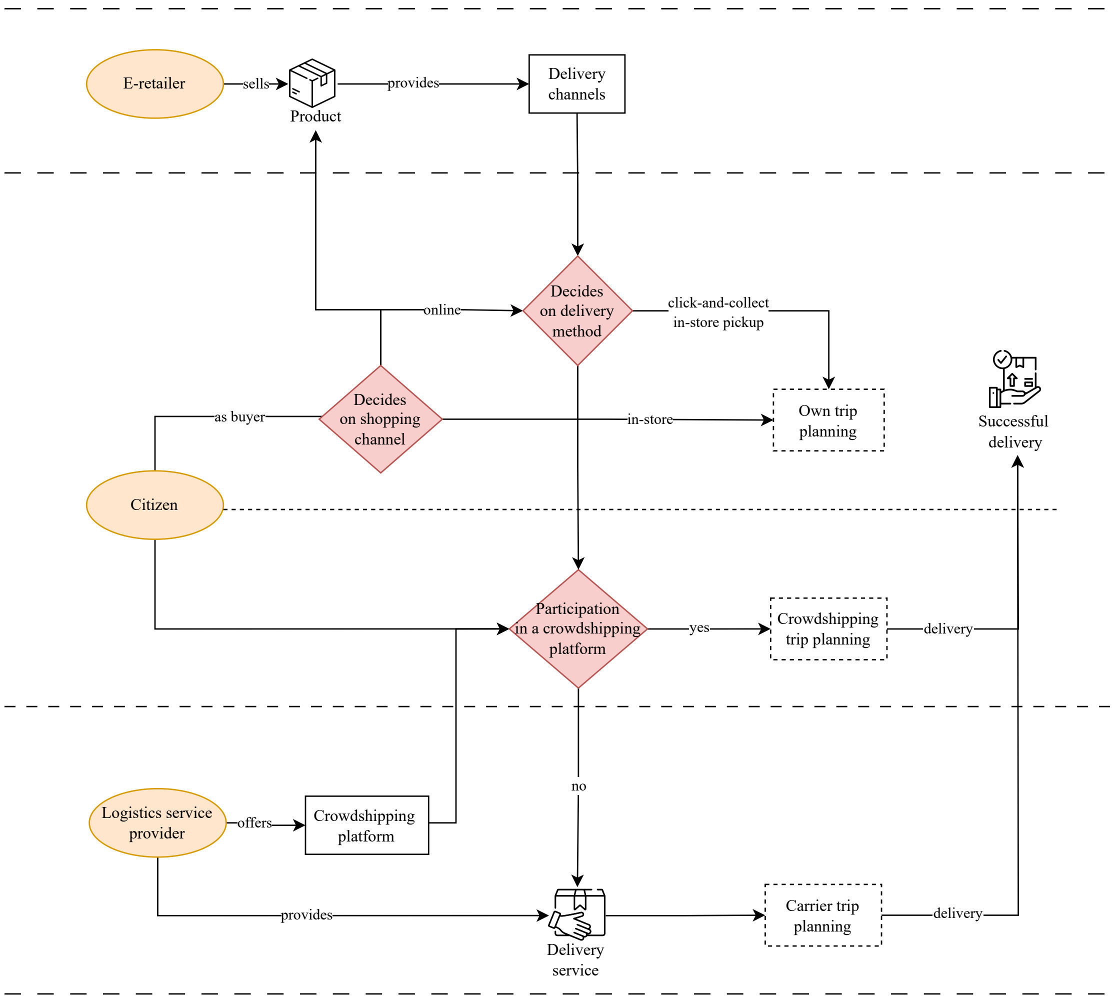


Figure 2.3: The conceptual framework for the review study (read the figure from left to right

Although e-retailers offer delivery services, these services are integrated into the omnichannel strategy, and consumer choices are heavily influenced by them. With a range of delivery methods available, such as click-and-collect, crowdshipping, or home delivery, consumers' trip planning behaviour varies. Depending on the chosen delivery method, logistics service providers also play a crucial role in last-mile delivery, which involves the execution of traditional delivery and the connection of travellers and senders through online platforms like crowdshipping.

In this context, a successful delivery refers to the parcel being delivered to the intended location of the consumer. The scheme also applies for return products, where delivery should be interpreted as “return delivery” and is implemented using the same decisions of a channel, a shipping method and an execution platform.

Beyond the consolidation of shipments by service providers, openly sourced and shared delivery networks also exist to support horizontal collaboration between service providers in e.g. freight platforms (Montreuil et al., 2013). In the PI vision, these networks are expected to broaden and merge so that fragmented flows can be interconnected (Ballot et al., 2018).

In the following sub-sections, we discuss the framework in detail, with a substantive review focusing on the 3 key consumer decisions, including choices regarding shopping channels, delivery methods, and decision to become a service supplier. Of all the literature reviewed, the choice of delivery method has been studied most extensively, with 47 publications identified. For the choice of shopping channel, we identified 11 studies and for crowdshipping participation 17 studies. Lastly, 18 PI-inspired studies 6 of which mentioning the general PI exploratory studies are identified. A detailed overview, describing the objectives and the system attributes considered in each study, is provided in Appendix 1.

Decision on the shopping channel

The shopping channel decision of a consumer impacts a chain of processes (Halibas et al., 2023). With the rise of e-commerce, consumers now have the option to make purchases online, revolutionising the conventional in-store shopping experience. This digital shift not only provides consumers with the convenience of browsing and buying products from the comfort of their homes but also poses a challenge for retailers in ensuring efficient and reliable last-mile delivery (Madlberger & Sester, 2005). The shift from multi-channel to omni-channel retailing empowers consumers to seamlessly combine various buying channels. For instance, they can explore products in-store and purchase online or research online and buy in-store (Halibas et al., 2023). This diversity underscores the importance of last-mile delivery services that enable product delivery. In line with this transition, Mahdi Zarei et al. (2020) find out that access to facilities and convenience are some of the most important factors affecting consumers’ shopping channel choice.

Piotrowicz & Cuthbertson (2019) highlight that consumer acceptance of online grocery shopping is influenced by factors such as delivery fees, delivery time, product quality, and convenience. Similarly, the parcel value and product category are some of the important specifications when it comes to the choice of shopping channel. In a choice experiment setting, Polydoropoulou et al. (2022) highlight that consumers would rather shop in-store if the item is large and of high value. The authors reveal that questions regarding the shipment, such as who will deliver the product and how the return process is done, influence preferences about the shopping channel choice. Similarly, Aziz et al. (2022) show that product availability (range) and parcel value are some of the determinants of the shopping channel choice. Chatterjee & Kumar (2017) investigate the willingness to pay for a delivery in different retail channels. The authors also conclude that consumers are in favour of omnichannel retailers for products such as furniture since omnichannel retailing allows consumers to connect online and physical stores (Chatterjee & Kumar, 2017).

In the PI context, Derhami et al. (2021) examine the product availability under uncertain demand conditions and find out that the available inventory has a positive impact on the customer's willingness to accept a transshipment. However, the underlying behavioural factors driving these preferences require further exploration. Levin et al. (2003) also highlight that the category of products affects consumers' choice of shopping channel. Madlberger & Sester (2005) show that the characteristics of the purchase and its availability in the physical store might lead to different shopping channel choice. With a consumer choice model, Rossolov & Susilo (2024) highlight that each product category has unique characteristics, such as shopping frequency and volume, as well as usage conditions like duration and consumption levels. This diversity influences the choice of channel with regards to purchasing cost and time.

Another study compares motivations of online and in-store shoppers based on product types, revealing distinct preferences (Haridasan & Fernando, 2018). In a choice model, Maltese et al. (2021) show that delivery cost has a negative effect on the choice of online shopping. Similarly, recent studies (Marcucci et al., 2021; Wieland, 2021) highlight that product price and delivery cost are the most important drivers for the shopping channel choice. Similarly, Hsiao (2009) identifies four attributes that affect consumers' utility when it comes to the choice of physical store and e-shopping: (1) travel cost, (2) travel time, (3) purchase price, and (4) delivery time. While existing research has examined the shopping choices independently, a significant research gap exists concerning an integrated approach, linking the context of several parallel shopping channels with various available delivery methods. Bridging this gap is essential for a comprehensive understanding of consumer behaviour in the evolving omnichannel landscape.

Decision on delivery method

The selection of a delivery method is linked to the choice of shopping channel as consumers can receive items immediately when purchased at a physical store whereas with online shopping, consumers have to wait for product delivery (Hsiao, 2009). Delivery method choice includes a range of options for delivering products to consumers. Most of the papers from our set that focus on consumer decision-making (47 out of 93) relate to this decision. The selection process involves choosing the most suitable delivery methods based on several factors, related to the product, the service attributes, and the individual making the decision. The identified variations in e-commerce consumers' preferences and behaviours regarding different delivery methods present a significant research gap. These differences underscore the importance of comparing and transferring e-commerce and transport research findings across different countries and context.

- **Product attributes**

In several recent studies, researchers have explored how consumer choices regarding last-mile delivery are influenced by specific product characteristics. The literature presents conflicting findings in places. Bjerkan et al. (2020) show that for small and medium-sized parcels, consumers mostly prefer collection points as delivery location. In the case of heavier goods, home delivery is mostly preferred delivery option. Conversely, Cauwelier et al. (2023) (2023) show that consumers choice of last-mile delivery method is not affected by the weight of the parcel. In a stated preference experiment conducted by Merkert et al. (2022), it is shown that parcel value significantly influences the choice of delivery method. The study emphasises that parcel lockers and drones become more appealing for high-value items. Additionally, consumers tolerate an increase in the delivery cost in the case of high-value product delivery (Merkert et al., 2022). In contrast, Nguyen et al. (2019) grouped products by value and found that consumers are willing to change their delivery preferences to reduce the delivery cost, regardless of the product category. X. Wang et al. (2024) emphasise the importance of socio-demographic factors and product value. In a recent review study, Titiyal et al. (2023) highlight that product type has a direct influence on the consumer's last-mile delivery method choice. Bjerkan et al. (2020) show that the use of pick-up points is prominent for non-heavy product segments such as shoes and textiles. Nguyen et al. (2019) highlight that various delivery attributes hold similar importance for different types of products; however, consumers' sociodemographic characteristics mostly drive their preferences for delivery service choices. Madlberger & Sester (2005) highlight that the product categories have a significant effect on the consumer preferences for delivery methods such as home delivery, pick up point and delivery to the working place. In a recent study, Wieland (2021) find out that the preferences of consumers differ depending on the product category for click-and-collect method.

- **Service attributes**

The plethora of available delivery methods, ranging from click-and-collect services to home deliveries, has transformed the way consumers choose their preferred delivery options. The plethora of available delivery methods, ranging from click-and-collect services to home deliveries, has transformed the way consumers choose their preferred delivery options. Click-and-collect services, for instance, allow consumers to make purchases online and collect them from a physical store within an omnichannel architecture (Risberg, 2023). Another delivery method where there is an active involvement of consumers is self-collection points, or parcel lockers. This service enables consumers to participate in the last-mile delivery operation by picking up or dropping off their merchandise at a specific point. Crowdshipping leverages a network of individuals to carry out deliveries, often providing a more personalised and localised solution. Recently, many businesses have appeared in crowdshipping such as Easybring and Friendshippr (Rougès & Montreuil, 2014). Next, we describe the delivery methods in more detail. Central to this transformation are specific attributes inherent in these delivery methods, playing a pivotal role in shaping consumers' preferences and decisions.

Research by Milioti et al. (2020) emphasise that factors such as the accessibility and timeliness of the click-and-collect point significantly influence consumer choices. Various service determinants of parcel lockers are identified, such as accessibility and location (Vakulenko et al., 2018). The active use of parcel locker service also greatly depends on the network structure offered, which affects the accessibility of such a service (Schaefer & Figliozzi, 2021). In the case of a logistics service provider owned parcel locker service, the use of these services requires interconnection between retailers, logistics service providers, and consumers' intention to use.

Convenience and ease of use (Vakulenko et al., 2018; Tang et al., 2021; Yuen et al., 2018, 2019; Tsai & Tiwasing, 2021) are some of the other attributes comprehensively studied by several scholars. Ease of use and convenience (Cai et al., 2021; Koh et al., 2023) are found to be influential in the choice of advanced technology-enabled services. A recent study (Koh et al., 2024) highlights that consumers' intention to use crowdshipping is due to the ease of use of the service. Generally, the choice of the home delivery option also lies in its convenience (Hübner et al., 2016).

Delivery time and reliability are among the key factors influencing the choice of parcel lockers (Merkert et al., 2022; Yuen et al., 2019; Tsai & Tiwasing, 2021). These characteristics of the delivery service also impact preferences for unmanned aerial delivery drones (Merkert et al., 2022). Some studies explore service attributes of crowdshipping, such as delivery time (Gatta et al., 2018). A recent study highlights that the willingness to use micro-depots highly depends on delivery time Hagen & Scheel-Kopeinig (2021).

Furthermore, certain studies focus on the choice of delivery methods for e-groceries, emphasising that high delivery costs strongly influence the preference for the click-and-collect option (Gatta et al., 2021; Marcucci et al., 2021), as well as consumers' willingness to pay for the service (Aziz et al., 2022; Maltese et al., 2021). Gatta et al. (2018) studied the effect of crowdshipping service cost from the perspective of consumer demand. Another study indicates that the delivery cost of parcel lockers should be lower than that of home delivery (Schaefer & Figliozzi, 2021)

Moreover, the perceived environmental impact of delivery methods is another crucial attribute that comes into play. Eco-friendliness is studied from the perspective of consumer acceptance for crowdshipping services (Wicaksono et al., 2022; Gatta et al., 2018). Buldeo Rai et al. (2021) found that potential users favour crowdshipping due to possible sustainability improvements. (Edrisi & Ganjipour, 2022) highlight that environmental concerns affect consumer choices of advanced technology-enabled services as well as the click-and-collect service (Marcucci et al., 2021).

Some concerns regarding the parcel lockers include fault handling capability, malfunctioning, lack of information (Tang et al., 2021; Vakulenko et al., 2018), and security (Felch et al., 2019; Yuen et al., 2019). Regarding the advanced technology-enabled services, safety and privacy (Kapser & Abdelrahman, 2020; Koh et al., 2023; Polydoropoulou et al., 2022) become some of the attributes that can impact the consumer choice. Zhou et al. (2020) find out that the perceived risk associated with the self-collection service negatively affects the intention to use the service and the user's satisfaction. There are also some crowdshipping specific attributes since the crowdshipping service involved occasional carriers for the actual delivery task such as reputation of the occasional carrier (Le & Ukkusuri, 2019b; Cebeci et al., 2024), and factors affecting user trust (Cebeci et al., 2023).

In a hyperconnectivity context, Kim et al. (2021) propose an agent-based model to implement the PI concept in urban logistics systems. This study sheds light on the benefits of such a hyperconnected network; however, consumers are modelled under naive behavioural assumptions in terms of their preferences for retailers, delivery pick-up times, and conditions (Kim et al., 2021). A recent study proposes a business model in which the consumer directly interacts with either a human operator or parcel lockers located at the micro-depot to pick up and return the parcels (Rosenberg et al., 2021). Interestingly, this study can be considered an implementation of PI in a last-mile context by creating a shared micro-depot network with parcel lockers, even though there is no reference to the PI literature. In the PI literature, smart and/or modular lockers are introduced, which can diminish the logistics flow through consolidation (Montreuil, 2016; Pan et al., 2021), and several designs of lockers are discussed (Faugère & Montreuil, 2020). Orenstein & Raviv (2022) propose a ”hyperconnected service network” (HCSN) for parcel delivery by using each delivery node, such as automated parcel lockers, as a point at which a parcel could be dropped off and picked up. By designing such a network, the authors conclude that HCSN has the potential to improve service levels and reduce delivery costs for service providers. However, it is important to mention that the studies focusing on parcel lockers in PI are either on the conceptual level or network design by applying operations research.

All in all, in terms of delivery method choice of the consumers, the previous research mainly focuses on delivery methods independently. The lack of interaction and collaboration between these last-mile delivery services creates ambiguity for consumers. They might face challenges in understanding how these services work together seamlessly, impacting consumers’ decisions to use these services.

- **Personal attributes**

Personal motivation plays a crucial role in shaping consumers’ last-mile behaviour (Mahdi Zarei et al., 2020). Chen et al. (2018) point out that consumers’ intentions to use a parcel locker service are positively affected by their optimism. Edrisi & Ganjipour (2022) investigate whether consumer optimism has a positive impact on the adoption of sidewalk autonomous delivery robots. Similar to optimism, consumers’ innovativeness is considered a factor affecting the adoption of parcel lockers (Chen et al., 2018; Yuen et al., 2018). However, there is a gap in understanding how these attributes influence different delivery options when they are all available for consumers.

Previous experiences, habits, and consumer satisfaction are expected to affect consumers’ perceptions and motivation to use a delivery method (Meuter et al., 2005). In particular, the omnichannel retailing strategy intends to provide positive consumer experiences at each consumer touchpoint. Vakulenko et al. (2019) investigate the effect of the online experience on consumer satisfaction. Cai et al. (2021) provide evidence that consumers’ intentions to use a service is also affected by their habits. Together with familiarity and engagement, consumers are more likely to form habits concerning the delivery service (Cai et al., 2021). Tang et al. (2021) show that consumer experiences is negatively affected by the service price. Consumer satisfaction has also been a topic in the PI. Bidoni & Montreuil (2021) study changing consumer behaviour and demand variability for new urban logistics services. The authors state that consumer satisfaction, advertisements, word-of-mouth, and incentives have a positive impact on the use of new services (Bidoni & Montreuil, 2021).

Personal characteristics also refer to emotional attitudes towards the use of the service. With the involvement of consumers in logistics activities, consumers take over some of the activities that logistics service providers usually provide, such as picking up or dropping off a parcel at a collection point and becoming an occasional carrier to deliver a parcel for other consumers. Consequently, consumers might feel that their time and effort are used and that they are treated unfairly, which in the end impacts their satisfaction level for a given service (X. Wang et al., 2021). Vakulenko et al. (2018) provide evidence that consumers find the use of parcel lockers fun and interesting as they actively engage in the service. Similarly, X. Wang et al. (2018, 2021) emphasise that the adoption of automated parcel stations is not only about the movement of the parcel and associated service characteristics but also about emotional attitudes. (X. Wang et al., 2021) find out that while some consumers find the use of self-collection points engaging as an empowerment tool, others would find the service intimidating.

In a recent review study, Bhukya & Paul (2023) focus on communication and social influence on consumer behaviour and discuss several research directions concerning e-retail, e-commerce, and the sharing economy. Giglio & Maio (2022) study the importance of communication between a logistics service provider and its consumers regarding the choice of crowdshipping. The author concludes that communication is essential for ensuring the quality and reliability of the crowdshipping service, as well as the trust and satisfaction of the participants. The paper mentions factors such as trialability and observability, which depend on the availability and accessibility of information and the use of feedback from new technology. These factors serve as predictors of consumers' choices. In a system dynamics model, De La Torre et al. (2019) explores the theory of word-of-mouth (WoM). The authors describe process of consumers evaluating a service and communicating that experience with other consumers (De La Torre et al., 2019) in a local food logistics network.

Yuen et al. (2018) highlight that the decision to use self-collection points can be influenced by consumers' conformance with their social environment, such as family and peers. Zhou et al. (2020) examine the degree to which opinions of others influence the adoption of self-service parcel delivery options such as collection points and parcel lockers. Given that new delivery services are not entirely experienced by the majority of consumers, the social environment is expected to play a vital role in the acceptability of the service (Felch et al., 2019). In an empirical study, Mahdi Zarei et al. (2020) find out that family and friends influence consumer's last-mile delivery method selection. Cai et al. (2021) find that consumer decisions about logistics technologies are affected by the opinions of others. Devari et al. (2017) propose a model to test the effect of crowdshipping by using consumers' friends or acquaintances to deliver the parcels. The study sheds light on the potential benefits of the service for friendship-based last-mile delivery. The paper mentions four levels of friendship that affect the willingness and preferences of consumers to perform or receive crowdsourced delivery. Akeb et al. (2018) study a crowdshipping service based on neighbour relay as a solution to diminish delivery failure. A recent study (Buldeo Rai et al., 2021) identifies four consumer segments to explore preferences for crowdshipping delivery. The findings show that consumers are more inclined to choose crowdshipping if the carrier is someone from their neighbourhood or one of the retailer's employees.

Decision to become a service supplier

Willingness to become a delivery service supplier, referred to here as an occasional carrier, has been the subject of several studies. In a recent review study, Mohri et al. (2023) identify key factors influencing individuals' participation as service providers. The authors emphasise factors like reimbursement schemes, flexibility, parcel characteristics and platform functionalities, such as tracking tracing.

In a behavioural study, Marcucci et al. (2017) demonstrate that compensation levels are one of the most significant incentives for becoming an occasional carrier. Similarly, Le & Ukkusuri (2019b) point out that the expectation of payment is influential, covering not only the cost of delivery driving time but also other expenses such as fuel and maintenance costs. Like Marcucci et al. (2017), the authors suggest that socio-demographic characteristics significantly influence respondents' decisions to become a bringer for a parcel. In another behavioural study, Wicaksono et al. (2022) reveal that additional travel time, compensation, and package weight can significantly influence the propensity to become an occasional carrier. Le et al. (2021) model occasional carriers' willingness to be paid under different pricing and compensation schemes. In a recent study, Cebeci et al. (2024) point out that the conditions under which crowdshipping exacerbates or alleviates environmental issues are critical. The study concludes that individuals from low-income groups are more inclined to participate as bringers and are more willing to take longer routes to deliver packages to others. Serafini et al. (2018) find that, besides remuneration and safety concerns, the location of delivery points is another important factor for occasional carriers in becoming a service supplier. Miller et al. (2017) highlight that delivery time and the purpose of the existing trip influence the choice of becoming an occasional carrier. The authors conclude that off-peak hours and leisure trips might lead to a greater willingness to consider becoming an occasional carrier since such trips typically offer more schedule flexibility. Alongside these characteristics, a few studies focus on the beliefs and attitudes of occasional carriers. For instance, Koh et al. (2024) studies the beliefs of occasional carriers in their ability to successfully perform specific tasks in terms of technology usage. Upadhyay et al. (2021) explore the willingness of occasional carriers to engage in crowdshipping services by assessing their motivations. X. Wang et al. (2024) discover that motivational factors like the willingness to participate in paid crowdshipping and the sense of shared responsibility in unpaid crowdshipping impact individuals' decision to become occasional carriers. In their work, Chen et al. (2018) introduce a novel approach for the collection of e-commerce returned goods using taxis as transportation means and shops as collection facilities. Their study, conducted in a crowdshipping context, leads to the conclusion that crowd-based reverse logistics can be both feasible and more sustainable.

While the optimisation studies discussed do not directly explore consumer behaviour, they provide practical insights into integrating crowdshipping with existing delivery services. For instance, Raviv & Tenzer (z. j.) design an open and shared PI infrastructure, highlighting the economic viability of crowdshipping. Similarly, Di Febbraro et al. (2018) present a model where ride-sharing and crowdshipping services could use the same infrastructure. In another study, crowdshipping is studied by combining parcel lockers and public transport passengers (Zhang & Cheah, 2024). By illustrating the practical implications of crowdshipping, these studies highlight its potential to enhance delivery efficiency, reshape consumer preferences, and mitigate last-mile delivery challenges.

2.4 Research directions

In this section, we provide several research directions building on the above. We distinguish 3 promising areas of work. Firstly, we examine several research directions concerning demand and supply decisions of active consumer participation in the delivery process. Secondly, we provide future research avenues, examining how social interactions influence decision-making in the context of delivery services. Lastly, we outline the effects of hyperconnected service networks.

2.4.1 From consumers to prosumers of last-mile delivery

As stated in previous reviews (Mishra et al., 2021; X. Wang et al., 2023; Ma et al., 2022) and supported by several empirical studies (X. Wang et al., 2018; Pisoni et al., 2022), the development of omnichannel retailing architecture has made meeting consumer expectations and fast delivery requests more crucial than ever before. Existing literature primarily examines the acceptance of new delivery services, either by focusing on a specific service(Chen et al., 2018) or by comparing multiple delivery options (Cai et al., 2021). However, in line with marketing literature, changes in consumer consumption patterns have transformed their relationship with businesses (Tax et al., 2013; Lemon & Verhoef, 2016; Vakulenko et al., 2019; Rimmer & Kam, 2018). Despite this, there is a notable research gap concerning the evolving role of consumers, who are not just users of services but also providers of services for others.

Notably, citizens are increasingly participating in last-mile deliveries (X. Wang et al., 2022). For instance, they send or deliver parcels for others through platforms like crowdshipping (Le & Ukkusuri, 2019b), or they handle their ordered products by picking up or dropping them off at designated locations such as collection points (Marcucci et al., 2021), parcel lockers (Vakulenko et al., 2018), or micro depots (Hagen & Scheel-Kopeinig, 2021). To our knowledge, until now, research has focused on only one of these perspectives of consumer: either as a service user or the service supplier. However, the behaviour of citizens as simultaneous producers and consumers, a phenomenon known as prosumers, in the context of last-mile delivery services is overlooked. This integrated approach of consumer decision-making presents a unique opportunity to formulate policies for future last-mile logistics, recognizing that consumers serve as both service users and contributors, impacting the logistics sector as a whole. This holistic view has the potential to provide a complete understanding of the relationships between consumers, retailers, and logistics service providers, thereby enhancing our insights into evolving market patterns.

Another aspect that is mentioned in the literature concerns the return deliveries in optimising last-mile deliveries and enhancing the overall consumer experience (Polydoropoulou et al., 2022; Rosenberg et al., 2021). A potential avenue for future research involves investigating consumer perceptions and attitudes towards the return process, where emotions like satisfaction or frustration play a significant role in decision-making. The influence of return policies on purchasing decisions is noteworthy. Additionally, there's an opportunity to explore the impact of environmentally friendly return options, similar to the approach suggested by Chen et al.

(2018) in the context of crowdshipping.

Existing research has primarily employed choice experiments and structural equation modelling techniques to explore the acceptance of new delivery services (Cai et al., 2021; Vakulenko et al., 2019; Merkert et al., 2022). The objective of these studies is to investigate the trade-off between delivery-specific characteristics and consumer behaviour based on consumer surveys. However, there is a need to use revealed preference data to empirically assess the use of these services. This is mainly because revealed preference data, derived from real consumer behaviour and choices, provides valuable insights into the actual preferences and decision-making processes of consumers. Additionally, integrating findings from consumer surveys into simulation studies enhances the robustness of the analysis. These surveys provide qualitative insights, helping contextualize the quantitative data obtained from revealed preferences. Together, these methodologies create a comprehensive framework for evaluating the use of services.

Lastly, the generalisability of many studies is limited due to specific choice situations or person-level indicators used to assess consumer decision-making. To address this limitation, we suggest that future studies consider the context dependency effect by incorporating cross-cultural and geographical comparisons, and that transferability evaluations are undertaken.

2.4.2 Role of consumers' social environment

As presented in the review framework, consumers become a critical part of the logistics operations because of their decisions about their deliveries as well as their participation in the delivery as carriers. Moreover, they have an interconnection with other actors in the last-mile, namely, retailers and logistics service providers. Individual decision-making of consumers is embedded in social networks and creates a system-wide effect. Future research could focus on exploring the interconnections between these actors and its influence.

As Harrington et al. (2016) also emphasise, consumers are highly affected by the community that they live in. In other words, consumer decisions are influenced not only by product and service characteristics but also by factors such as active communication, information sharing, and peer referrals. Consumers might be willing to use their social network, such as their family, friends, and co-workers, if they think that their shopping experience is improved (Mishra et al., 2021). Future studies should consider these elements to expand our understanding of consumer acceptance of these innovative services. In the literature, there are a few studies focusing on the influence of social networks on innovative delivery services. However, their predominant focus is on the preferences and tendency of consumers to use social networks for an individual service or a technology by means of choice modelling (Devari et al., 2017), linear regression (Felch et al., 2019), or structural equation modelling (Cai et al., 2021; X. Wang et al., 2021). With these approaches, the complex relationship between the decisions of consumers may be oversimplified. For instance, choice models assume independence of irrelevant alternatives, neglecting the complex interplay of various factors. Linear regression techniques, on the other hand, might miss nonlinear relationships crucial in decision-making. Structural equation models, while powerful, heavily rely on model specification and may not fully capture the complex interactions. While all these methods offer valuable insights, traditional approaches often lack the ability to incorporate dynamic elements representing the evolving nature of social interactions. These dynamic aspects are vital, especially when examining complex, real-time social environments. We recommend extending the literature on consumer decision-making by considering the effect of the social environment with dynamic and scalable models, which consider both the evolving nature and the scalability of social interactions. Another research direction can be concerning how interactions between different social network groups would influence consumers' choice preferences. As an approach, simulation studies could be used to explore different scenarios by considering the evolution of social interactions and their impact on the adoption of novel delivery methods as a network.

Social influence plays a significant role in shaping consumer behaviour. As suggested in a recent review study (Bhukya & Paul, 2023), social influence can enhance delivery by leveraging cutting-edge information and communication technology, motivating consumers to become carriers (Devari et al., 2017; Akeb et al., 2018) and jointly deliver for others (Bhukya & Paul, 2023). With the emergence of a new type of consumer valuing sustainable practices throughout the supply chain, highlighted by Pan et al. (2021), the eco-friendliness of these social networks could drive a shift in consumer preferences under certain conditions such as delivery time, delivery distance and remuneration levels. However, it is crucial to explore the safety and privacy aspects for the success of such platforms.

Previous studies have shed light on the impact of several personal attributes, such as consumers' innovativeness, previous experiences and habits, on the acceptance of a new service. However, there have not been many studies investigating the influence of different social groups on the acceptance of a new delivery service considering these attributes. This is important for two reasons. Firstly, as mentioned in Akeb et al. (2018), there are many stakeholders involved in the last-mile delivery. Secondly, consumers typically do not have prior experience with the new service and their choice is highly influenced by their social environment, as mentioned in Yuen et al. (2018), Zhou et al. (2020) and Devari et al. (2017). By studying the relationship between social networks and the choice of a service, consumer decision-making could be better explained. To achieve this, both qualitative and quantitative approaches can be applied. Interviews and focus group analysis can be useful for exploring the objectives and preferences of different stakeholders. Additionally, piloting activities, field surveys, and simulation studies can be employed to better understand the complex structure of consumer decision-making.

2.4.3 Effects of hyperconnected service networks

There is a lack of comprehensive empirical studies that investigate the effect of horizontally as well as vertically connected, collaborative services. Existing literature concentrates on identifying characteristics of individual delivery services (Vakulenko et al., 2018; Polydoropoulou et al., 2022; Cauwelier et al., 2023), or horizontal collaboration of private channels (Kim et al., 2021). Future studies could explore the combined vertical and horizontal integration of partial delivery services as a network. Vertical integration involves the creation of new service chains by connecting individual services This could include crowd-based delivery services seamlessly integrating with parcel lockers or micro-depots. In terms of horizontal integration, collaboration between competing actors could impact the use of capacity and increase efficiency. Their combined deployment results in hyperconnected urban freight networks.

The interconnectivity issue is not trivial and requires further exploration through multiple scenario analyses, as also mentioned by Treiblmaier et al. (2016). In our context, interconnectivity involves the technological and social potential for actors to connect vertically or horizontally. Hyperconnectivity emerges as a system property resulting from ubiquitous interconnectivity, giving rise to a horizontally and vertically integrated service network. Particularly in the context of last-mile delivery, numerous small-scale micro-services often operate independently without interconnection. If these services could collaborate and interconnect, they could collectively form a hyperconnected last-mile delivery network that is more robust and impactful than the sum of its individual parts.

Connectivity between platforms and ease of use are some of the other aspects that need further investigation since they influence consumers' experience and loyalty to use these connected services. In particular, the question of aggregation of service experiences requires attention. Marketing studies focusing on consumer involvement show that different service providers together form consumer experience irrespective of their individual role in the core service (Vakulenko et al., 2019). Finally, the question of coordination among services and building trust towards a new service become increasingly important as mentioned by Tax et al. (2013); Lemon & Verhoef (2016).

In the PI literature, the aspect of consumer decision-making considering the service attributes is either overlooked or limited to the constraints of consumer time-windows (Crainic et al., 2020), the spatial distribution of consumers (Ben Mohamed et al., 2017), demand uncertainty (Crainic et al., 2020), deterministic time of the day (Orenstein & Raviv, 2022), and service time choices (Ben Mohamed et al., 2017; Orenstein & Raviv, 2022) in optimisation studies. In line with some scholars (e.g., (Kim et al., 2021; Bidoni & Montreuil, 2021)), demand modelling, forecasting, and a more accurate reflection of practice regarding delivery times, delivery failures, and consumer preferences need to be investigated further. Considering realistic behavioural assumptions about consumers (as an end-user or the service supplier in the PI) can allow for more comprehensive and well-directed research outcomes towards a fully connected PI network.

In summary, noting there is a limited body of research dedicated to exploring consumer decision-making in the realm of the PI, future investigations have the opportunity to contribute significantly by advancing our understanding of last-mile logistics services collaborating in an open network. There is a need in this context to explore the synergies among different service providers and investigate the feasibility of implementing white-label services, where multiple logistics service providers use the same delivery person or share infrastructure such as delivery vehicles and parcel locker facilities.

The connection of these services as a network and the inclusion of consumers as essential decision-makers, considering their specific preferences and trust towards these services, are overlooked in the literature. To address this gap, the PI vision can provide guidance on how to connect these services through advanced information technologies and online platforms.

Moreover, there are several policy instruments that can be tested in this context. These may include implementing zero-emission zones and providing subsidies for the use of shared and connected delivery services.

Lastly, an essential avenue for exploration lies in the seamless integration of crowd-based delivery services with conventional options such as parcel lockers and micro-depots. Understanding the dynamics of this integration is crucial, as it directly impacts consumer behaviours. Research efforts should focus on designing dynamic models that simulate scenarios integrating crowdshipping, parcel lockers, and other emerging services. These simulations can provide insights into how these services collectively influence prosumer decisions within the omnichannel retail landscape.

2.5 Conclusions

Despite the strong growth of the literature on omnichannel logistics, PI, and city logistics in recent years, there is little empirical research available on consumer decision-making. We position our review in the context of the vision of the PI as service supplier and the omnichannel services that shape the demand for transport. Incremental shifts in retailing operations toward a seamless omnichannel architecture have transformed consumers from mere end-users of services into service providers and logistics operators. This includes initiating, receiving, and returning purchased goods, as well as carrying out a delivery for others. These developments underscore the pivotal role of consumers in last-mile logistics.

We define three distinctive decisions: (1) selecting the shopping channel, (2) choosing the delivery method, and (3) accepting to carry a shipment for others. The shopping channel encompasses the choice between online and in-store or hybrid shopping choices, which ultimately affects the selection of different delivery methods. Within this context, the choice of delivery method is elaborated upon, considering product-specific, delivery-specific, and personal-specific characteristics. Lastly, we emphasise the importance of crowdshipping as a novel concept within the PI framework, where citizens become carriers.

Our review shows that only a few connect multiple last-mile logistics services into a PI-like service network, in order to study the impact of this hyperconnectivity, taking into account consumer behaviour. Current studies either focus on optimisation or use naive behavioural assumptions. Complementing these with behavioural studies are recommended. Important further gaps include the simultaneous nature of consumers as producers of services termed prosumers, the role of social networks, interconnectivity among delivery services and attention to the transferability of findings across the multiple pilots reported.

Chapter 3

Consumer trust in crowdshipping services as users

As demonstrated in Chapter 2, consumer decision-making becomes increasingly complex when assuming dual roles of consumers as both service users and providers. In services like crowdshipping, consumers transition from mere users to occasional carriers. Central to this dynamic is the concept of trust, that might influence the acceptance of such services.

This chapter, as a next step, aims to explore the role of trust in influencing crowdshipping adoption decisions through empirical analysis. By investigating the relationship between trust and the crowdshipping service adoption, our research contributes insights into consumer behaviour in the evolving landscape of urban transport services.

This chapter is based on the following journal paper: Cebeci, M. S., Tapia, R. J., Kroesen, M., de Bok, M., & Tavasszy, L. (2023). The effect of trust on the choice for crowdshipping services. Transportation Research Part A: Policy and Practice, 170, 103622. DOI: https://doi.org/10.1016/j.tra.2023.103622.

3.1 Introduction

Increasing urbanisation brings several changes to the cities, together with consumer-to-consumer (C2C) and business-to-consumer (B2C) e-commerce. First of all, demand for last-mile delivery has grown rapidly as consumers are getting used to shop online. Also, customers are seeking more customised on-demand deliveries, leading to an increase in parcel shipments in urban areas by couriers. According to Yrjölä et al. (2017), C2C e-commerce is evolving into a new retailing sector, causing competitive pressure on retailers. Concerning B2C deliveries, most retailers provide a home delivery option to their customers with specific time windows so that the service can be customised. This creates additional fragmentation of flows, adding to negative externalities in urban areas, such as congestion and pollution (Ranieri et al., 2018). As an innovative solution to tackle these issues, shared mobility services such as crowdshipping are proposed for on-demand delivery requests.

The general idea behind crowdshipping is that the item is transported by a commuter who is already making their trip for other purposes, thus, not adding extra travelled kilometres to the operation (Le et al., 2019; Tapia et al., 2023). The service provides potentially faster and cheaper parcel deliveries for users since the system uses existing infrastructure and passenger flows to deliver the parcel (Devari et al., 2017; Arslan et al., 2019). In this way, traditional carriers could use fewer vehicles and make fewer vehicle kilometres in total, reducing the negative impact of last-mile shipments on the environment. In some cases, it can occur that new routes are generated, and existing trips are not reduced. Then, the service can lead to increase in travel times and fuel consumption (Gatta et al., 2018; Buldeo Rai et al., 2018). Also, since the supply side of the market is not regulated, there are concerns about unreliability of the service due to damage and theft (Le et al., 2019). Jaller et al. (2020) provide an extensive review of the state-of-practice and discuss preconditions for a large-scale breakthrough of the service. While the number of service providers is steadily growing, the main current niches include long-distance haulage in remote areas (e.g. Nimber in Norway) and the provision of additional flexible capacity for mainstream logistics service providers (see also: (Economist, 2018)). Although conceptually crowdshipping fills a gap in the logistics services market for small parcels (Le Pira et al., 2021), it is not yet widely established, and there is no crowdshipping operation in the Netherlands. Research studying adoption behaviour is therefore of societal interest in order to investigate the possible impacts of crowdshipping.

Behavioural studies focusing on user adoption incorporate various factors that affect choice for the service. These include price, time, reliability, privacy, safety, and liability (Rougès & Montreuil, 2014; Punel & Stathopoulos, 2017; Le & Ukkusuri, 2019a; Punel et al., 2018a,b). An emerging topic in the literature on crowdshipping has been the concept of trust in the capabilities of the service provider. Several studies focusing on the behavioural acceptance of crowdshipping state that trust is an important factor enabling service adoption (Rougès & Montreuil, 2014; Punel et al., 2018b,a). In a more recent study, Upadhyay et al. (2021) assess the mediating structure of trust on sharing economy platforms. The research also addresses the mediating role of attitudinal variables towards the crowdshipping platform from the perspective of social, economic and reward point of view. The authors highlight the positive relation between intention to participate in sharing platforms and trust in crowdshipper. Even though this study identifies trust as a critical factor in the general context of sharing economy applications, it is still not clear how the level of trust can be measured and to what extent trust has a mediating role in the service adoption. Our research aims to address this void in the literature.

Given this background, the main objective of this research is to investigate the user's acceptance of crowdshipping services focusing on the role of trust. Firstly, a literature review is conducted to define trust in crowdshipping and the attributes that might impact the level of trust. Crowdshipping service platforms are not yet widespread, and records of these platforms store insufficient data to address the issue of trust. Therefore, we have constructed a stated preference experiment (SPE) for data collection. To test the effect of trust on crowdshipping service choice, six attributes are defined and validated through a crowdshipping service provider. A hybrid choice model is deployed to estimate the attribute weights. While the design of the SPE enables us to explore the effect of trust on crowdshipping per choice situations, the estimated HCM allows us to disentangle the direct, indirect (through trust) and total effects of the main attributes on the service adoption. This is the first time that trust is included in a hybrid choice model as a mediating latent variable in the crowdshipping domain. Hence, this study adds to an empirical understanding of crowdshipping service choice in the context of last-mile deliveries.

In the following section, a literature review on crowdshipping and trust is presented. Next, the applied methodologies are described, followed by the research results and their discussion. Lastly, research conclusions are presented.

3.2 Literature review

This section aims to find possible conceptual connections between consumer trust and the adoption of crowdshipping as well as the attributes highlighted in the literature that can be applied to measure trust.

Crowdshipping is an emerging service that requires the cooperation of technology firms, retailers, consumers, and travellers (Punel & Stathopoulos, 2017). This new delivery service emerged as an alternative to urban freight distribution by commercial carriers, by utilising existing personal travellers to perform goods transportation. The service is defined as a platform that links customers to a crowd of travellers that are willing to pick up and deliver packages. Research on crowdshipping acceptance is relatively recent. In their review study, Le et al. (2019) analyse real-world data to conceptualise the discussions and policy implications of crowdshipping service. The study uses three data sources including stated preference surveys and real-world data and shows that crowdshipping platform needs key functionalities such as ease of use, real-time assistance and hands-free capabilities. More recently, Le et al. (2021) and Wicaksono et al. (2022) documented the scarcity of studies in this context.

A limited number of studies have addressed trust of users in crowdshipping. According to Rougès & Montreuil (2014), building trust is a key performance indicator. A recent study regarding trust in crowdshipper explores the mediating role of trust in the context of shared economy applications for emerging economies (Upadhyay et al., 2021). Surprisingly, however, there is no study on measuring trust in crowdshipping context from the users' perspective. Trust has a clear relation to various service attributes. These include delivery time (Punel

& Stathopoulos, 2017); the ability to define pickup time (Punel & Stathopoulos, 2017); delivery cost (Rougès & Montreuil, 2014) as well as driver performance, courier expertise, and experience. These latter features might also affect the trustworthiness of the crowdshipping service (Punel & Stathopoulos, 2017). Moreover, reliability is an indispensable part of a successful crowdshipping operation (Rougès & Montreuil, 2014; Punel et al., 2018b; Le et al., 2019). There is also a strong relationship between reliability and level of trust (Chancey et al., 2017). When the service is perceived as reliable, the user's trust will be higher for that specific service. Literature shows that availability of tracking and tracing affects the choice of crowdshipping service (Le & Ukkusuri, 2019a; Gatta et al., 2018); together with insurance for loss or damage, this might also increase users trust in the service (Rougès & Montreuil, 2014). Jøsang et al. (2007) state that there is a direct correlation between reputation and trustworthiness. Reputation is directly linked to trustworthiness, and it enables the user to envision the service quality as it provides other users' reviews and comments. This feature can be evaluated based on customer reviews and app ratings. Interestingly, in some studies, the reputation of a crowdshipping company was found more influential than the cost of the delivery and the delivery time (Le et al., 2019). In parcel delivery, users can be exposed to risky service or poor service quality, with missed delivery or damage as unwanted outcomes. As a company's reputation provides information about the service, this knowledge can also be used to reduce unwanted service outcomes (Shao et al., 2019).

Finally, the literature shows that there is a relation between sociodemographic characteristics and crowdshipping service adoption. According to Punel et al. (2018a), young men and full-time employed individuals are more likely to adopt crowdshipping. Additionally, the building of trust would differ between different sociodemographic segments. Therefore, sociodemographic characteristics could be considered another important parameter for service adoption, in relation to trust.

Trust has been researched by different disciplines of social sciences such as psychology, political science, and economics. Each discipline explains the role of trust in social processes from a different perspective. Various trust categories can be found in the literature such as characteristic trust, rational trust, and institutional trust (Laeequddin et al., 2010; McEvily & Tortoriello, 2011). A plethora of studies assess the antecedents of trust, and the literature converges defining this behavioural factor as a complex psychological phenomenon (Laeequddin et al., 2010; McEvily & Tortoriello, 2011). Trust is necessary for organisational success but requires an effort that cannot be created in a short time (Lin et al., 2020). Building customer's trust in the organisation provides an effective operation and continuity of the business; as a result, the development of trust is expected to increase the willingness to use the service. Although there are different definitions of trust, the literature extensively cites two of them. First, trust can be seen as one person's willingness to act on another person's action or decision (McAllister, 1995). Based on this definition, trust is credence and positive expectation of the individual towards a person, situation or service. In crowdshipping, expectations that delivery will be carried out in a safe manner can improve trust levels. Secondly, trust is defined as one party's willingness to be vulnerable to another party's action (Mayer, 1995). Thus, one party's willingness to be involved in crowdshipping service plays a pivotal role in the trust-building process.

Trust has also been studied in different areas of technology adoption. In the area of financial technology, recent studies find that trust positively impacts the intention to use internet, mobile banking, robo-chat and mobile payment services (Dawood et al., 2022). Different approaches have been used to measure the effect of trust including multivariate regression (Lien et al., 2020) and structural equation modelling (Mainardes et al., 2023; Roh et al., 2024). Trust is treated as either an independent variable (Lien et al., 2020) or a dependent latent variable with a mediating effect (Roh et al., 2024; Mainardes et al., 2023). Trust has also been an important topic in the area of artificial intelligence (AI) and healthcare technology. Several studies envision trust as a critical determinant of human-machine interaction (Gille et al., 2020). Research on how to measure trust in healthcare is limited (LoCurto & Berg, 2016). Alrubaiee & Alkaa'ida (2011) explore the mediating effect of patient satisfaction on perceived healthcare quality and patient trust by using a service quality model (SERVQUAL). Another study investigates the mediation effects of trust in healthcare providers (Hong & Oh, 2020). In the above studies, trust is generally measured with a Likert scale based on person-level indicators provided in the experiment.

In the context of passenger transportation, establishing trust in services is challenging as technology evolves quickly and transportation methods vary widely. Novel services such as ride-sharing and ride-sourcing often include trust in the consideration of service adoption (Coulter & Coulter, 2002; Akhmedova et al., 2021). Promoting customer trust has been extensively explored. The mediating effect of trust has been studied with the help of structural equation modelling (Shao & Yin, 2019; Shao et al., 2020). While trust is measured related to service platforms (Shao & Yin, 2019), government support and reputation of a ride sharing company have also been considered recently (Shao et al., 2020). In addition, the ride sourcing literature considers various features to measure trust including travel time, cost, safety and privacy. The measurement of trust in ride sourcing is based on perceptions of vehicle or driver related risks (Nguyen-Phuoc et al., 2021), app related risks (Nguyen-Phuoc et al., 2021) and other perceived concerns (Asgari & Jin, 2020). In our study, similar to the previous research, trust is treated as a dependent mediating variable. However, in this study, the level of trust is measured through situation-specific attributes that affect trust rather than person-level statements indicating trust (Roh et al., 2024; Mainardes et al., 2023; Shao & Yin, 2019; Shao et al., 2020).

Based on the above review, the study is positioned as a first endeavour to model the mediating role of trust for the adoption of crowdshipping services, using a choice modelling approach with trust as a situation-specific latent variable. Our contributions include the conceptualisation of the model and its estimation within a SPE setting, as well as empirical findings that underline the important role of trust in this market, including its antecedents in the form of relevant service attributes. The research thereby supports the design of policies by private and public actors to strengthen trust in crowdshipping services.

3.3 Methodology

This section explains the conceptual framework derived from the literature review as well as the data collection and analysis method.

3.3.1 Conceptual model

Based on the research objective, the conceptual framework aims to represent not only the direct effect of the attributes on service choice but also their indirect effect on choice, via the concept of trust. The conceptual model of this approach is given in 3.1. While rectangular boxes are used to show the observed variables, the round boxes are used to represent the estimated variables.

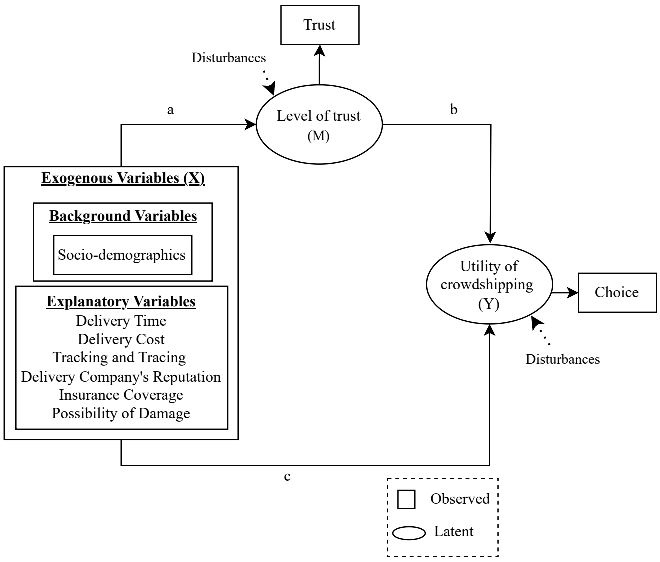


Figure 3.1: Conceptual model

Explanatory variables include delivery time, delivery cost, tracking-tracing options, insurance coverage, possibility of damage and reputation, along with some sociodemographic background variables. These have a direct effect on utility (arrow c' in the figure). The direct effect of these attributes on trust and the direct effect of trust on utility are shown by arrows a and b respectively. Based on this conceptualisation, respondents are provided with several hypothetical scenarios concerning crowdshipping. By relating observed choices to observed attributes and the latent variable, their influence can be inferred statistically. As can be seen from the conceptualisation, mediating variable trust (M) and utility of crowdshipping (Y) are estimated with the help of observed variables in the experiment. If one is able to measure trust directly, its influence can be distinguished from that of the utility variable. In this study, the level of trust is observed from a direct rating by respondents, specifically for each choice situation. This is based on their level of trust for the crowdshipping service on the provided attributes. Hence, it is assumed that respondents are able to assess the impact of different attributes generating a choice set and to provide an overall trust level for a given choice task. Moreover, the level of trust is assumed to impact the utility of crowdshipping, that is, high level of trust is expected to increase the probability of opting for crowdshipping comparing to traditional delivery.

3.3.2 Stated preference experiment

In this research, a stated preference (SP) survey is used since no crowdshipping service has been applied in the Netherlands yet, so there is no revealed preference (RP) data available. This experiment technique enables the authors to capture the decision to use the crowdshipping service, including all alternatives and their trust rating.

Data collection and survey design

In the SP experiment, individuals are asked to make choices based on a set of hypothetical situations. The attributes related to trust and the service itself were selected from the literature and validated through discussions with a crowdshipping service provider. The attributes identified in the literature and incorporated in the survey include delivery time (Devari et al., 2017), delivery cost (Wicaksono et al., 2022), tracing and tracking options (Rougès & Montreuil, 2014; Le & Ukkusuri, 2019b), insurance coverage (Rougès & Montreuil, 2014), possibility of damage (Le & Ukkusuri, 2019a), and delivery company's reputation (Le & Ukkusuri, 2019a; Jøsang et al., 2007).

Table 3.1 below shows the attributes which are used in the SP experiment for crowdshipping alternative.

Table 3.1: Attributes and their operationalisation for crowdshipping

Attribute	Number of attribute levels	Levels	Coding
Delivery time	2	Next day delivery Same day delivery	0 1
Delivery cost	4	5€ 7€ 10€ 12€	5 7 10 12
Tracking tracing options	2	Only main steps can be seen in the app/website Real time driver tracking by the app/website	0 1
Delivery company's reputation	2	★★ ★★★★	0 1
Insurance coverage	2	Up to 500€ Up to 1000€	0 1
Possibility of damage	2	1 in 20 damaged delivery (5%) 1 in 30 damaged delivery (3%)	0 1

Two levels are defined for delivery time: same day or next day delivery. There are two reasons of this choice. Firstly, the main goal of the research is to understand how the relevant attributes affect trust and if trust has a mediatory role in the service adoption, therefore, delivery time is not needed to be represented with hours specifically. Secondly, in practice, the parcel deliveries are also framed this way. Hence, only generic information (either same day or next day) is provided to assess the importance of delivery speed for the respondents. The cost of the service is assumed to be 5-7-10 and 12 €. Although crowdshipping service cost is usually calculated based on the distance travelled, as travel distance is not included in the experiment, respondents are directly provided with pre-specified cost values. The tracking and tracing options indicate whether the alternative has real-time tracking. Due to the novelty of the platform, it is assumed that this feature might impact the reliability of the service and users' level of trust. Insurance coverage is represented with an upper bound value in the choice set. These values are used to describe the limit of the insurance since this is also the way insurance coverage is represented in real-life. The possibility of damage is expressed in the probability of the item getting damaged or lost. To show the delivery company's reputation, the number of stars is provided using a typical app-based rating system. The stars reflect the credibility of the delivery company, expressing the level of trustworthiness. Earlier, reputations have been measured as low, medium, or high based on driver's app ratings (Punel & Stathopoulos, 2017; Le & Ukkusuri, 2019b). In another study, (Yin, 2023) uses a star rating system for consumer reviews for acceptance of automated taxis. However, this is the first time that a stars-based rating scheme is considered in a user's service choice, without extreme ratings such as one or five stars that might lead to bias in attributes; hence, two and four stars are applied in the experimental design.

While the attribute levels of crowdshipping vary, the traditional delivery option values are fixed. The reason for this choice is that the traditional delivery option is considered the base alternative permitting respondents to compare it with the crowdshipping option. Table 3.2 represents the selected intermediate attribute levels for traditional delivery.

Table 3.2: Summary of the attributes and attribute levels for traditional delivery

Attribute	Levels
Delivery time	Next day delivery
Delivery cost	10€
Tracking tracing options	Only main steps can be seen in the app/website
Delivery company's reputation	★★★
Insurance coverage	Up to 750€
Possibility of damage	1 in 25 damaged delivery (4%)

In practice, delivery time for local-to-local (L2L) parcels is generally the next day since these delivery requests are executed via small number of depots in the city. Tracking and tracing facility for traditional delivery company is generally provided as main steps throughout the delivery operation. Similarly, in our experiment, traditional delivery is assumed to have only next day delivery option and only main steps can be seen as a tracking and tracing feature. With these selections, it is possible to represent the realism in the case of traditional delivery. Moreover, delivery cost in Dutch transport market ranges from 8€ to 15€ among main carriers for L2L parcels. In our experiment, 10€ is attributed for traditional delivery option to be comparable with the crowdshipping alternative. Lastly, the attribute levels of traditional delivery for insurance coverage, possibility of damage and reputation of the company are defined as average values comparing to crowdshipping option. This is done in order to avoid bias in the experiment.

To combine the defined attribute levels into a choice set, an orthogonal fractional factorial design with one 4-level (delivery cost) and five 2-level attributes (the rest) are chosen, which result in 16 unique profiles. The experiment was designed in two different blocks. These blocks were randomly assigned to the respondents. In this part of the survey, individuals filled in 8 choice sets with two sub-questions each (shown in Figure 3.2). Ngene software was used to generate the choice tasks (Ngene, 2018).

As the crowdshipping service in the Netherlands can be seen as a relatively new concept, there is no service present that one can relate to. For this reason, in the choice experiment, people were asked to make the selection between two different unlabelled alternatives, namely crowdshipping delivery and traditional delivery options. In the beginning of the online survey, respondents encountered the information below, highlighting the context for respondents to make them consider the same assumptions while selecting their preferences. To this end, respondents were asked to consider the last item that they had bought and the value of that item while choosing their preferences. In addition, the statements given in the box below were provided in the choice experiment so that every respondent could imagine a similar context.

Imagine the last item that you bought online; the shop (website) provides two alternatives to deliver your package to your intended location with the following features. In this specific case;

- *It is assumed that you don't need the product urgently,*
- *It is assumed that you have to be at your predefined location to collect the package,*
- *Imagine that you can only reach out to the commercial transportation company for your claims in case of damaged or wrong delivery.*

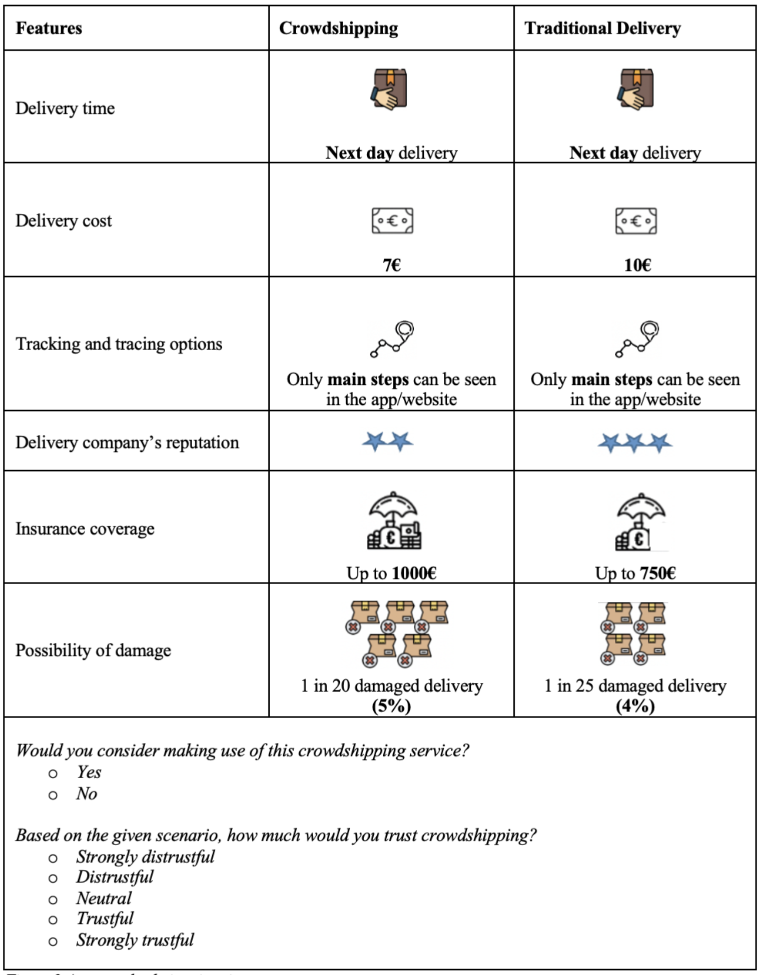
In the beginning of the SPE, respondents were notified with explanations of the attributes. In Table 3.3 below, we show the attributes and their explanation.

After defining the general context and assumptions of the experiment, respondents were asked to answer two questions. In the first part, they were asked whether they prefer the crowdshipping delivery option or not. Secondly, in line with the conceptual model, they were asked to rank their level of trust towards crowdshipping, even if they did not select the crowdshipping option in the first question. Figure 3.2 shows an example of these two questions.

Table 3.3: Context of the experiment

Features	Explanation
Delivery time	This feature refers to **same day** or **next day** delivery options.
Delivery cost	This feature represents the **cost** of the service.
Tracking and racing options	This feature represents whether the alternative has a tracking and tracing feature or not (**real-time/only main steps).**
Delivery company's reputation	This feature refers to **credibility** of the delivery company and the rating of the company's app.
Insurance coverage	This feature shows the **insurance limits** for the alternative.
Possibility of damage	This feature represents the possibility that the item can get **damaged or lost**.

From the delivery options below, select the one that fits your preference the most:



Features	Crowdshipping	Traditional Delivery
Delivery time	**Next day** delivery	**Next day** delivery
Delivery cost	**7€**	**10€**
Tracking and tracing options	Only **main steps** can be seen in the app/website	Only **main steps** can be seen in the app/website
Delivery company's reputation		
Insurance coverage	Up to **1000€**	Up to **750€**
Possibility of damage	1 in 20 damaged delivery **(5%)**	1 in 25 damaged delivery **(4%)**

Would you consider making use of this crowdshipping service?
- *Yes*
- *No*

Based on the given scenario, how much would you trust crowdshipping?
- *Strongly distrustful*
- *Distrustful*
- *Neutral*
- *Trustful*
- *Strongly trustful*

Figure 3.2: An example choice situation

Along with the SPE, the survey consists of a description of the respondent's online purchasing behaviour and sociodemographic characteristics (gender, age, occupation, education level, and monthly income). The questionnaire was developed in the online web platform: Qualtrics. The data collection process took place in the last week of April 2021 and was kept online for three weeks. Respondents who lived in the Netherlands and were above 18 years of age were asked to fill in the survey. In the end, 248 responses were collected, of which 215 were fully completed with 1720 choice observations.

Sample Characteristics

In the survey, five sociodemographic variables are used: gender, age, occupation, education and income level. Since the main focus of the research is to explore the effect of trust on the crowdshipping service choice, it is also important to investigate the heterogeneity in preferences which is estimated through these variables. Hence, the levels of these variables were selected in a way to realise this aim. Based on the sample data, the frequency distribution of sociodemographic characteristics is shown in Table 3.4.

Table 3.4: Frequency distribution of sociodemographic characteristics of the sample (N=215)

Sociodemographic Characteristic	Category	Frequency (N)	Relative (%)
Gender	Male	116	54.20%
	Female	93	43.50%
	Non-binary/ Third gender	4	1.90%
	Prefer not to say	1	0.50%
Age	18-25	100	46.70%
	26-33	83	38.80%
	34+	31	14.50%
Occupation	Working full time	61	28.50%
	Working part time	9	4.20%
	Student	135	63.10%
	I have no work at the moment	8	3.70%
	Volunteer work	1	0.50%
Education level	High school	10	4.70%
	Bachelor	52	24.30%
	Master	129	60.30%
	PhD	23	10.70%
Income level	Less than 500 €	56	26.20%
	501-1000 €	45	21.00%

Continued on next page

Table 3.4: Frequency distribution of sociodemographic characteristics of the sample (N=215) (Continued)

	1001-1500 €	20	9.30%
	1501-2000 €	15	7.00%
	2001-2500 €	10	4.70%
	2501-3000 €	11	5.10%
	3001-3500 €	8	3.70%
	More than 3500 €	16	7.50%
	I prefer not to answer this	33	15.40%
Total		214	100%
Missing value*		1	0.50%

A set of sociodemographic characteristics has not been filled by a respondent.

As can be seen, the sample consists of approximately the equal number of men and women. Regarding the age group, a considerable number of respondents (85%) belong to the 18-33 age segment, and more than half of the respondents are students who are doing master's or bachelors. People older than 33 years of age account for almost 15% of the data set. As the most dominant responses belong to students, the monthly income represented with less than 1000€ in a month appears to be 47.2% of the total respondents. According to the sample characteristics, the sample consists of slightly more men than women, which accounts for almost 55% of the sample. Moreover, there is a large share of young population with a low-income level. Therefore, multiple groupings are done to test the sociodemographic characteristics in order to have a sufficient number of respondents in each category, which is needed to test heterogeneity in discrete choice models. To this aim, the age group is classified as 18-25 years of age and older than 25 years of age. In addition, occupation is combined as students and working and others. Next, education is represented as highly educated respondents (master/PhD) and others. Lastly, income level is combined as less than 500€ of income and more than 500€ of income.

Due to the fact that the survey circulation was initiated among student groups and their social networks, in the end almost 65% of the sample consisted of students. In addition, part of the data collection took place in the train station in Delft, the Netherlands in order to have more heterogeneity in sociodemographic characteristics. Even though the sample had a large proportion of students and low-income level respondents, we had sufficient number of people from the non-student population to test if there are differences in preference between the groups (M. E. Ben-Akiva & Lerman, 1985). As reported below, this is confirmed by the estimations which indicated significant levels of heterogeneity in some of the population groups. In addition, young individuals are more keen to use crowdshipping, as also highlighted in previous studies (Punel & Stathopoulos, 2017; Wicaksono et al., 2022). In any case, it is important to highlight that generalising the findings of the study should be done with care.

3.3.3 An Adapted Hybrid Choice Model

To estimate the direct, indirect, and total effects of the main attributes on the crowdshipping service choice, a hybrid choice model (HCM) is applied. This method provides a modelling framework where the aim is to bridge the gap between discrete choice models and behavioural theories by explaining unobserved parts of the decision-making process, such as attitudes, perceptions, and preferences (Abou-Zeid & Ben-Akiva, 2024). The novelty of these types of models is the availability of combining discrete choice models with models including latent variables, namely trust in the current study. Finally, a three-variable system is needed in order to ensure that there is a mediating structure in the modelling framework. As a consequence, HCMs requires two essential estimations: (1) the measurement model and (2) the structural model. The measurement model represents the link between estimated parameters to their observable indicators and several indicators are included to measure the latent variable. The structural model represents the link between observable and latent variables to the utility (M. Ben-Akiva et al., 2002; Walker & Ben-Akiva, 2002).

In HCMs, a psychological construct is usually measured on the level of a person with multiple indicators. However, in this study, unlike in a traditional HCM, the regressors are the service attributes. We build on the approach of Molin & Kroesen (2022) to include the construct of trust in choice situations. In their paper, the authors assess the safety perceptions of and support for policy measures by applying two approaches: (1) a mediation choice model and (2) a latent class choice model. In their mediation choice model, the authors use six attributes to measure the safety perception in a SPE. We proceed along the same line focusing on the concept of trust. Prior studies applied similar techniques, combining choice models with latent mediators. Burke et al. (2020) test the effect of multiple product features on consumer choices and the perceived benefits in terms of healthiness and cost. Borriello et al. (2021) propose a hybrid choice model by taking into account electricity mix choices among renewable and non-renewable energy alternative choice situations. Another recent study explores the attractiveness of incentives on the choice for difficult-to-staff and remote schools (Burke & Buchanan, 2022). A benefit of these types of models is that they allow us to explore the direct and indirect effects of a latent construct. Moreover, the latent variable varies across product attributes instead of person level characteristics, as also mentioned by Burke et al. (2020).

In this study, unlike traditional conceptualisations of trust as a person-level characteristic, the latent variable is conceptualised as a situation-specific variable. In addition, it is assumed that trust varies depending on the attributes of the crowdshipping alternative. In line with this conceptualisation, we measured the level of trust for each choice situation instead of using a multiple-item scale at the person level. In the model design, two causal paths are used in order to estimate the dependent variable, as shown in Figure 3.3, where path c' shows the direct effect of the exogenous variable (independent variable, X) on the dependent variable (Y) and path a indicates the role of the mediating latent variable (M), namely trust. Finally, from the mediating variable, there is another path b showing the direct effect of the mediating latent variable on the dependent variable (Y).

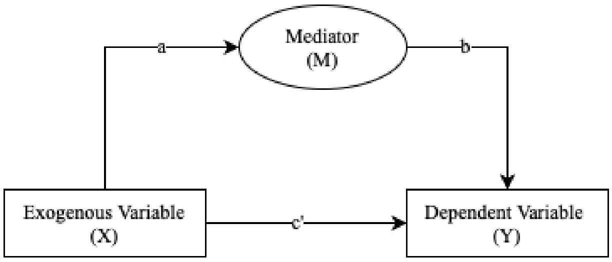


Figure 3.3: Structure of the mediation model (Source: Adapted from (Hayes & Preacher, 2014; MacKinnon et al., 2007)

Thanks to this analysis, mediation can be explored in independent, dependent, and mediating variable settings (Hayes & Preacher, 2014; MacKinnon et al., 2007). This analysis is preferred to quantify direct and indirect pathways where an independent variable transmits its effect on a dependent variable through a mediating variable (MacKinnon, 2012). The generic equations below are used for the mediation choice model (MacKinnon et al., 2007).

$$Y = i_1 + cX + \varepsilon_1 \tag{3.1}$$
$$Y = i_2 + c'X + bM + \varepsilon_2 \tag{3.2}$$
$$M = i_3 + aX + \varepsilon_3 \tag{3.3}$$

Where:

- X = The independent variable
- Y = The dependent variable
- M = The mediator
- a = The coefficient showing the direct effect of the independent variable on the mediator
- b = The coefficient linking the direct effect of the mediator variable to the dependent variable
- c = The coefficient representing the total effect of the independent variable on the dependent variable
- c' = The coefficient linking the direct effect of the independent variable on the dependent variable
- i_1, i_2, i_3 = Intercepts
- $\varepsilon_1, \varepsilon_2, \varepsilon_3$ = Residual terms

In the hybrid model, it is tested if the level of trust acts as a mediator between the choice situations and the utility of the crowdshipping. Moreover, background variables, namely, sociodemographic characteristics, are estimated as independent variables to test their effect on the utility of crowdshipping as well as the level of trust, as represented in the conceptual model 3.1. Our exogenous variables consist of six main attributes: delivery time, delivery cost, tracking and tracing options, insurance coverage, the possibility of damage, and the delivery company's reputation. The level of trust, which is the mediating latent variable, is assumed to be a dependent ordered level measurement and directly measured with a 5-point Likert scale in the choice experiment. This part of the model is investigated through an ordered logit regression model. In this way, it is possible to analyse how relevant attributes in the choice sets would impact the level of trust. To estimate this relation, the following equation is used.

$$\text{Trust}_j^* = C^{\text{Trust}} + \sum_i \beta_i^{\text{Trust}} X_{ij} + \varepsilon_{\text{Trust}} \tag{3.4}$$

The categorical assignment of trust is given by:

$$\text{Trust} = \begin{cases} 0 & \text{if } \text{Trust}_j^* \leq \mu_1 \\ 1 & \text{if } \mu_1 < \text{Trust}_j^* \leq \mu_2 \\ 2 & \text{if } \mu_2 < \text{Trust}_j^* \leq \mu_3 \\ 3 & \text{if } \mu_3 < \text{Trust}_j^* \leq \mu_4 \\ 4 & \text{if } \mu_4 < \text{Trust}_j^* \leq \mu_5 \end{cases}$$

Where:

- Trust_j^* = Level of trust for a crowdshipping choice situation j
- C^{Trust} = Regression constant
- β_i^{Trust} = Regression coefficient for attribute i on level of trust
- X_{ij} = Dummy-coded attribute i (shown in Table 1) for crowdshipping choice situation j
- $\varepsilon_{\text{Trust}}$ = Error term for trust, assumed to follow an independent and identically distributed (i.i.d.) Gumbel distribution (Extreme Value Type I)

Concerning the utility of crowdshipping (Y), the respondents are asked to make a choice if they would opt for the crowdshipping service or not. Thereby, the choice of the service is treated as a dichotomous dependent variable. This part of the model is measured with a binary logistic regression model. The function below is applied to estimate this part of the model.

$$\text{Adopt}_j^* = logit = \ln\left(\frac{P_{\text{Yes}}}{P_{\text{No}}}\right) = C^{\text{Trust}} + \beta_{\text{Trust}}^{\text{Adopt}} \cdot \text{Trust}_j + \sum_i \beta_i^{\text{Trust}} X_{ij} + \varepsilon_{\text{Trust}} \tag{3.5}$$

Where:

- Adopt^*_j = Choice of the crowdshipping service for choice situation j
- P_{Yes} = Probability of opting for the crowdshipping service
- P_{No} = Probability of rejecting the crowdshipping service
- C^{Trust} = Regression constant
- $\beta^{\text{Adopt}}_{\text{Trust}}$ = Regression coefficient for level of trust on the adoption of crowdshipping
- Trust_j = Level of trust for a crowdshipping choice situation j
- β^{Trust}_i = Regression coefficient for attribute i on level of trust
- X_{ij} = Dummy-coded attribute i (shown in Table 1) for crowdshipping choice situation j
- $\varepsilon_{\text{Trust}}$ = Error term for trust, assumed to follow an independent and identically distributed (i.i.d.) Gumbel distribution (Extreme Value Type I)

The impact of sociodemographic characteristics is studied in order to improve the model and to test if the heterogeneity in preferences exists. Sociodemographic variables are introduced as interaction effects in the utility equation both for the trust and the choice of the service. This enables the authors to capture the effect of each sociodemographic which might vary in the attributes. To do this, interaction terms are defined similar to the approach in Tapia et al. (2021) and computed as follows:

$$\beta \cdot (1 + \beta_{\text{interaction}} \cdot \delta) \tag{3.6}$$

In the equation, while β is the coefficient of the variable at hand, $\beta_{\text{interaction}}$ and δ are the interaction coefficient and the dummy variable for the interaction respectively. The HCM was estimated using R studio-Apollo (Hess & Palma, 2019), which allows to model latent variable models and discrete choice models.

3.4 Results

This section first presents the estimation outcomes. Next, we interpret the coefficients found and compare these results to existing literature, where appropriate.

3.4.1 Estimation outcomes

The model results in a final loglikelihood (LL) value of -2694.76 and AIC and BIC values are 5433.51 and 5568.67 respectively. In terms of goodness-of-fit, adjusted McFadden's rho-squared (ρ^2) is estimated 0.31. Normally, a value of 0.2-0.4 for (ρ^2) represents a good fit (McFadden, 2021). Moreover, the bootstrap estimation has been conducted to draw inferences about the population by resampling. The results of the test did not lead to different coefficient values compared to the HCM, which shows the accuracy of the sample estimates.

Based on the conceptual model represented in Figure 3.1, the HCM is estimated, and results are shown in this section. Table 3.5 shows the direct effect of exogenous variables on crowdshipping service choice, as well as their effect on trust.

Table 3.5: Estimation results (direct and total effects)

		Direct effect on the service adoption		**Direct effect on trust**		**Total effect on the service adoption**	
	Reference level	Est.	p-value	Est.	p-value	Est.	p-value
Main attributes							
Delivery time (Same day delivery)	Next day delivery	0.266	0.028*	0.141	0.100	0.410	0.005*
Delivery cost	—	-0.338	0.000*	-0.095	0.000*	-0.435	0.000*
Tracking and tracing options (Real-time driver tracking)	Only main steps can be seen	-1.183	0.000*	0.408	0.000*	-0.766	0.000*
Delivery company's reputation (Four stars)	Two stars	0.199	0.207	1.548	0.000*	1.782	0.000*
Insurance coverage (Up to 1000€)	Up to 500€	0.251	0.030*	0.288	0.000*	0.545	0.000*
Possibility of damage (1 in 30 damaged delivery (3%))	1 in 20 damaged delivery (5%)	0.113	0.189	0.378	0.000*	0.499	0.000*
Socio-demographics							
Education level (Master/PhD)	Others	-0.651	0.003*				
Interaction effects							
Tracking-Occupation	Student	-1.013	0.011*				
Tracking-Education	Others	-1.082	0.000*				
Intercepts		-3.235	0.000*	1.365	0.000*		
Cut 1		-4.839	0.000*				
Cut 2		-1.686	0.000*				
Cut 3		1.022	0.000*				
Cut 4		3.966	0.000*				
Level of trust		1.023	0.000*				
Model fit							
LL (0)				-3960.45			
LL (final)				-2694.76			
Adj. McFadden's rho-squared (ρ^2)				0.31			
AIC				5433.51			

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Table 3.5 continued from previous page

		Direct effect on the service adoption		**Direct effect on trust**		**Total effect on the service adoption**	
	Reference level	Est.	p-value	Est.	p-value	Est.	p-value
BIC				5553.42			
Number of individuals				215			
Number of choice sets				1720			

*Significance level on 95% confidence interval (p<0.05). The coefficient values stand for unstandardised estimates.

The result of the direct effect of trust on crowdshipping service adoption is statistically significant and the coefficient, with a value of 1.023, is fairly strong. Combined with the satisfactory model fit, this provides strong evidence for the role of trust in crowdshipping.

Regarding the calculation of indirect effects, the form of coefficient values can be estimated by multiplying the trust coefficient (1.023) and the direct effect of the corresponding variable on trust. However, the Sobel test, so-called Delta method gives an accurate calculation of the standard errors for such derived measures (MacKinnon, 2012; Cheung, 2009). Hence, we applied the Sobel test to derive standard errors of the indirect effect of the exogenous variables on the crowdshipping service adoption through trust, as shown in Table 3.6. Finally, the total effect is the sum of the direct and indirect effects.

Table 3.6: Estimation results (indirect effects))

		Indirect effects on the service adoption	
	Reference level	Est.	p-value
Main attributes			
Delivery time (Same day delivery)	Next day delivery	0.144	0.102
Delivery cost	—	-0.097	0.000*
Tracking and tracing options (Real-time driver tracking)	Only main steps can be seen	0.417	0.000*
Delivery company's reputation (Four stars)	Two stars	1.582	0.000*
Insurance coverage (Up to 1000€)	Up to 500€	0.295	0.000*
Possibility of damage (1 in 30 damaged delivery (3%))	1 in 20 damaged delivery (5%)	0.386	0.000*

In this part, only the indirect effects of the main crowdshipping attributes on the service choice are given. The reason for this is that sociodemographic characteristics are only found to be significant on the choice of crowdshipping. Concerning the effect of trust, no significant indirect effect on the background variables is found. Finally, the results show that only delivery time is not mediated by the level of trust, and trust has a mediating role for the rest of the attributes. We compare the detailed findings to the existing literature in the Discussion section that follows.

3.5 Discussion

Tables 3.5 and 3.6 present different outcomes for each attribute and sociodemographic variables. These can be compared to earlier findings in the literature, and they provide new interpretations of the role of trust in crowdshipping. We discuss these below.

The results show that same day delivery has a positive impact (0.266) on the crowdshipping service adoption, confirming the findings of earlier studies (Le & Ukkusuri, 2019a; Dayarian & Savelsbergh, 2020). However, the direct effect of the same attribute on trust is not statistically significant (0.100). This means that trust has no mediating effect on this attribute. These results are in line with the expectations due to the fact that providing shorter delivery times for on-demand delivery requests is essential in the delivery service choice. However, when taking trust into account, delivery time is not a factor affecting the perceived level of trust.

The direct effect of delivery cost on the crowdshipping service choice is statistically significant with the value of -0.338. This means that as the cost increases the possibility of opting for crowdshipping service decreases; hence, the negative relation of the cost can be seen as an expected outcome and is in line with the previous studies (Punel & Stathopoulos, 2017; Le & Ukkusuri, 2019c). An interesting point is the direct effect of delivery cost on trust. The value of delivery cost is negatively correlated, meaning that when the cost of the delivery increases, the perceived level of trust decreases. This outcome can be linked to different perspectives of trust, in this case rational trust. According to Laeequddin et al. (2010), a reduced expectation of reward can affect trust negatively. Another reason for the negative correlation could be that people think they are being overcharged and the service provider is not well-organised to provide low delivery costs. The direct effect of the cost on crowdshipping service choice and trust show that trust has a partially mediating effect on the delivery cost.

Surprisingly, the tracking and tracing feature of the crowdshipping service negatively correlates with service choice. This result conflicts with the literature where real time tracking was so far reported to have a positive impact on service choice (Le & Ukkusuri, 2019c; Gatta et al., 2018). A plausible reason may be the detailed distinction in our model between 2 levels of availability of tracking and tracing. Possibly due to privacy concerns, a basic level of transparency could suffice, and higher levels are appreciated less. Concerning the direct effect of the same feature on trust, real-time tracking and tracing is statistically significant and has the value of 0.408. This result is in line with expectations since the mere existence of this service could install trust in the service. In the end, there is a partially mediating role of trust through the adoption of the service.

The delivery company's reputation and possibility of damage are not significant for the adoption of crowdshipping directly, but these attributes have a significant direct impact on trust. This means that when the crowdshipping service provider has a good reputation and provides a lower number of damaged deliveries, the user's trust would be positively impacted by the corresponding values (1.548 and 0.378, respectively). All in all, trust has a fully mediating effect on the service choice for the delivery company's reputation and the possibility of damage. Although in a narrow sense, the absence of a direct effect of these variables conflicts with previous research (Le & Ukkusuri, 2019c), it is consistent with the novel finding of a fully mediating role of trust in service adoption for these variables.

Next, the direct effect of insurance coverage on the service adoption is statistically significant. The reason could be that this feature positively affects service quality, hence, the choice of the service. Concerning the effect of trust, there is a positive correlation with the value of 0.288. This outcome is also interesting to investigate in detail since there is a partially mediating effect of trust. A likely explanation for this outcome might be that higher insurance coverage of the delivery enables individuals to trust the system and indirectly affects the choice of the crowdshipping service. Finally, the result shows that trust has a partially mediating effect on the service choice.

The findings reveal that certain attributes most notably reputation and tracking and tracing have a stronger mediating effect on trust compared to attributes like delivery time. This can be attributed to the fact that reputation serves as a proxy for perceived reliability, often shaped by the shared experiences and evaluations of others. Similarly, the possibility of real time tracking and tracing signals security, which is central to the formation of trust. These attributes strongly influence a user's willingness to engage with crowdshipping under uncertainty. In contrast, delivery time may be regarded primarily as a functional or service-level feature, rather than a determinant of trustworthiness.

Overall, the significant direct effect of same day delivery, delivery cost, reputation, insurance coverage and possibility of damage is consistent with earlier studies which applied a reduced version of our model (Wicaksono et al., 2022; Le & Ukkusuri, 2019c; Le et al., 2019; Le & Ukkusuri, 2019a). However, this research provides evidence that, in addition, trust has a partially or fully mediating effect for these attributes, except delivery time, which constitutes a new finding to the crowdshipping literature.

In the experiment, five sociodemographic characteristics were asked: age, gender, education level, occupation and income level. To be able to test the heterogeneity in the choices, it is also necessary to test the effect of sociodemographic characteristics on the crowdshipping service adoption and trust. In Table 5, only the statistically significant results are represented. The results show that the direct effects of sociodemographic characteristics on trust are not statistically significant. Unlike the result of the study from Punel et al. (2018b), where the effect of the level of education was found to be not significant, the model findings show that the direct effect of education level on the service adoption is statistically significant, and decision to choose crowdshipping service is higher among the bachelor's and less educated people.

Moreover, interaction effects of main attributes and sociodemographic characteristics are also included in the model to investigate heterogeneity in preferences. Although there is no significant interaction effect associated to trust, the results show that there is an interaction effect between tracking and tracing and sociodemographic characteristics on the crowdshipping service choice. The findings show that students who are holding a bachelor's degree (at the most) are more inclined to choose crowdshipping even if there is no real-time tracking and tracing feature in the service. This result shows that even if there is no real-time tracking provided by the service, young people would opt for crowdshipping. The reason for this could be related to the privacy concerns of young individuals which is in line with the findings of the tracking and tracing feature of the crowdshipping.

Finally, the intercept is defined as the mean of the dependent variable if all the independent variables are set to zero. In the model, dummy coding is used, and the reference values are set to 0, which can also be seen in Table 3.2. To this arrangement, the intercept for the trust is 1.365 and it is in between the regression cut points 3 and 4, meaning that the level of trust towards crowdshipping adoption on the reference points is nearly trustful on the ordered rating scale. Additionally, the alternative specific constant for traditional delivery ASC_{TR} shows the choice probability of the crowdshipping alternative when all the independent variables are set to 0. As the value (-3.235) is statistically significant, it indicates that the preference towards crowdshipping is also systematically affected by unobserved attributes which are not considered in the scope of this research.

3.6 Conclusions

The adoption and application of an innovative service is significantly influenced by the trust that users have for a service. Hence, it is also of interest to identify factors that directly or indirectly affect the level of trust. In this study, various service attributes were explored in an HCM, answering the question to what extent the effects of these attributes are mediated by the perception that the delivery of the parcel is executed in a trustworthy manner. To do this, we conceptualised trust as a situation-specific latent variable and measured the level of trust for each choice situation in the experiment. The findings showed the importance of trust and to what extent it affects crowdshipping service adoption. By disentangling the direct and indirect effects of trust towards the service adoption, it became clear that trust has a partially and, for some features, fully mediating effect towards the crowdshipping service choice. The main contributions of this study are threefold. Firstly, this is the first time that trust is included in a choice model as a mediating latent variable in the crowdshipping domain. Although SP experiments are already applied to other studies, the concept of trust has not been included before. Secondly, there is no existing research using a direct measurement of trust in a crowdshipping context. Generally, studies measure trust with the help of trust-related indicators, whereas in in this paper, we observe trust in the survey and employ the features of crowdshipping services, to model their relation to trust and the adoption of the service. Thirdly, this study provides tangible evidence on the effect of trust and its associated features for the future development of such a service in The Netherlands.

The results of the estimations largely confirm earlier findings and enrich these with the specific role and influence of trust on the crowdshipping service choice. The main highlights are the following. Firstly, the model shows that trust has no mediating effect on the same-day delivery feature. This outcome is important to highlight since the direct effect of the same feature positively affects the service choice. Secondly, the delivery company's reputation and the possibility of damage are fully mediated by trust, meaning that these features directly affect trust towards service adoption. This outcome is interesting since a strong reputation and lower damage risk increase the level of trust towards the service adoption. As the rating given in the experiment provides different levels of reputation strength, this could create different levels of trust towards crowdshipping. Thirdly, for the remainder of the attributes, trust has a partially mediating affect. Fourthly, our model shows that there is no mediating effect of trust on sociodemographic characteristics on the service choice, However, the propensity to choose a crowdshipping service is stronger among people with a lower education; interestingly, the lack of real-time tracking and tracing is less of a barrier for students than for other segments

One of the main limitations of the research is the large participation of students and low-income segment interviewees in the sample. Without future research, this might limit the application of the model findings for business recommendations and policy making; therefore, an extended sample is recommended in future studies. Even though sociodemographic profiles are not a reflection of Dutch socioeconomic profile for each segment of the population, we note that (1) we were able to test heterogeneity in preferences through different sets of segments with a sufficient number of respondents and (2) significant estimates were obtained for education level and significant interaction effects were found for occupation and education level on the tracking and tracing feature. Additionally, the SP approach is known for not necessarily providing reliable population levels elasticity values and forecast models – this requires revealed preference data (Kroes & Sheldon, 1988). Moreover, we need to have particular care regarding the post-rationalisation effect that might occur. Due to the design of the choice experiment, respondents' level of trust rating might be affected by their choices, which might potentially lead to bias on the trust scale. Finally, dominant alternatives in choice situations might emerge, especially in SP experiments with unlabelled alternatives (Bliemer et al., 2017). In this research, two of the choice situations have dominance over traditional delivery option. Due to the fact that the existence of dominant alternatives provides insights on the level of trust towards crowdshipping, these choice situations are not excluded from the experiment. However, a replication of this study might help to further explore whether the dominance of crowdshipping over traditional delivery (one in each block) biases parameter estimates in the model.

For future research, more service alternatives to crowdshipping could be added in a future choice experiment. To be able to investigate the impact of policy making, various aspects of trust such as institutional trust can be included. As regulation of crowdshipping services is in a far less advanced state as in incumbent logistics services, several regulatory policy issues could be studied. For instance, the level of trust in service could be affected by various standards for services, prices or insurance. Next, the proposed experimental design needs to be seen as one of the possible ways to measure trust for crowdshipping users. Other ways to measure trust include structural equation modelling (SEM) (see, for example, (Shao & Yin, 2019; Shao et al., 2020; Upadhyay et al., 2021)) or traditional HCM (see, for example (Jin et al., 2020)). Even though our research is unique in terms of measuring trust as a situation-specific variable, trust can also be treated as a person-level characteristics in a SEM or traditional HCM context. Hence, further research is needed exploring multiple item scale to measure trust. The current research takes only the user side of the service into account. To have a deeper understanding of the actors, the level of trust from the carrier point of view needs to be studied since the carrier can also be asked to deliver dangerous/illegal or hazardous items. Therefore, considering the carrier's point of view would provide more detailed knowledge regarding the trust and the parties involved in crowdshipping. So far this supplier perspective on trust has not yet been considered in research.

From a practical point of view, various recommendations can be given to provide roadmaps for crowdshipping service providers. Firstly, our research showed that the reputation of the delivery company has the biggest impact on the level of trust towards the service choice. Even though flexible or outside service hours parcel delivery would be possible in crowdshipping, these advantages can only be effective if the company has a good reputation. Thereby, a crowdshipping service provider who is new in the market might have difficulty establishing a profitable demand without building a high service quality reputation. Secondly, distinguishing between market segments could be important as our findings also indicate significant heterogeneity in acceptance behaviour between user groups.

Chapter 4

Consumer willingness to become occasional carrier as suppliers

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Following our exploration of trust and user acceptance in crowdshipping in Chapter 3, it is essential to investigate consumer decision-making behaviour from the service provider's perspective. Hence, this chapter focuses on crowdshipping as a sustainable parcel delivery solution and its potential for generating new trips.

In this study, we compare how private individuals and occasional carriers respond to crowdshipping delivery tasks. We analyse factors influencing their choices, including values of time and the trip-generating potential of crowdshipping.

This chapter is based on the following journal paper: Cebeci, M. S., Tapia, R. J., Nadi, A., de Bok, M., & Tavasszy, L. (2023). Does Crowdshipping of Parcels Generate New Passenger Trips? Evidence from the Netherlands. Transportation Research Record, DOI: https://doi.org/10.1177/03611981231196149.

4.1 Introduction

Consumers' expectations for last-mile delivery are becoming more sophisticated with on-demand, customized, and low-cost delivery requests (Schröder et al., 2018). Currently the share of same-day or instant delivery orders lies around 25% and is increasing among younger consumers (Joerss et al., 2016). As a consequence, last-mile delivery has become the least efficient segment of the supply chain, responsible for almost 30% of total delivery costs (Ranieri et al., 2018), as well as the most polluting part (Brown & Guiffrida, 2014). Logistics service providers are continuously challenged to meet customer demands and reduce the resulting pressure on delivery costs. One option is to outsource shipping assignments to private individuals who can act as an occasional, cheap carrier. While this approach may reduce costs, it may also lead to new trips and hence increase the burden on traffic and the environment. Whether this outsourcing relieves or exacerbates the negative externalities of last-mile deliveries is still an open question.

Crowdshipping is defined as a service that links customers to a crowd of travellers (occasional carriers, OCs) who are potentially willing to pick up and deliver packages (Rougès & Montreuil, 2014). In current implementations of crowdshipping, app-based platforms play the role of matching the senders of shipments to the OC community (n.d., 2012a,b) and arrange for their monetary compensation (Le et al., 2019). OCs will make a trade-off between the effort involved in the pickup and delivery versus this fee. The most efficient case is when a traveller who has already planned a trip for their own private purposes agrees to deliver a package, on the way to their destination. The service could result in a more environmentally friendly delivery of goods and reduce the volume of freight trips in a city (Devari et al., 2017) . Despite these theoretical benefits, it is still not completely clear whether the expected positive outcomes of such a service can be achieved in practice. Partly, this is due to the possibility of detours taken by carriers from their original trip (Simoni et al., 2020). In addition, however, there might be OCs who had not planned a trip yet and generate a new trip just to deliver the parcel. Our focus in the paper is on this second possibility.

Much of the crowdshipping research has focused on crowdshipping users (Punel et al., 2018c; Wicaksono et al., 2021; Punel & Stathopoulos, 2017) and travellers who occasionally act as couriers, hereinafter referred as occasional carrier (Wicaksono et al., 2021; Archetti et al., 2016; Le & Ukkusuri, 2019d). Several lines of evidence in previous studies show promising effects of crowdshipping when the service is connected to other logistics services such as parcel lockers which is also the main focus of this study (Gatta et al., 2018, 2019; Ghaderi et al., 2022). In the literature, the mentioned benefits of such a service are similar to the ones attributed to ride-hailing applications, such as Uber or Lyft, in their early times. However, after the initial implementation, the use of ride-hailing platforms resulted in an increase of vehicle km and full-time professions for some of its drivers (Schaller, 2021). With this in mind and to foresee such side effects, we aim to investigate the willingness of people to become an occasional carrier in more detail, with two main crowdshipping modes: trip-based and home-based. The trip-based crowdshipping relates to a delivery based on regular commute patterns such as work, education or recreational purposes, similar to the ones by (Wicaksono et al., 2021; Archetti et al., 2016; Le & Ukkusuri, 2019d). These carriers were characterized as "those who travel anyway" (Le et al., 2019). We argue that crowdshipping can also cause new trips. We will call this second category the home-based trips.

The objective of this research is twofold. First, we aim to investigate the willingness of OCs to execute deliveries in a crowdshipping system, during planned commute trips as well as with newly generated delivery trips. In this system, carriers can make use of complementary parcel lockers. Second, we aim to identify any heterogeneity in preferences amongst OCs. Noting the novelty of crowdshipping, our study aims to provide new insights on crowdshipping by applying the state-of-the-art models: (1) a Stated Preference (SP) survey with settings for crowdshipping: commute-based and home-based; and (2) a Latent Class Analysis revealing user groups with distinctly different preferences.

In the following, a brief literature review on crowdshipping is provided. Next, the methodology used, and the research results are presented. Finally, conclusions of the research are discussed.

4.2 Literature Review

Several streams of research can be identified on the topic of on-demand delivery crowdshipping from the OCs perspective. Archetti et al. (Archetti et al., 2016) propose that crowdshipping can be modeled as a novel variation of the vehicle routing problem. The authors find out that crowdshipping can achieve significant cost savings if there is a large number of OCs available and if they show flexibility executing the delivery task. In addition, crowdshipping will require fewer freight vehicles (Archetti et al., 2016). Another optimization study shows that OCs are preferred to perform last-mile deliveries with a large-scale mobile crowd tasking model (Y. Wang et al., 2016).

Studies on the determinants of the behavior of occasional carriers are limited (Le & Ukkusuri, 2019d). A recent behavioural study shows that occasional carriers are willing to travel longer distances depending on the compensation they are offered (Le & Ukkusuri, 2019d). It is generally assumed that occasional carriers have free capacity in terms of space and time (Le et al., 2019). Another behavioural study shows the market potential of bicycle crowdshipping for users and occasional carriers (Wicaksono et al., 2021), taking into account the demand and supply sides of such a service. Punel et al. (Punel et al., 2018c) highlight that crowdshipping is generally cheaper than traditional delivery which brings economical convenience. However, the important assumption is that the participation of the crowd is based on minimizing the detour for drivers (Miller et al., 2017), in other words, the willingness of picking up a parcel is determined by the nearest delivery location of the OC's working place, home or close to their destination point.

Not all studies are positive about the possible impacts of crowdshipping. A simulation study (Simoni et al., 2020) found that car-based crowdshipping may be less environmentally friendly than public transport-based crowdshipping. Similarly, Tapia et al. (Tapia et al., 2023) highlight that crowdshipping is likely to increase congestion and emissions due to its trip generating effect. Another study states that the mode is crucial when evaluating the crowdshipping performance and impact in the cities (Gatta et al., 2019). Crowdshipping has been named "a double-edged sword" for sustainable logistics operations (Simoni et al., 2020). Depending on the different implementations of crowdshipping, its impacts might result in unintended changes in emissions, travel times, as well as congestion.

Since crowdshipping is in its early growth stage in most countries, there is not enough data available to analyse the actual impact of such a service. There is some recent research on the possible risks of ride-hailing and shared economy services for sustainable mobility (Mouratidis et al., 2021). A recent study highlighted the effects of ride-hailing services on vehicle kilometres travelled as well as on environmental inefficiencies (Tirachini, 2020). Well known service providers such as Uber and Lyft (Frenken & Schor, 2019), see crowdshipping services as a possible addition to their business model, to fill idle capacity and time. However, it is still not clear if such a service might create new trips for people who are available to pick up the delivery and drop it off to its destination. Some studies point out that sociodemographic characteristics can be determinants of becoming an OC. Buldeo Rai et al. (2021) find out that age, gender, ethnicity, and education affect the willingness to become an occasional carrier. Le & Ukkusuri (2019d) also include relevant socioeconomic variables such as age, employment, ethnicity, gender, and financial circumstances. The consequences for the generation of new trips have not yet been studied systematically, however. Our study aims to contribute to filling this void.

In addition to the above, limited research has been done regarding the potential of connecting parcel lockers with crowdshipping services. The success of crowdshipping depends on connectivity of the service to other last-mile delivery options (Gatta et al., 2019). The authors assert that crowdshipping is a promising way to diminish pollution originated from last-mile deliveries in the city by making use of metro network and smart lockers inside or outside of the station (Gatta et al., 2018). Another study investigates the possibilities of connecting these two last-mile logistics services (Ghaderi et al., 2022) through optimization. The authors find that this type of joint delivery can result in higher delivery success rates. As parcel lockers potentially could fuel the emergence of crowdshipping services, it could also contribute to the generation of new trips.

In summary, crowdshipping service markets have been studied by behavioural and optimization studies. These studies generally assume that travelers have already decided to make a trip close to the pick-up or drop-off point. The research question that arises from the literature review is the following:

When are occasional carriers willing to accept a delivery request, even if the delivery operation generates a new trip?

In the next section we present the modelling methodology and the data acquisition approach taken.

4.3 Methodology

The general approach taken in this study is the modelling of the discrete choice of OCs whether or not to accept to deliver a parcel. We introduce the experiment design and the mathematical formulation of the model below.

4.3.1 Experiment Design

Figure 4.1 shows the conceptualization of the problem of the selection of alternatives, made by occasional carrier. It is expected that various attributes of the trip affects the choice of the delivery directly. For example, some people may be more inclined to become an occasional carrier if the total remuneration is high whereas others may be reluctant because of the distance that needs to be travelled. Additionally, personal characteristics will influence the sensitivity to different attributes, leading to variations in individual preferences.

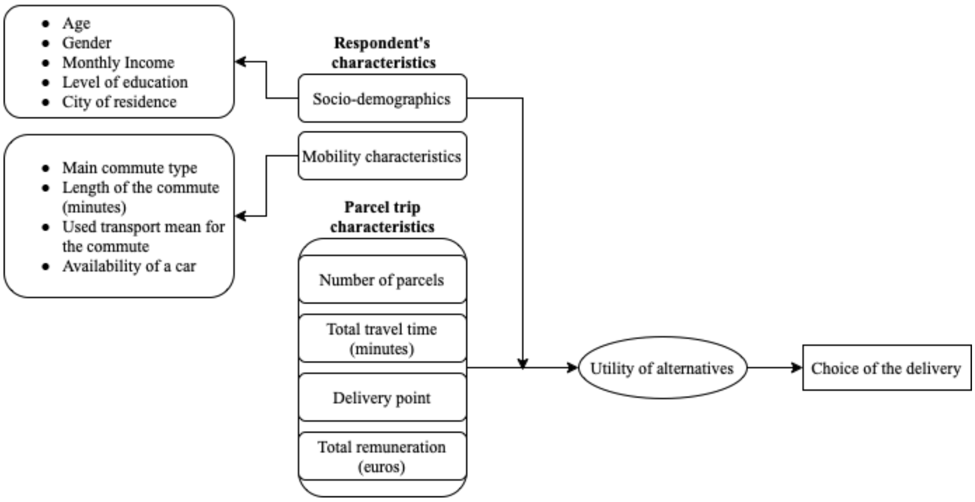


Figure 4.1: Conceptual Model

To test the conceptual model shown in Figure 4.1, a stated preference experiment (SPE) was prepared. There are two reasons for this choice. Firstly, no data is available on crowdshipping services which is linked to the required characteristics of OCs, including their surrounding personal travel choices. Secondly, a stated choice experiment enables control over the choice sets presented to decision makers (Hensher, 1994).

Our objectives for this survey are twofold, and positioned in different choice situations. Firstly, we are interested in exploring the willingness to carry a parcel while travelling, given specific parcel characteristics. Secondly, we focus on the possibility of carrying a parcel by starting a new trip from the home base. As both situations address the question whether or not to become an occasional carrier, they need to be designed consistently.

For the first SP situation, the aim is not only to investigate willingness to bring a parcel to a parcel locker or to its final destination, but also to explore changing preferences depending on the possibility of picking it up before or after the activity. In this part of the SP, the respondents are asked to choose whether they preferred to pick up a parcel before, after or continue with their current trip (opt-out) to see whether the moment of the delivery affected the willingness to become an occasional carrier. Additional data characterizing the mobility characteristics of the respondents were collected, such as trip motive, frequency and available vehicles. It is important to point out that crowdshipping via public transport (PT) trip was not considered in the experimental design. PT travellers only filled in the home-based survey. In the second SP situation, respondents are asked to make a choice based on the assumption that they are at home and could deliver a package. This part of the survey aims to explore trip generation due to new opportunities to earn money. The choice set includes 'stay at home' (opt-out) or to do the pick-up and delivery either by bike or by car (if available in the household). Every respondent was assumed to have a bicycle available for the design, which was further confirmed by the descriptive characteristics of the respondents. Attributes related to parcel characteristics were identified and validated through interviews with a crowdshipping company. These attributes are: number of parcels, total travel time, delivery point and total remuneration. The number of parcels was included to generate a credible variability in the remuneration and extra travel time, as it allowed us to test larger remunerations and travel times.

It is important to highlight that in both SP surveys total travel time and total remuneration were calculated as a function of the number of parcels, in order to increase the experimental realism of the study. Total travel time and total remuneration were generated by multiplying the number of parcels with a detour per parcel and remuneration per parcel. Only the total remuneration and total travel time were shown to the respondents.

Tables 4.1 and 4.2 show the attributes and attribute levels for home- and commute-based SP experiments. These attribute levels were validated through discussions with a crowdshipping service provider. As can be seen from the tables, three levels were defined for the number of parcels and two levels were defined for delivery points (DPs). Due to the specific focus of the experiment, parcel lockers (PL), as a delivery point (DP) option, were considered together with person-to-person (P2P) delivery. Importantly, extra travel time and remuneration are illustrated with different attribute levels. The reason for this choice is that there is no travel time effect in the home-based scenarios. Hence, choice sets were designed with larger extra travel times and more levels for remuneration. Additionally, unlike the commute-based SP experiment, these levels are not pivoted around the current travel times of the respondents in the home-based part.

Table 4.1: Summary of the attributes and attribute levels for the commute-based part of the SP

Attribute	Number of attribute levels	Levels
Number of parcels	3	1 2 3
Extra travel time (minutes/per parcel)	3	5 10 15
Delivery point	2	Parcel locker Person-to-person

Continued on next page

Table 4.1 – Continued from previous page

Attribute	Number of attribute levels	Levels
Remuneration (euros/per parcel)	3	5 7 10

Table 4.2: Summary of the attributes and attribute levels for the home-based part of the SP

Attribute	Number of attribute levels	Levels
Number of parcels	3	1 2 3
Extra travel time (minutes/per parcel)	3	15 30 40
Delivery point	2	Parcel locker Person-to-person
Remuneration (euros/per parcel)	5	3 5 7 10 15

An efficient design approach was used to generate the choice scenarios (Rose & Bliemer, 2009). The prior beta values for remuneration and cost were used from a Dutch VoT survey (de Jong et al., 2020). The effect of the parcel locker was assumed to be slightly positive for three reasons. Firstly, the use of parcel lockers provides a new level of flexibility for the distribution of the products (Rohmer & Gendron, 2020). Secondly, parcel lockers enable different entities in the delivery channel to participate in a joint delivery (Thompson et al., 2019). Lastly, due to the nature of the crowdshipping service, OCs are travellers who are not employed by a commercial carrier, which might lead to privacy and safety issues (Le et al., 2019). Parcel lockers might facilitate high privacy and secure delivery since OCs and receivers do not need to have a physical connection.

The delivery cost in the Dutch transport market ranges from €8 to €15 among main carriers for a small Local to Local (L2L) parcel. By defining travel time and delivery cost as a function of the number of packages transported, we aimed to increase the realism of the study. Both SP settings have the same set of attributes, base equations and priors. The experiment was designed in two blocks, and six choice situations for both commute and home-based trips are randomly assigned to the respondents. This meant that each respondent was faced with six choice situations for the delivery during a commuting trip and six for a home-based delivery.

In the literature, there has been an increasing tendency in favor of SC experiments, in which the characteristics of the alternatives are based on the knowledge of the sampled respondents (Hess

& Rose, 2009). In this study, for the commuting experiment, a pivot design of the choice set was made incorporating the actual mobility characteristics of the respondents, including factors such as car availability, main commute type and length, and the actual transportation means used. These variables are used to create pivoted SP situations specifically tailored to the context of the commute-based experiment. Figure 4.2 shows an example choice task for a respondent who commutes for 5 to 15 minutes.

	Normal trip	Pick up BEFORE activity	Pick up AFTER activity
Number of Parcels		1	2
Total Travel Time (minutes)	10	15	30
Delivery Point			
Total Remuneration (euros)		5	20

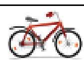
Which of the alternatives above you would choose?

- Do not pick up any parcels
- Pick up and deliver the parcels before the activity
- Pick up and deliver the parcels after the activity

Figure 4.2: An example choice task for the commute-based part of the SP

In the second part of the SP, based on the availability of car and/or bicycle, two different SP settings were directed to the respondents. Figure 4.3 shows the choice task for the home-based scenarios, a respondent who has both car and bicycle (a) and Figure 4.4 shows when only bicycle is available (b).

a

	Deliver parcels by Car	Deliver parcels by Bike
Number of Parcels	1	1
Mode		
Total Travel Time (minutes)	15	30
Delivery Point		
Total Cost (euros)	1	0
Total Remuneration (euros)	3	3

Would you:

- Stay home and do not pick up any parcels
- Pick up and deliver the parcels by bike
- Pick up and deliver the parcels by car

Figure 4.3: An example choice task for the home-based part of the SP (both car and bike available)

b

	Deliver parcels
Number of Parcels	3
Total Travel Time (by bike, in minutes)	40
Delivery Point	
Total Remuneration (euros)	45

Would you:

- Stay home and do not pick up any parcels
- Pick up and deliver the parcels

Figure 4.4: An example choice task for the home-based part of the SP (only bike available)

Figure 4.5 gives an overview of the SP experiments used in this study. As can be seen, commute-based trips and home-based trips have different SP settings. It is worth noting that an approximation of travel cost by car was added when the car mode was available to illustrate the cost.

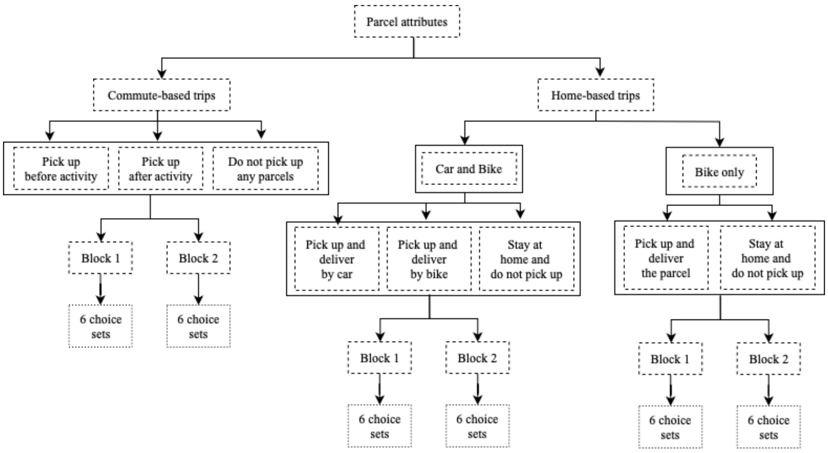


Figure 4.5: Layout of the SP experiments

Along with the SP, the survey inquired about sociodemographic characteristics (age, gender, income level, level of education) and mobility characteristics of respondents (main commute activity, the length of the commute and used transportation mode). The questionnaire was developed in the Qualtrics online web platform and the data collection process took place during July 2022. The survey was circulated among the authors' direct contacts and social media platforms. Moreover, flyers were handed out to reach more respondents in public areas. There is a particular interest in the student population because of previous research findings (Wicaksono et al., 2021; Punel & Stathopoulos, 2017). Only respondents who live in the Netherlands and are above 18 years of age were allowed to fill in the survey. Finally, 298 responses were collected, of which 250 were fully completed.

4.3.2 Discrete Choice Models

Discrete choice models (DCMs) were deployed to analyse the decision-making of the respondents (Bierlaire, 1998). Here, behavioural preferences of respondents are identified using econometric modelling techniques. DCMs employ the principle of Random Utility Maximization (RUM) (McFadden, 1974). Based on this principle, a decision-maker is assumed to choose the alternative i which has the highest utility (U_i) in the choice set M as shown in the equation below (Hess et al., 2018).

$$U_i > U_j \qquad \forall\, j \in M,\, j \neq i \tag{4.1}$$

The utility of an alternative i is composed of a systematic component (V_i) which includes observed factors such as travel time, travel cost and an error term ε_i which captures uncertainty in choice-making (Bierlaire, 1998).

$$U_i = V_i + \varepsilon_i \qquad \forall\, i \in M \tag{4.2}$$

The total utility is defined as a linear additive function and an error term as shown in Equation 4.3. In the equation, β_m stands for the coefficient of an attribute m and (X_{im}) is the value of the attribute.

$$U_i = \sum_m \beta_m X_{im} + \varepsilon_i \qquad \forall\, i \in M \tag{4.3}$$

The Equations 4.4 and 4.5 show the utility functions in relation to total travel time and total remuneration, with respect to the number of parcels. Here, ETT, DP, Rem and n_{parcel} stand for extra travel time, delivery point, remuneration and number of parcels, respectively.

$$\begin{aligned} V_i = {} & \beta_{ETTcommute[1/min]} \cdot ETT_i[5{,}10{,}15] \cdot n_{parcel} + \beta_{DP} \cdot DP_i[\text{PL, P2P}] + \\ & \beta_{Rem[1/euro]} \cdot Rem_i[5,7,10] \cdot n_{parcel} \end{aligned} \tag{4.4}$$

$$\begin{aligned} V_i = {} & \beta_{ETThome[1/min]} \cdot ETT_i[15,30,40] \cdot n_{parcel} + \beta_{DP} \cdot DP_{(i)}[\text{PL, P2P}] + \\ & \beta_{Rem[1/euro]} \cdot Rem_i[3,5,7,10,15] \cdot n_{parcel} \end{aligned} \tag{4.5}$$

By using the coefficient for remuneration as the marginal utility of money, we can calculate the Value of Time (VoT) values. To do this, the Delta method is applied (Daly et al., 2012; Hess & Palma, 2019). The VoT values with regards to low-income and high-income classes are calculated as follows:

$$VoT = \frac{-\beta_{ETT[1/min](commute/home)}}{\beta_{Rem[1/euro]}} \cdot 60[h/min] \tag{4.6}$$

The Multinomial Logit (MNL) model is the most common and simple way to model discrete choices under the RUM assumption. It assumes independent and identically Gumbel distributed error terms. In this type of model, the probability of a person n to opt for an alternative i is estimated by computing Equation 4.7. Here, I stands for the set of alternatives used in the experiment.

$$P_i = \frac{e^{V_i}}{\sum_{j \in I} e^{V_j}} \qquad \forall i \in I \tag{4.7}$$

In order to improve the model and explore the impact of sociodemographic characteristics, interaction effects are added in the utility equations of the alternatives. At least one variable in these interaction terms varies depending on the alternative. The interactions are defined similar to the approach in (Tapia et al., 2021) and are computed as follows:

$$\text{Interaction effect} = (1 + \beta_{interaction} \cdot \delta) \tag{4.8}$$

where β is the coefficient of the variable, $\beta_{interaction}$ is the coefficient for the interaction variable and δ is the dummy variable for the interaction effect. With this representation of the interaction term, interactions can be interpreted as the magnifying effect. The coefficient becomes β and $(1 + \beta_{interaction})$ if the dummy variable (δ) has the value of 0 and 1, respectively Tapia et al. (2021).

The MNL models including only main attributes are estimated by using Equations 4.4 and 4.5 for different alternatives defined in the experiment with the addition of socioeconomic interactions according to Equations 4.9 and 4.10. The resulting utility functions with interactions for the MNL is shown below.

$$\begin{split} V_i = \beta_{ETTcommute[1/min]} \cdot ETT_i[5,10,15] \cdot n_{parcel} + \beta_{DP} \cdot DP_i[\text{PL, P2P}] + \\ \beta_{Rem[1/euro]} \cdot Rem_i[5,7,10] \cdot n_{parcel} \cdot (1 + \beta_{interaction} \cdot \delta) \end{split} \tag{4.9}$$

$$\begin{split} V_i = \beta_{ETThome[1/min]} \cdot ETT_i[15,30,40] \cdot n_{parcel} + \beta_{DP} \cdot DP_i[\text{PL, P2P}] + \\ \beta_{Rem[1/euro]} \cdot Rem_i[3,5,7,10,15] \cdot n_{parcel} \cdot (1 + \beta_{interaction} \cdot \delta) \end{split} \tag{4.10}$$

Although the MNL model is easy to interpret, the assumptions regarding the error term are very simplistic and provide little room to model heterogeneous groups of individuals. To better account for the heterogeneity of preferences within the sample, a Latent Class Choice Model (LCCM) is applied.

Latent Class Choice Model (LCCM)

The LCCM probabilistically splits the respondents into a number of nontrivial classes based on their choices and sociodemographic characteristics, and then allocates each individual stochastically into those classes (Vij et al., 2013). The model was run for an increasing number of classes, resulting in two optimum classes. The Bayesian Information Criteria (BIC) and Akaike Information Criterion (AIC) were used to determine the local measures of the model fit (Tein et al., 2013) .

The LCCM is defined with the following Equation 4.11 (Hess, 2014) where, $P_n(i|\beta)$ refers to the probability that individual n chooses alternative i, conditional on the model parameters β. For classes s, π_{ns} represents the class membership probability, i.e. the probability that an individual n belongs to class s. Lastly, $P_n(i|\beta_s)$ refers to the probability of an individual n choosing alternative i, while individual n belongs to the class s.

$$P_n(i|\beta) = \sum_{s=1}^{S} \pi_{ns} P_n(i|\beta_s) \tag{4.11}$$

To investigate the individual's probability of belonging to each class, a class membership function is estimated. This enables to examine whether this probability is related to personal characteristics or not. The formulation is given in Equation 4.12 (Hess, 2014). The class-specific constants δ_s along with the vector of parameters γ_s need to be estimated. The function g(○) refers to the functional form of the utility for the class. Lastly, in the formulation, z_n refers to observed variables which are taken into consideration in the model such as socio-demographic or attitudinal variables.

$$\pi_{ns} = \frac{e^{\delta_s + g(\gamma_s, z_n)}}{\sum\limits_{l=1..S} e^{\delta_l + g(\gamma_l, z_n)}} \tag{4.12}$$

To find the best number of classes, the Bayesian Information Criterion (BIC) and Akaike Information Criterion (AIC) are employed as indicators of global and parsimonious model fit. In general, the smaller these values, the better the fit (Muthén & Muthén, 2000). We also consider the interpretability of the models and the size of the classes. It is important that the behavioural model is realistic, that classes are distinguishable and that they can be easily labeled based on the heterogeneity they represent (Muthén & Muthén, 2000; Muthén & Kaplan, 2004; Lanza et al., 2007). When we compare Tables 5 and 6, we can see from the LL, Rho^2, BIC, and AIC values that the LCCM provides a better model fit compared to the MNL model. Based on the results, we determine that the model with 2 classes provides a satisfactory explanation of respondent behaviour and is easily identifiable as low- and high-income classes. It is important to recognize that the results may vary when working with a larger sample size.

4.4 Results

4.4.1 Sample Characteristics

Based on the data, the frequency distribution of respondents characteristics is presented in Table 4.3. As can be seen, around 25% of the respondents belong to the age group of 18-24 and about 35% of the respondents have a monthly net income of less than €1000. Since one-fourth of the sample data consists of students this result is as expected. Regarding the gender ratio, the sample is representative for Dutch context (CBS, 2019). The data shows highly educated people in the Netherlands. Not surprisingly, the sample also shows that a considerable part of the respondents commutes due to either study or work-related purposes and all respondents have a bicycle available which confirms the assumption mentioned in 4.3.1.

Table 4.3: Frequency distribution of respondents' characteristics of the sample (N=250)

Respondents' characteristics	Category	Frequency (N)	Relative (%)
Age	18 - 24	64	25.60
	25 – 34	127	50.80
	35 – 44	33	13.20
	45 – 54	15	6.00
	55 - 64	8	3.20
	65 - 74	3	1.20
Gender	Female	109	43.60
	Male	139	55.6
	Non-binary/third gender	1	0.40
	Prefer not to say	1	0.40
Income level (Net)	Less than €1000	88	35.20
	€1000 - €1499	38	15.20
	€1500 - €1999	11	4.40
	€2000 - €2999	56	22.40
	€3000 - €3999	48	19.20
	€4000 - €4999	5	2.00
	>€5000	4	1.60
Level of education	High-school	16	6.40
	Bachelor	96	38.40
	Master	116	46.40
	Doctorate	22	8.80
Commuting activity	Leisure	26	10.40
	Shopping	7	2.80
	Study	102	40.80
	Work	115	46.00
Commute length	<5	11	4.40
	5 - 15	81	32.40
	16 - 25	38	15.20
	26 - 35	42	16.80

	36 - 45	27	10.80
	>45	51	20.40
Transportation mean	Bicycle	130	52.00
	Car	19	7.60
	Public transport	79	31.60
	Walking	22	8.80
Vehicle availability	Bicycle	172	68.80
	Both	78	31.20

4.4.2 Descriptive characteristics of the SP experiments

Table 4.4 shows the frequency distribution of the sample choices within the two SP settings, namely commute and home-based crowdshipping.

Table 4.4: Descriptive characteristics of the SP experiments

Trips	Choice	Frequency (N)	Relative (%)	Times chosen when available (%)
Commute-based	Do not pick up any parcels	296	12.30	30.20
	Pick up and deliver after the activity	404	16.80	41.20
	Pick up and deliver before the activity	280	11.70	28.60
Home-based	Stay home and do not pick up any parcels	830	34.60	58.50
	Pick up and deliver by car	56	2.30	15.60
	Pick up and deliver by bike	534	22.30	37.60

In total, 40.8% of the responses were collected from commute-based trips, and the rest consisted of home-based trips. The reason for this difference is that in the commute-based SPE, public transportation was not included as a choice alternative. However, respondents who commute by public transport were able to complete the home-based SP experiment. Based on the sample data, an overview of choices for the LCCM is shown for commute and home-based trips. To do this, three indicators are used: (1) the times when an alternative is chosen, (2) relative percentage overall, and (3) the percentage of a chosen alternative when it is available. For commute-based trips, more than 40% of the responses indicate a preference to deliver the parcels after the main activity. In addition, almost 30% of the responses point at pickup and delivery before the activity. We observe that 30.2% of the respondents would rather not pick up the parcel. Regarding home-based trips, around 38% of the responses prefer picking up and delivering the parcels by bike, as expected due to the convenience of cycling in the Netherlands. Moreover, a considerable portion of the responses (58.5%) shows that it would be preferred to stay at home instead of delivering the parcels. Because of the novelty of crowdshipping, it can be expected that some would be skeptical about the service.

4.4.3 Modelling results

The two SP situations, namely commute and home-based SPEs, were combined into one model. Both settings reflect similar behaviours and have the same base design. By joining them in one model, we can consider the panel effect for each individual. To have a better integration of both models, the same remuneration coefficient is used. This allows us to link both situations and to guarantee consistency with the broader micro-economic theory, which states that the marginal rate of substitution of money is constant (Batley & Ibáñez, 2013). Moreover, we allow differences in the travel times and the parcel locker preferences. This generates different VoT values for each situation (home- and commute-based crowdshipping).

We have tested different utility function specifications, including non-linearities and correlation between alternatives through the Nested Logit model (Zachary, 1978). The estimations showed that the MNL model and the LCCM provide the best model fit. Hence, we opted for modeling the willingness to become an occasional carrier in the commuting setting as shown in Equation 4.4, while the home based utility is shown in Equation 4.5.

From Tables 4.5 and 4.6, it can be seen that the MNL and the LCCM share the same variables: total travel time (commute-based), total travel time (home-based), delivery point (parcel locker) and remuneration. All coefficients have the expected sign: negative for the total travel times and positive for the remuneration and the use of parcel lockers. Specifically for car-based crowdshipping, we included total delivery cost in both models, as shown in Figure 4.3. Since this attribute was not statistically significant in home- and commute-based crowdshipping settings, we added delivery cost to the utility function by equalizing it with the difference in remuneration. With this, we aimed to capture the effect of the travel cost by car on the remuneration. Regarding statistical significance, we set a threshold of a p-value less than 0.05. If the p-value of a coefficient exceeds 0.05, it indicates that the corresponding parameter is not statistically significant, whereas a p-value below 0.05 indicates statistical significance (Ott, 1977). As a general guideline, if an observed result is statistically significant at a p-value of 0.05, it implies that the null hypothesis should not fall within the 95% confidence interval (Ott, 1977).

Table 4.5: MNL model results

	Est.	p-value
Main attributes		
Total travel Time (Commute-based)	-0.052	0.000*
Total travel Time (Home-based)	-0.034	0.000*
Parcel locker (Commute-based)	0.362	0.008*
Remuneration	0.069	0.000*
ASC-Before Activity	0.236	0.077
ASC-After Activity	0.634	0.000*
ASC-Bike from Home	-0.673	0.002*

Continued on next page

Table 4.5 – Continued from previous page

	Est.	p-value
ASC-Car from Home	-1.709	0.000*
Sociodemographic characteristics (Interaction effects)		
Income-Remuneration (> €2000)	-0.775	0.002*
Model fit		
Final LL	-1862.93	
Adj. McFadden's rho-squared	0.15	
AIC	3743.86	
BIC	3795.91	
Number of individuals	250	
Number of choice sets	2400	
*Significance level on 95% confidence interval (p<0.05)		
"ASC" stands for Alternative Specific Constant		

Table 4.6: LCCM results

	Low-income class		High-income class	
Main attributes	Est.	p-value	Est.	p-value
Total travel Time (Commute-based)	-0.055	0.000*	-0.190	0.000*
Total travel Time (Home-based)	-0.020	0.022*	-0.110	0.000*
Parcel locker (Commute-based)	0.387	0.035*	0.387	0.035*
Remuneration	0.087	0.000*	0.092	0.000*
ASC-Before Activity	0.641	0.002*	-0.262	0.318
ASC-After Activity	1.054	0.000*	-0.041	0.477
ASC-Bike from Home	-0.733	0.003*	-0.834	0.085
ASC-Car from Home	-1.105	0.005*	-3.203	0.000*
Class membership (Sociodemographics)				
Income (>€2000)	-1.782	0.000*		
Class membership constant	1.884	0.003*		
Model fit				
Final LL (whole model)	-1663.86			
Adj. McFadden's rho-squared	0.24			
AIC	3365.72			
BIC	3475.60			
Number of individuals	250			
Number of choice sets	2400			
Class share	71.00%		29.00%	
*Significance level on 95% confidence interval (p<0.05)				
"ASC" stands for Alternative Specific Constant				

The main differences between these two models are the socioeconomic characteristics included. In both models, we have tested multiple model specifications with different sociodemographic characteristics, such as age, gender and income level. Income level appeared to be the only one of these that was statistically significant. Finally, the MNL model incorporates income as interaction effect with remuneration while the LCCM incorporates heterogeneity by including income in the class membership function.

Statistics on the goodness-of-fit of the two models, MNL and LCCM, need to be compared to determine which model fits better. While the higher final loglikehood (LL) indicated a better model fit (Walker & Ben-Akiva, 2002), smaller values of BIC and AIC indicate a better the model fit (Muthén & Muthén, 2000). Lastly, Rho-squared (Rho^2) can have a value between 0 and 1, and the higher the value, the better the model fit (McFadden et al., 1973). Based on the model results, LCCM shows a higher fit in all metrics; thus it is the preferred model and will be discussed in detail in the next section. However, it is essential to provide the outcomes of the MNL in order to represent the base model. Thereby, the results of the MNL and LCCM models are given in Tables 4.5 and 4.6, respectively.

Based on the model estimations, 5% of the sample consists of the respondents who have chosen the same alternative (called non-traders) most of the time. However, they were not excluded from the sample since there was no difference in their characteristics compared to the respondents who did show variation (traders) in their response pattern.

To assess the predictive power of the model on unseen data we used out-of-sample validation. We therefore divided the individuals from the data to 80% training and 20% test sets which are randomly drawn from the main data set. Then, we used the likelihood ratio index, also known as Rho-squared as presented in Equation 4.13 (Parady et al., 2021; Glerum et al., 2014). Rho-squared is a measure that evaluates the proportion of variance in the data explained by the fitted model compared to a baseline model. A higher rho-squared value indicates a better fit, suggesting that the model captures a larger portion of the observed variation in the choices (McFadden et al., 1973).

$$\rho^2 = 1 - \frac{LL(\widehat{\beta})}{LL(0)} \tag{4.13}$$

In this equation, $LL(\widehat{\beta})$ is the final loglikelihood of the choice model component and $LL(0)$ is the likelihood of the models where all parameters are set to 0.

The likelihood ratio index shows that the prediction power of the model for training and testing data sets are 0.23 and 0.17, respectively. The results suggest that the model performance on the testing data is slightly worse than its performance on the training data. It is important to highlight that slightly low prediction power of the model, as opposed to machine learning models (MLMs), should not be misinterpreted as a weakness of the model. Firstly, MLMs are predictive as they are mostly data-driven methods (Ratrout et al., 2014) as opposed to theory-driven traditional discrete choice models (DCMs) (M. E. Ben-Akiva & Lerman, 1985). Secondly, DCMs have an explanatory nature, assuming parametric relationships, and do not guarantee high prediction power compared to MLMs, which excel in prediction but often lack interpretability (Sfeir et al., 2022).

It is important to acknowledge that the predictive performance of the model may be influenced by inherent bias when only one validation sample is tested, as that particular sample might not be representative of the entire population. To address this issue, a potential solution is to randomly select multiple pairs of estimation and validation samples from the complete dataset and repeat the process for each pair, allowing the calculation of a confidence interval for the out-of-sample measure of fit (Hess & Palma, 2019). We employed k-fold cross-validation to assess the model's prediction stability (Geisser, 1975). This involves dividing the dataset into roughly equal-sized segments; one segment serves as the training set while the remaining data is used for evaluation. The process is repeated K times, with each segment designated as the training data in a progressive manner during each iteration (Jung, 2018). We conducted 30 runs of k-fold cross-validation and found that, on average, the model's prediction power on the test data sets was 3.26% lower than that on the training set.

4.5 Discussion

The LCCM shows two clearly differentiated classes: Low-income and high-income groups. This differentiation is based on the estimated choice constant, which is 1.884, and the income level of the respondents. The structure of the utility functions across groups is the same, favouring the comparison across classes. On average, around 70% of the sample are from the lower income group, while 30% from the higher income one. By using Equation 4.12, we calculated the probability of belonging to the low-income group in the case of lower and higher monthly income of €2000. The results show that if the monthly income of a person is higher than €2000, the probability of belonging to the low-income group is 53% and the probability becomes 87% if the level of income is lower than €2000.

The two classes share the same overall behaviour with respect to the value of travel time and parcel lockers. The valuation of travel time for commute is larger than the home-based one. Moreover, the usage of parcel lockers is relevant for the realization of commute-based crowdshipping, probably because of the flexibility it can provide for the existing trip. The fact that there is a preference for doing a delivery after a trip also supports the idea that the parcel locker can help to avoid delays in the trip. Additionally, parcel lockers are also important in the delivery process as they allow to ensure that there is a pickup and delivery without any problems such as lack of coordination between the sender and receiver, or unsuccessful delivery. The benefit of time flexibility of parcel lockers was acknowledged earlier by Rohmer & Gendron (Rohmer & Gendron, 2020). We note that for home-based crowdshipping deliveries this might be less relevant, since departure times can relatively easily be coordinated by the parties involved.

Alternative Specific Constants (ASCs) are parameters that represent the effect on utility of unobserved attributes (Bierlaire et al., 1997). The ASCs are estimated for each alternative, relative to one base alternative, for which the parameter is fixed to 0 (Bierlaire et al., 1997). The interpretation is of a baseline preference for one alternative, given that all the other attributes are equal. In this study, two constants are introduced for each SP setting (commute and home-based trips), since each has three alternatives, including an opt-out option. The ASCs also highlight the notion of flexibility. The ASC for 'after the trip' is higher than the 'before the activity' one, indicating a preference for this alternative not captured by trip characteristics. Everything else being equal, having a delivery after an activity reduces the risk of being late, thereby making it a preferred option. In the ASCs there is also a difference between classes. For the low-income group, all four ASCs are larger than the high-income one. This indicates an overall preference for participating in crowdshipping, as highlighted in the literature (Buldeo Rai et al., 2021).

The findings on values of time are interesting to note, as our study is the first to produce such numbers for crowdshipping carriers, differentiated by type of trips and income class. This can be of relevance for benefit-cost studies which assess accessibility changes for parcel delivery services. The largest difference between classes is shown in the VoT. The VoT values are shown in Table 4.7, with the p-ratio estimated through the delta method (Daly et al., 2012). The use of a threshold with a p-value lower than 0.05 (0¡0.05) indicates a 95% statistical confidence, suggesting that the values of both the low and high-income classes are statistically significant in terms of their VoT (Ott, 1977).

Table 4.7: Commute-based and home-based trips for different income levels

	Home-based trips		**Commute-based trips**	
	VoT (€/hour)	p-value	VoT (€/hour)	p-value
Low-income	14.43	0.018*	38.57	0.000*
High-income	73.83	0.002*	122.77	0.002*

*Significance level on 95% confidence interval ($p<0.05$)

The model provides new indicators as well that are worthwhile to discuss here. As expected, the VoT for the higher income class is larger than low-income class. In terms of the ratio between commute and home-based VoT, the value for commute-based trips for low-income class carriers is around 2.5 times higher than for home-based trips. Interestingly, high-income class carriers for commute-based trips have a VoT of around 1.5 times higher than for home-based VoT. This result suggests that for the commute-based crowdshipping, there is a trade-off between commuting time and working time. A possible interpretation of this is that respondents perceive the crowdshipping task as an extension of their working time, thus, they give more importance and expect higher remuneration for their time. In the case of home-based trip crowdshipping, respondents expect lower remuneration and would be willing to become a occasional carrier. A trade-off for home-based crowdshipping can be seen between leisure time and commuting time. This might have several reasons. Firstly, occasional carriers might think that they are earning financial compensation when they are available. Secondly, in the case of bicycle crowdshipping, occasional carriers might think that they are exercising and earning money at the same time. Lastly, they might feel like they are contributing to diminish the negative impacts caused by last-mile deliveries.

A recent study investigating ride acceptance behaviour in the context of ride-sourcing indicated that part-time and full-time drivers have different VoTs ranging from 35$/hour to 81.6$/hour (Ashkrof et al., 2022). The study also found that full-time working drivers have a higher VoT than part-time working drivers. It could be said that part-time working drivers perceive the ride-sourcing activity as their working time instead of commuting. Although our categorization is different, this interpretation provides a base of comparison with our commute vs. home-based crowdshipping case. An earlier study on bicycle crowdshipping found that VoT for a student occasional carrier is 24€/hour which is in the range between the commute and home-based VoT for the lower income class. (Wicaksono et al., 2021). Altogether, we conclude that our results are consistent with values known for crowdshipping carriers from the current literature.

Translated to practice, by obtaining the journey time by bicycle from Google Maps, the VoT results imply that for commute-based trips respondents belonging to the high-income group are willing to deviate just around 5 minutes from their tour for a remuneration of €10, which is roughly the price of express parcel delivery between cities in the Netherlands. This value goes up to 16 minutes for the lower income groups, approximately a detour of 5 km by bicycle. A 5 km detour for a commute between two points can provide a good population coverage, providing some support for the feasibility of a crowdshipping market for L2L parcel deliveries. Feasible detours and times are similar for home-based trips as for the commute-based trips, in line with the needs of L2L deliveries, where trips remain within the urban agglomeration (Tapia et al., 2023), conveniently taking a €5 remuneration. Although we cannot draw definite conclusions on whether the participants would actually take a parcel given these conditions due to the hypothetical bias of SP experiments (Murphy et al., 2005), we can say that there is a possibility for crowdshipping to be feasible for L2L deliveries, especially if the group that earns below €2000 is targeted as potential occasional carriers, which is in line with the findings by (Buldeo Rai et al., 2021; Le & Ukkusuri, 2019d). Figure 4.6 presents the coverage of a person living in the a big cities in the Netherlands: The Hague (Den Haag) on the up left, Rotterdam on the up right and Amsterdam centre below with the radius is of 2.5 km.

Figure 4.6: Representation of 2.5 km radius of three big cities. Den Haag (up left), Rotterdam (up-right) and Amsterdam (centre below)

Even though the distance in diameter is only 2.5 km, the maps show that a big portion of the populated areas are covered of these cities, in the order of 100,000 inhabitants. The large coverage for home-based deliveries in high-dense areas, such as the Dutch cities, can potentially make home-based crowdshipping a competitive service in the L2L delivery landscape. Also, this availability of occasional carriers can generate a significant amount of trips to perform L2L delivery tasks. Part of this is potential already evidenced by the success of food deliveries such as Uber Eats or the Dutch Thuisbezorgd (Lalor, 2021).

4.6 Conclusions

In this research, we investigate the supply side of the crowdshipping system, considering the willingness of occasional carriers to carry parcels, based on an existing commute trip, or a new, home-based trip. The research was built on a choice experiment within these two different settings. The main contribution of this study is this separation of the motivation for crowdshipping. While commute-based crowdshipping is closer to the original concept, taking advantage of existing trips to do deliveries, home-based crowdshipping implies the generation of new dedicated trips. Due to the high volumes of e-commerce deliveries, traditional couriers tend to be highly efficient with their practice of consolidation. Replacing these by new trips in the form of home-based individual deliveries may increase the total amount of travelled km in urban areas, and contribute to traffic problems. The experiments suggest that crowdshipping is feasible for local-to-local deliveries and can generate a significant amount of new trips, by bicycle and to a lesser extent by car.

The two-class LCCM provided new insights into the willingness to become an occasional carrier, by separating respondents into low- and high-income groups. People belonging to the low-income group are more likely to become occasional carriers, and more willing to take a long detour to deliver a parcel. This is reflected by two estimations results from this study: (1) the VoT values for the low-income group, which are approximately five and three times lower than those of the high-income group for home- and commute-based crowdshipping, as shown in Table 4.7; and (2) the constants (ASCs), indicating a higher overall appreciation of crowdshipping by low-income groups. These insights are relevant for economic assessments of urban accessibility improvements, which take both induced traffic as well as values of time as inputs.

The study shows that home-based crowdshipping might be feasible for L2L deliveries. Notably, low-income respondents, who have less than €2000 monthly income, can be attracted more as their VoT is lower than the high-income group. In countries like the Netherlands, the impact of these extra trips could be relatively low due to the high quality of cycling infrastructure and the high willingness of commuters to use bike as an active mode. However, for countries where the dominant mode of transport is the personal car, these added trips could be considered a potential downside to the crowdshipping system.

One of the limitations of this study comes from the novelty of the service, and the consequential lack of revealed preference data. In this research, an SP survey is necessary since crowdshipping services have not yet been offered in the Netherlands. Due to their unfamiliarity with the service, respondents of the survey might under- or overestimate some of the attributes provided in the experiment due to hypothetical bias (41). As a consequence, it is not possible to investigate real elasticity of demand, and claim forecasting ability without revealed preference data. Moreover, we have limited the factors involved in the delivery choice to keep the survey execution feasible. Further research could be done, using revealed preference data from other countries, to shed more light on demand elasticity and aggregate impacts at city level.

From a practical point of view, the following conclusions are relevant. Firstly, we have obtained numbers that may be important for crowdshipping business models. Considering an average value of a parcel in the Netherlands, with commute-based crowdshipping, a low-income group carrier is willing to make a 16 minutes detour to execute a delivery with €10 remuneration, while a high-income group carrier might be willing to do only 5 minutes detour from their original trip. With respect to home-based trips, for a similar detour time, they would be willing to settle for earning less than €5 for the trip. Further validation is recommended with revealed choices to repair potential bias resulting from the hypothesized choices. Secondly, by using the results of this study, it is possible to estimate the probability of a person becoming an occasional carrier by generating a new trip. This is necessary input for future simulation studies to understand the mobility impact of new services. Thirdly, the suggestion that there is a market for L2L deliveries with new trips creates a need for further consideration of the possible negative consequences for urban traffic. The mode used for deliveries would have an important impact on this, since bicycle-based crowdshipping raises different concerns (safety, health) than the car mode (congestion, emissions). This highlights the need for the public sector to be engaged in the introduction of crowdshipping services.

Chapter 5

Potential market outlook of crowdshipping last-mile logistics

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Building upon our exploration of crowdshipping from both demand (Chapter 3) and supply (Chapter 4) perspectives, this chapter introduces a simulation study. It aims to examine how various delivery services interact within a last-mile delivery network, inspired by the principles of the Physical Internet. By connecting traditional delivery companies and crowdshipping in a network, we explore the potential efficiencies and synergies in urban logistics.

This chapter is based on the following paper: Cebeci, M. S., de Bok, M., Tapia, R. J., Nadi, A., & Tavasszy, L. (2025). Feasibility of crowdshipping for outlier parcels in last-mile delivery. Research in Transportation Economics, 112, 101607. DOI: https://doi.org/10.1016/j.retrec.2025.101607

5.1 Introduction

Logistics service providers (LSPs) offering parcel delivery services have a wide variety of parcels to process and understanding which deliveries might cause monetary loss is important. Usually, these deliveries will require long driving distances, and the marginal costs will not weigh up against the revenues. Such outlier parcels will be considered for outsourcing to other service providers, to keep losses low (Qi et al., 2018). Crowdshipping presents a potential market that could absorb these parcels. It has emerged recently, as a paradigm shift from traditional delivery services through crowd-sourced, cheap and flexible delivery. Crowdshipping platforms connect LSPs to private individuals which act as occasional carriers, offering the opportunity to sign up to deliver packages on a part-time or gig basis (Shen, 2022). The investigation of how crowdshipping fits into the broader landscape of urban logistics is necessary to understand its potential synergies or conflicts with other delivery modes, and eventually its system level impact on flows, costs and sustainability. Business models of crowdshipping are diverse, such as peer-to-peer model (Le et al., 2019; Stathopoulos et al., 2011), retailer-oriented (Ciobotaru & Chankov, 2021; Gatta et al., 2018; Ni et al., 2019), reverse logistics (Pan et al., 2015), and outsourcing (Le et al., 2019; Archetti et al., 2016). In this study, our focus centres on parcel delivery being outsourced by courier companies to the crowdshipping market.

While some studies explore the effects of crowdshipping from the standpoint of couriers, the primary emphasis in these studies lies in optimising routes for the individual firm (Archetti et al., 2016; B. Li et al., 2014). These optimisation studies provide a detailed analysis at the company level but lack a network level perspective, considering multiple clients, carriers, and service types. To understand the volumes of demand for the crowdshipping market, insight is needed in how all LSPs together determine their outlier parcels, in line with their logistics costs-based reasoning in the construction of delivery tours. To our knowledge such research has not yet been undertaken.

Hence, the objectives of the paper are twofold. Firstly, we aim to develop a decision rule that allows LSPs to identify outlier parcels that are candidates for the crowdshipping market. By replicating freight market conditions aligned with the actual economic considerations faced by couriers, we establish the potential demand for crowdshipping from the perspective of LSPs. Secondly, we aim to evaluate the impacts on the last-mile delivery volumes across all modes namely, private car, public transport and active modes.

In the following sections, we provide a brief literature review on crowdshipping (Section 5.2) to position our work in the literature and state our contributions. This is followed by the modelling methodology (Section 5.3). Section 5.4 describes the study area and data used. Results are discussed in Section 5.5. Finally, we present our conclusions in Section 5.6.

5.2 Positioning and contribution

The literature on crowdshipping is large and addresses various questions, including business models, behavioural mechanisms, optimisation of services, and the evaluation of impacts on last-mile logistics. Various studies have explored the potential of crowdshipping as a potentially disruptive force in the delivery service landscape. Our study is concerned with the capacity of crowdshipping to absorb parcels outsourced by regular service providers. We have identified only one study into the exploration of optimal strategies for an LSP to select portion of its parcels for fulfilment via a crowdshipping platform. Zhang & Cheah (2024) argue that prioritising outlier parcels for crowdshipping might lead to environmental and economic benefits. Their study investigates the impacts of outlier parcel crowdshipping, focusing on spatial location as the primary criterion to identify outlier parcels. In this study, we extend the modelling by considering marginal delivery cost as the decision criterion.

Many studies examine the feasibility of crowdshipping, focusing on how delivery tasks and available occasional carriers are matched; in other words, how crowdshipping demand is fulfilled by occasional carriers. The literature indicates that the business model of a crowdshipping service and its mode of use are among the factors that influence the service's sustainability (Carbone et al., 2017; Tapia et al., 2023). Boysen et al. (2022) generate deterministic instances of number of parcels and number of occasional carriers. Similarly, Mousavi et al. (2024) design a dynamic programming to assess the feasibility of crowdshipping by using predefined number of orders and crowdshippers. Le et al. (2021) also apply an optimisation approach to match parcels with occasional couriers with hypothetical instances. These studies explore the influence of factors, such as detour distance, compensation, and service levels on crowdshipping. However, they lack decision-making processes of wilingness to send and bring a parcel and the challenges of synchronising deliveries with existing travel patterns. In this research, we build on these foundations by using an activity-based model to match demand and supply, leveraging synthetic trip diaries. The activity-based model has previously been used on a smaller scale in other study (Tapia et al., 2023) in the crowdshipping context. Our research extends this application by covering a larger geographical area and using the cost-logic of logistics service providers, providing a more accurate account of the potential for crowdshipping in diverse urban environments.

Mousavi et al. (2022), propose a stochastic routing model where the uncertainty in finding an occasional carrier for a specific task is considered. The authors conclude that outsourcing crowdshipping services can help couriers reduce costs, increase flexibility, and improve customer satisfaction by leveraging the availability and diversity of occasional carriers. However, no study has been found that explores the market segmentation and parcel volume targeted by crowdshipping services when used as an outsourcing strategy. This is crucial because occasional carriers also pose challenges, such as uncertainty in their availability and coordination with the depots of LSPs. Arslan et al. (2019), propose a two-stage stochastic programming model to optimise the outsourcing decisions of LSPs under demand and supply uncertainties. The authors demonstrate that choosing to outsource crowdshipping services has the potential to enhance the profitability and service quality of LSPs. The optimal outsourcing strategy, they argue, depends on various factors such as demand distribution and cost structure. While these investigations offer valuable insights into the operational necessities for crowdshipping, covering aspects such as vehicle routing and pickup and delivery assignments, they generally overlook a crucial aspect—determining the condition at which an LSP is open to outsourcing such a service. The current study addresses this specific point, filling a gap in the existing literature. Moreover, pricing models developed by Peng et al. (2024) develop a model to optimise pricing strategies between crowdshipping platform and LSPs to design a profitable outsourcing scheme. The authors assume that the LSP offers an outsourcing service price to the crowdshipping platform for all its parcels. Subsequently, the crowdshipping platform evaluates both parcel delivery and passenger ride requests to determine which ones to fulfil. Eventually, any unfulfilled parcel requests are handled by the LSP. The study draws a model for outsourcing delivery price, however, behavioural elements of the crowdshipping service such as willingness to send and receive a parcel are overlooked.

To date, no study has analysed the potential demand for crowdshipping services in which an LSP would be willing to engage from a profit, or cost perspective. In this study we consider the perspective of LSPs to gain more realistic insights on the crowdshipping demand. On one side, outsourcing crowdshipping services for spatially dispersed delivery destinations could be economically beneficial for a courier due to their higher delivery cost. On the other side, certain delivery trips might lead to higher costs for the courier due to lower truck loads on particular routes. Additionally, some tours in a courier's delivery plan could result in higher CO_2 emissions, a concern that might be mitigated by outsourcing specific delivery tasks to occasional carriers.

Hence, this study explores the influence of a cost-based decision rule on parcel segregation from the LSP's perspective, employing a simulation approach. We contribute to the literature by (1) connecting outlier parcel decisions with the crowdshipping market to arrive at a realistic estimate of crowdshipping demand; (2) operationalising outlier parcel decisions from the cost-based logic of a carrier and (3) using detailed data on tours, grounded in observations of parcel deliveries of individual firms, to provide an estimate of crowdshipping demand characteristics. Besides an addition to the literature, the above is of practical value for business development managers of parcel shipping platforms.

5.3 Methodology

5.3.1 Conceptual framework

Figure 5.1 provides the conceptual framework of the study. We assume a two-stage approach, where the first stage builds on a decision made by the carrier, and the second on suppliers and users of crowdshipping services. After filtering out outlier parcels from their total flow of parcels, carriers transfer these to the crowdshipping market. For the first stage, cutoff cost per parcel is calculated and parcels with a marginal delivery cost above this cutoff are deemed eligible for crowdshipping, as detailed in 5.3.2. In the second stage, we use willingness-to-send and willingness-to-bring choice models to establish the share of outliers handled by crowdsourced carriers, forming a pool of eligible crowdshipping parcels. After this stage, the crowdshipping cost per parcel can be obtained and compared with the traditional delivery cost for further economic and environmental analysis.

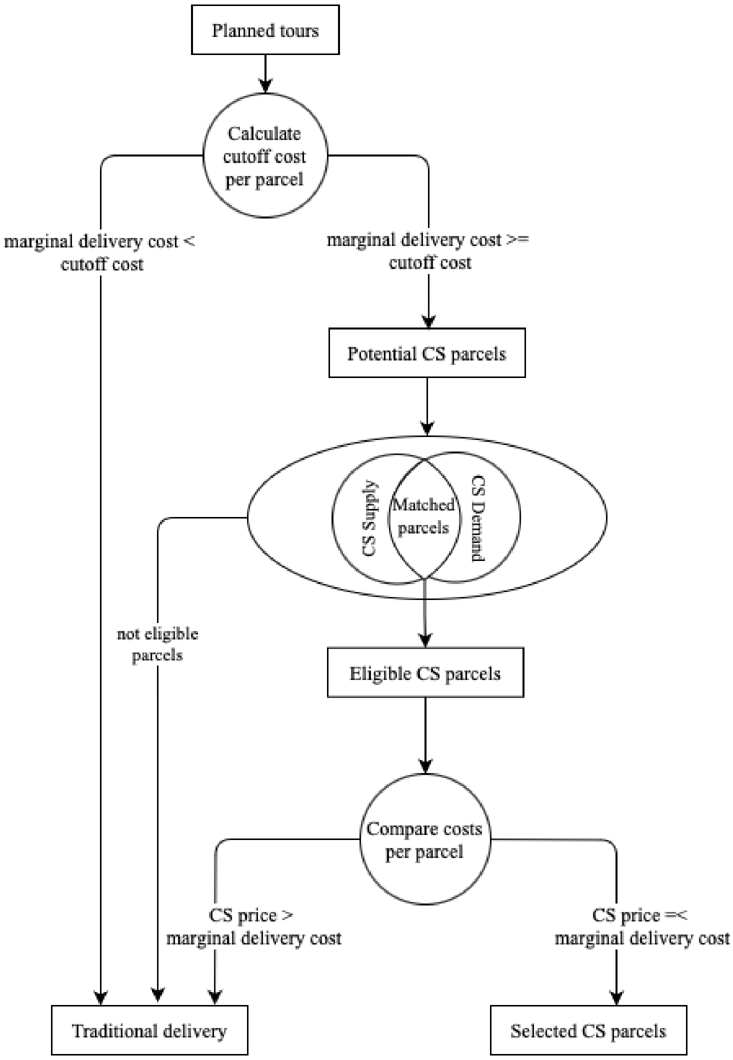


Figure 5.1: Conceptual model

5.3.2 Outlier selection model

Since the first objective of the paper is to define parcels that have high negative impacts (outliers) to LSPs, it is necessary to explore the marginal delivery costs produced by a parcel. A challenge in calculating the cost of service within the logistics sector is the distribution of transportation expenses across a specified route (Sun et al., 2015). To this end, cost allocation is mostly studied in collaborative networks to plan how to allocate the total cost and how to divide the savings (Sun et al., 2015; Dahlberg et al., 2018; Frisk et al., 2010; Guajardo & Rönnqvist, 2016).

By systematically assigning costs to activities, cost allocation allows for a detailed analysis of profitability and efficiency (Guajardo & Rönnqvist, 2016). The methodologies employed in cost allocation vary, each with distinct principles and implications for business strategy (Sun et al., 2015; Guajardo & Rönnqvist, 2016). For instance, the Nucleolus allocation method seeks the most stable allocation of costs or benefits, ensuring that no group of participants can deviate to achieve a more favourable outcome (Frisk et al., 2010). The Shapley value allocates costs (or profits) based on each participant's contribution to the collective outcome. Other cost allocation principles include allocation based on volumes or standalone cost, based on separable and non-separable costs, or the equal profit method. For more information, readers can refer to (Sun et al., 2015; Frisk et al., 2010; Guajardo & Rönnqvist, 2016). In this study, we opt to employ the marginal cost method which is used not only in transportation domain (Bickel et al., 2006; Dahl & Derigs, 2011) but also in other research areas (Massol & Tchung-Ming, 2010). This method reflects each service point's true economic footprint and effectively measures the additional expense incurred. Compared to complex techniques like the Nucleolus and the Shapley value (Sun et al., 2015; Frisk et al., 2010), marginal cost allocation is straightforward and easier to communicate, aligning costs directly with their causes and making it a practical choice for managerial decisions. In this paper, the marginal cost method is used to analyse the cost difference if a certain parcel is not delivered, shown in Figure 2. It involves the analysis of planned delivery tours originating from a depot and covering a series of delivery zones. The objective is to assess the impact of marginal delivery cost per parcel in this plan. Figure 5.2 illustrates the planned route as a closed loop, beginning and ending at the depot and covering zones identified as $Z = z_1, z_2 \dots z_n$.

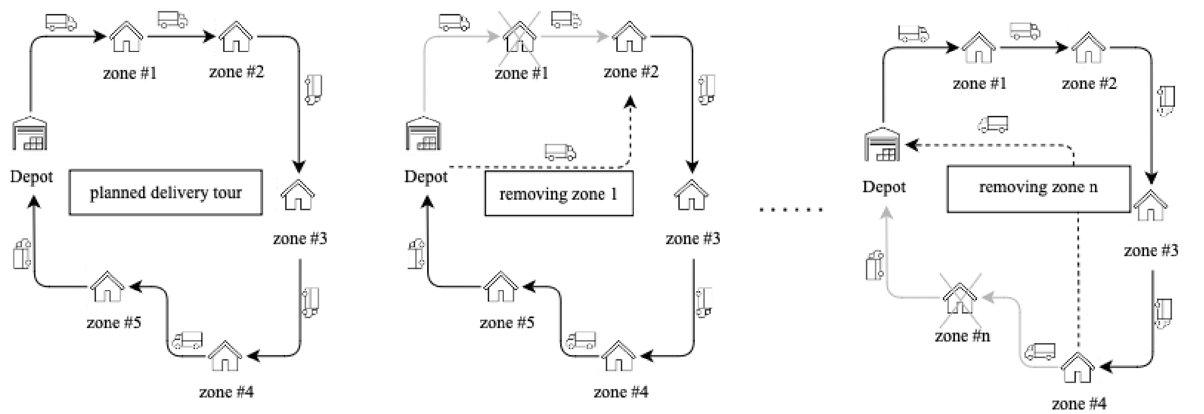


Figure 5.2: Planned delivery tour

We define a graph structure where the depot d and the zones Z are the vertices of the graph. The edges represent the delivery trips between the vertices with associated costs. These costs are derived from the distance matrix D and time matrix T, that are elaborated in Section 5.3.3, coupled with the unit cost per kilometre u_d and cost per hour u_t. The generalised cost function for the path from i to j is expressed as:

$$c_{ij} = u_d \cdot d_{ij} + u_t \cdot t_{ij} \tag{5.1}$$

Under the marginal cost allocation mechanism, when removing a zone z_n from the delivery tour, the marginal cost is calculated by considering the costs of the incoming and outgoing legs associated with z_n and the cost of the new route that connects the nodes that were previously adjacent to z_n. Let c_{in} be the cost of the leg entering z_n, c_{out} be the cost of the leg exiting z_n, and c_{bypass} be the cost of the new route z_n'. This represents the change in cost due to excluding zone z_n from the tour, considering the rerouting that takes place. The marginal cost ΔMC_{z_n} of removing zone z_n is then given by:

$$\Delta MC_{z_n} = (c_{ij(in)} + c_{ij(out)}) - c_{bypass} \tag{5.2}$$

The cutoff point for selecting the number of outlier parcels is calculated using the elbow-finding method. This method involves finding the point on the curve where the rate of increase in cumulative frequency with respect to cost changes most significantly, in other words, where the curve has the sharpest slope. The gradient of the cumulative frequency curve is calculated by finding the difference between successive values of cumulative frequency and dividing by the difference in cost. The index of the maximum gradient is considered the elbow point. Unlike z-score methods, elbow fitting does not assume a normal distribution of the data. As discussed in Section 5.5, our data is mostly skewed, which makes elbow fitting a better choice. Moreover, this method is commonly used in cluster analysis and outlier detection (Syakur et al., 2018; Saraswat et al., 2023). Additionally, the method is straightforward to implement in different areas (Syakur et al., 2018). In our context, the elbow point is leveraged for identifying parcels with a high negative impact—high delivery cost—compared to the rest of the parcels.

5.3.3 Shipping mode choice

After the selection of the outliers, the fulfillment of these parcels is simulated using the crowdshipping module of the MASS-GT model suite (de Bok & Tavasszy, 2018; De Bok et al., 2022; Thoen et al., 2020). Here, parcels are matched with travellers (i.e. potential bringers) based on their willingness to send and deliver parcels along their existing routes. The model evaluates potential trips using a utility-based approach by considering the behaviour of both senders and bringers (Tapia et al., 2023).

For the matching calculation, we have used a choice model for senders on the demand side (Cebeci et al., 2023) and a parcel delivery choice model for bringers on the supply side (Cebeci et al., 2024). On the demand-side we consider a hybrid choice model which includes the effect of trust on crowdshipping service choice. The demand function is the following:

$$U_{CS} = \beta_{Cost} \cdot Cost + \beta_{Time} \cdot Time + \beta_{Trust} \cdot Trust + \varepsilon_{CS} \tag{5.3}$$

$$U_{TR} = ASC_{TR} \tag{5.4}$$

Considering the supply side of the system, delivery time and compensation are used in the simulation model as the following:

$$U_{pickup} = ASC_{pickup} + \beta_{Time} \cdot Time_{pickup} + \beta_{Compensation} \cdot Compensation + \varepsilon_{pickup} \tag{5.5}$$

$$U_{current} = \beta_{Time} \cdot Time_{currenttrip} + \varepsilon_{current} \tag{5.6}$$

The crowdshipping model considers three modes of transportation with specific adjustments for travel times, costs, and drop-off times associated with each mode: (1) cars, (2) public transport (PT) and (3) biking and walking. For the latter, we assume that the trips are mainly done by bikes due to the fact that the trips are relatively long between origin and destination pairs and the Netherlands has a large bike market share. For cars, travel time is calculated based on distance and average speed, with additional considerations for vehicle operating costs. For public transport, a fixed time is used, and it is assumed that the origin and destination of the PT traveller and the parcel are the same resulting in no additional time and cost for PT travellers. For biking and walking, the time is calculated based on the distance and average speed for each mode. Compensation is determined by the parcel distance required to deliver the parcel. Each parcel is matched with the most suitable bringer who has the highest utility. Each traveller is coupled with a parcel providing a probability of picking up or not picking up the parcel. The traveller having the largest difference between picking up and not picking up is assigned to the parcel. This approach enables the efficient use of available trips for parcel delivery, optimising the crowdshipping process by maximising utility and minimising detours for the bringers across different modes of transport. Moreover, it allows to establish an individual matching between traveller and parcel, in the setting of an agent-based model. Although for the purposes of this study this individual match is not used further, it is the basis for a uniquely detailed crowd-shipping choice model.

5.4 Application: study area and data

This study focuses on the province of South-Holland, the most urbanised region in The Netherlands, with a population of 3.8 million (CBS, 2024). Due to this high population density, a significant proportion of parcel demand can be generated, making it an ideal area for testing and implementing last-mile delivery solutions. South Holland has a diverse urban landscape, including both large cities as well as major industrial regions like the Maasvlakte port landfill area.

Data on parcel demand is available for South Holland from the MASS-GT simulation model (de Bok & Tavasszy, 2018; De Bok et al., 2022; Thoen et al., 2020). This model divides the study area into 6,668 zones and includes data from 29 depots operated by various parcel delivery companies in the Netherlands. The parcel demand module is developed using multiple datasets to realistically estimate Business-to-Consumer (B2C) and Business-to-Business (B2B) parcel demand in each zone. For B2B parcel demand, MASS-GT uses zonal employment, provided by the National Bureau of Statistics (CBS) (CBS, 2019), along with market monitor data from the Netherlands Authority for Consumers and Markets (ACM) (Autoriteit Consument Markt, 2024). This ensures that the model accurately reflects logistics demand. The B2C parcel demand is calculated using an ordered logistic regression model, incorporating individual and household characteristics from the Mobility Panel Netherlands (MPN) to predict the frequency of online shopping for each person, which in turn helps determine parcel demand across zones (Hoogendoorn-Lanser et al., 2015). The demand is calibrated against market monitor data from the base year to match actual market sizes, keeping differences in demand between zones and ensuring the overall demand volume is accurate. In the reference case, the total demand is estimated as 242,866 packages on a single day. ACM data also includes the market share of different courier, express, and parcel companies in the Netherlands. Once the parcel demand is established, it is allocated based on the market share of each courier. Parcels assigned to specific couriers are further distributed to their depots. Table 5.1 presents the market share statistics for each courier in the Netherlands, as used in the parcel demand module.

Table 5.1: Courier market shares

Courier company	Market share (Netherlands, %)	Market share (Foreign, %)	Market share (Total, %)	Number of parcels
Company 1	0.63	0.24	0.51	123406
Company 2	0.28	0.13	0.23	56098
Company 3	0.03	0.28	0.10	24872
Company 4	0.03	0.08	0.04	10127
Company 5	0.03	0.24	0.09	21923
Company 6	0.03	0.03	0.03	6440

To calculate the marginal delivery cost, we have used cost figures for freight transport in the Netherlands (Knowledge Institute for Mobility Policy (KIM), 2023). The values for delivery time cost and vehicle kilometre cost are €32 per hour and €0.20 per kilometre, respectively, in line with the literature (Gevaers et al., 2014). The unit time cost includes fixed costs, personnel costs, and general operating costs, while the unit kilometre cost includes variable costs for fuel and depreciation. Besides transport time, drop-off times were included in the calculations. In line with (Ranjbari et al., 2023; Allen et al., 2018) a drop-off time of 3 minutes per parcel is used.

Data on passenger flows is obtained from ALBATROSS, a multi-agent, rule-based model designed to simulate and analyse personal activity pattern decisions (Arentze et al., 2000). The model generates synthetic trip diaries of individuals, considering their activities within specific household, institutional, and spatial-temporal constraints (Arentze et al., 2000). The data is used to match travellers with outlier parcels, allowing for realistic assignment of parcel delivery tasks.

Table 5.2 below provides an overview of the simulated trip diaries for the South Holland region, consisting of 3.5 million trips and 850 thousand travellers. which are 3.92 and 12.37 kilometres per trip on an average day, respectively (CBS, 2023). For car trips as a driver and as a passenger, CBS reports average trip distances of 17.36 and 19.94 kilometres (CBS, 2023), respectively, which are shorter in ALBATROSS trips. Cycling is particularly common for shorter trips, making up a significant portion of total trips across demographics. Car usage is also high, especially among higher-income and full-time workers, reflecting a demand for convenience and flexibility in commuting. Public transport, with the longest average trip distance, is commonly used for intercity or longer-distance travel, appealing especially to those under 35 or individuals with lower incomes.

Table 5.2: Overview of ALBATROSS trip diaries

		Bike	**Car as driver**	**Car as passenger**	**Public transport**
Gender	Female	1464815	1176042	323589	158431
	Male	220439	96840	41606	25082
Age	35	928458	700972	197645	107757
	35=55	340952	296487	69353	37478
	55=65	143248	121244	30897	13410
	65=75	137231	92373	32397	11747
	75+	135365	61806	34903	13121
Income	High	386529	437905	82642	39635
	Low	416779	169830	89983	53236
	Medium	365062	315321	76591	37021
	Minimum	516884	349826	115979	53621
Employment	32hrweek	68943	52089	13756	7105
	=32hrweek	901237	848155	177841	103888
	No work	715074	372638	173598	72520
Average distance per trip (km)		2.85	9.33	10.71	14.72
Number of travellers (total)				853993	
Number of trips (total)				3506844	

Figure 5.3 below provides an overview of the origin counts of the trip diaries (the spatial pattern is similar to the daily destination counts).

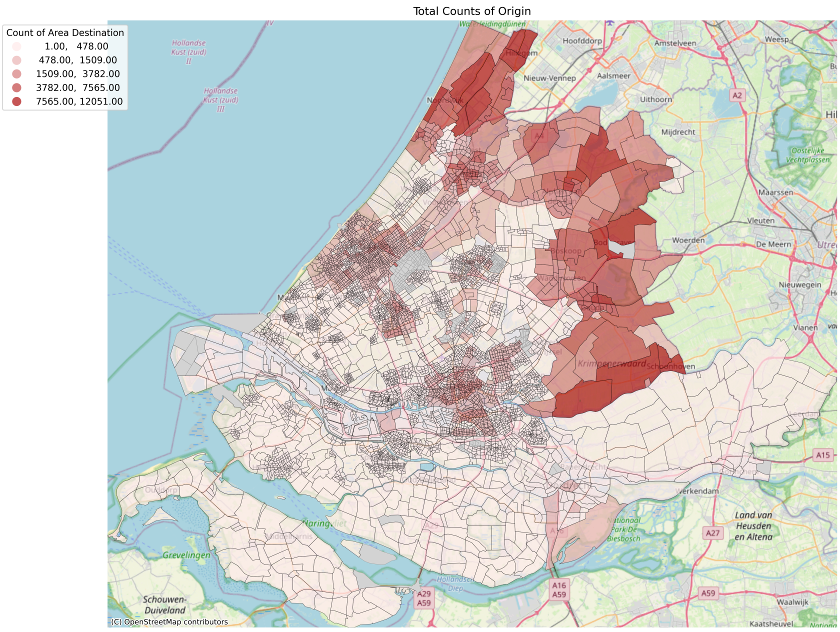


Figure 5.3: ALBATROSS daily trips in the study area (origin counts)

5.5 Results

5.5.1 Outlier Selection

By using Equation 5.2, we calculate the marginal delivery cost of removing a zone from an existing simulated travel plan. As explained in Section 5.3.3, the delivery plan includes the six largest delivery companies in the last-mile delivery market in the Netherlands (Autoriteit Consument Markt, 2024). The proportion of parcel demand for each courier company is given in Figure 5.4. As can be seen, more than half of the parcel demand is handled by Company 1, followed by Company 2.

Differences among the courier companies parcel demand structure is shown in Figure 5.5. The violin plot displays the distribution of marginal costs per parcel for six courier companies, with varying widths indicating the frequency of different costs. For all companies, we see a similar range of costs, with some individual parcels exceeding the general cost range, as indicated by the points above the main body of the violins. Company 6 exhibits wide violins, suggesting a greater diversity in parcel costs, while Company 1, 2 and Company 5 have narrower shapes, implying more uniform costs. The figure shows a peak at the lower end of the cost scale as the main body of the violins are around €2. This indicates that the vast majority of parcels incur minimal marginal costs, suggesting a high level of operational efficiency across the companies. The overlapping nature of the distributions for companies suggests that their cost structures are similar, particularly in the most common cost range.

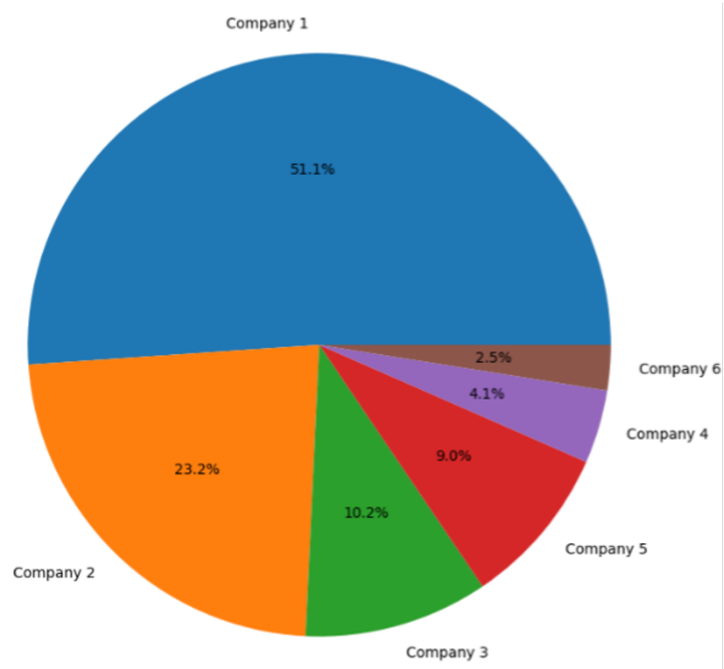


Figure 5.4: Parcel distribution per courier

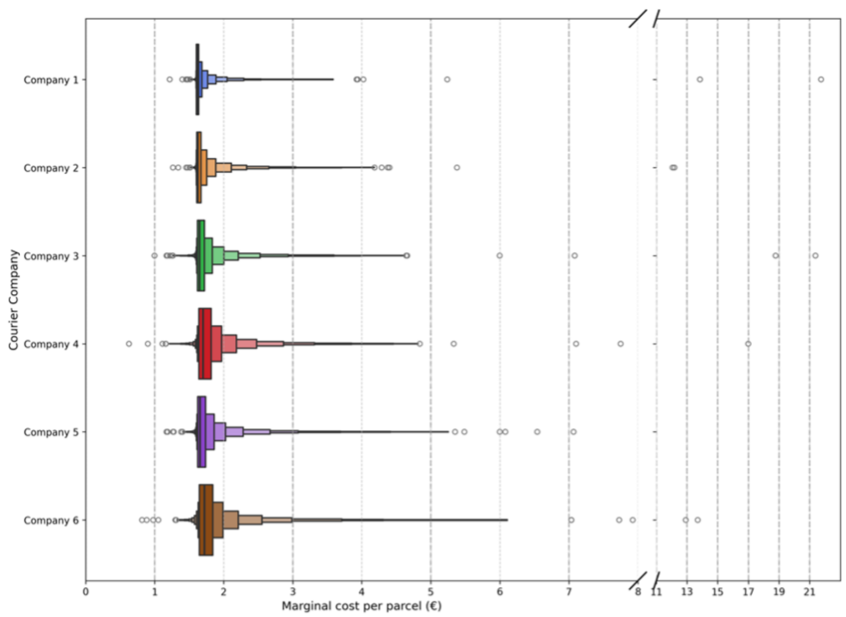


Figure 5.5: Violin plot of marginal costs per parcel for each courier

Figure 5.6 below shows a comparative analysis of marginal delivery cost (€) distributions for six different companies. Each subplot combines a Kernel Density Estimation (KDE) plot and a cumulative frequency curve. The KDE, indicated by a light blue area, shows the density of marginal delivery costs, with the vertical axis representing the frequency of costs and the horizontal axis representing cost values. The cumulative frequency, shown with blue dots, indicates the proportion of shipments with their marginal cost, summing the frequency as costs increase. A red vertical line, shows in a red dashed line, highlights a specific cost cutoff point of interest across all companies. Figure 5.6 shows that the majority of marginal delivery costs are clustered at the lower end, with an increase in cumulative frequency at this lower cost range, meaning that most shipments fall below the cutoff point.

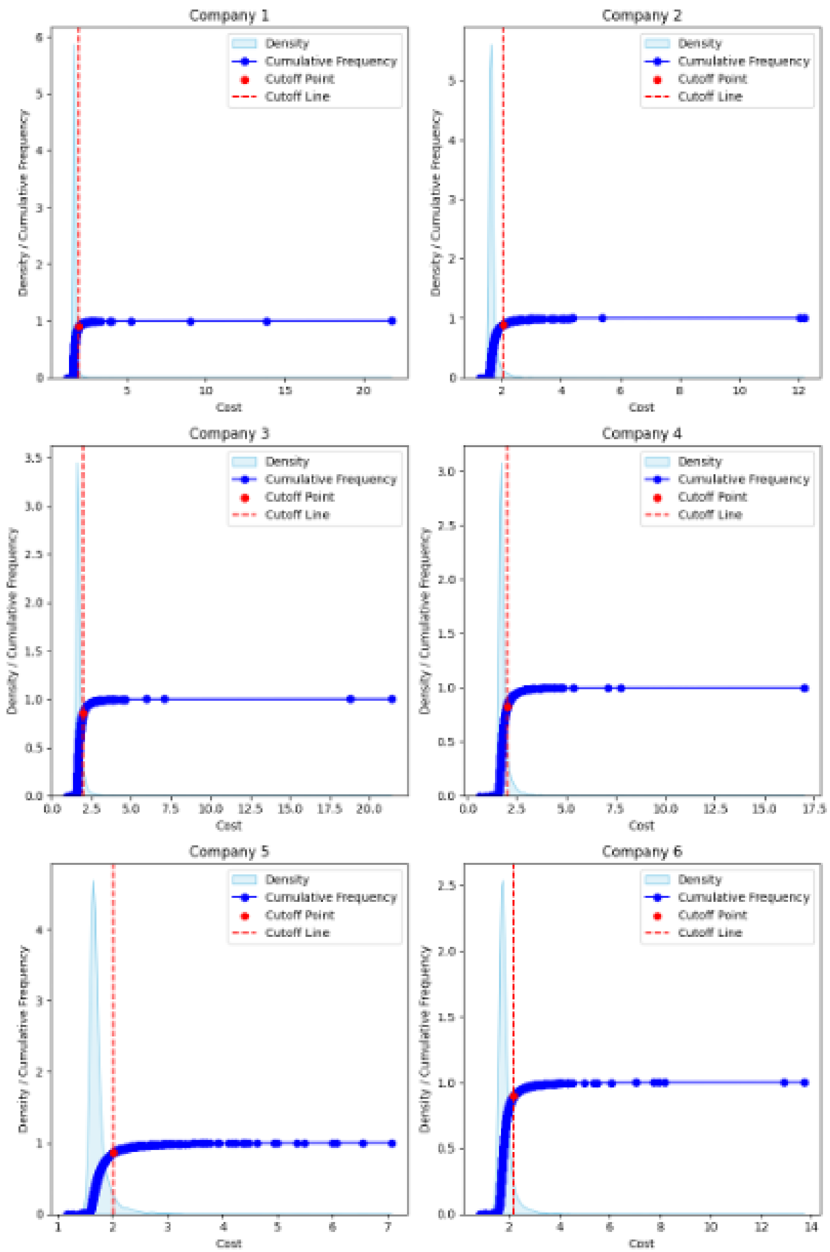


Figure 5.6: Combined Cumulative Frequency and Density Plot with Outliers for Each CEP Company

With the cutoff point determined through the elbow curve, we find 2700 parcels as outliers which together for all carriers represent about 1% of the total parcel demand in the study area. The cutoff cost per courier company and the percentage of parcels considered as outliers is shown in Table 5.3. Typically, these costs lie around 2 Euro/parcel for all carriers. The consequences for the outlier volumes vary strongly, however, with an order of magnitude (between 0.23% and 8.1%).

Table 5.3: Overview of the outlier parcels per courier company

Courier company	Cutoff cost (€)	Number of outlier parcels (%)
Company 1	1.94	0.23
Company 2	2.04	0.61
Company 3	2.00	1.99
Company 4	2.01	6.27
Company 5	2.01	2.21
Company 6	2.01	8.10

The validity of Table 5.3 can be discussed in more detail, to determine if our approach to the elbow point cutoff mechanism is economically reasonable in the urban freight market. It is important to note that the delivery cost for last-mile deliveries includes several components. The main cost factors are variable and fixed costs. In the context of this research, we consider only variable costs based on delivery time and distance and the fixed costs are not considered as there is no information available. In our calculations, using the elbow point outlier selection, we find that the average delivery cost at which a courier company would be willing to deliver a parcel is around €2 per parcel, meaning that above this rate an LSP might be willing to outsource crowdshipping service. In the literature, Gevaers et al. (2014) model the parcel delivery cost using various sources, such as expert interviews and literature on a variety of cost items. In their study, the base cost is calculated based on a 200 km distance with a delivery person working 7.5 hours and delivering 175 parcels. The delivery cost is estimated as €1.3 per parcel for dense urban areas. Although our selection mechanism does not specifically target urban areas and does not include all the cost components considered in Gevaers et al. (2014), with a unit cost of €32.21 per hour and €0.20 per kilometre for the Netherlands (Knowledge Institute for Mobility Policy (KIM), 2023) and using the average tour distance of all couriers (103km), the delivery cost per parcel becomes €1.7. Additionally, another study found that the total cost of a parcel ranges between €1.36 and €1.41 (EIT, 2024). These findings further validate our cost estimates.

Besides the delivery cost calculation on average terms, the position at which the cutoff is found per courier company is critical for measuring the network structure of the courier as well as determining the number of inefficient parcels. In their recent study, Zhang & Cheah (2024) use spatial density and neighbourhood distance as indicators of outliers in parcel delivery patterns. By using local outlier factor (LOF), the authors identify local density deviations of parcels relative to their neighbours. The LOF approach assumes that isolated parcels, defined by their low density relative to nearby parcels, have higher delivery inefficiencies. By only considering spatial density and neighbourhood distance, the LOF algorithm may misclassify the inefficient parcels, even if these parcels do not add significant costs. Not all isolated parcels are necessarily inefficient to deliver; for instance, a parcel in a low-density area might still be cost-effective if it aligns well with existing delivery routes. The LOF approach resulted in 11% of the parcels being classified as outliers (Zhang & Cheah, 2024). The share found here, based on cost logic, is considerably lower.

Figure 5.7 shows that the outlier parcel distribution in the network is dispersed around the network. As expected, a greater number of parcels are located in areas remote from urban areas. Considering the concentration of courier companies in the densely populated central and northern areas, the southern part of the network appears to have a higher number of high-cost parcels, due to the longer detours required for deliveries.

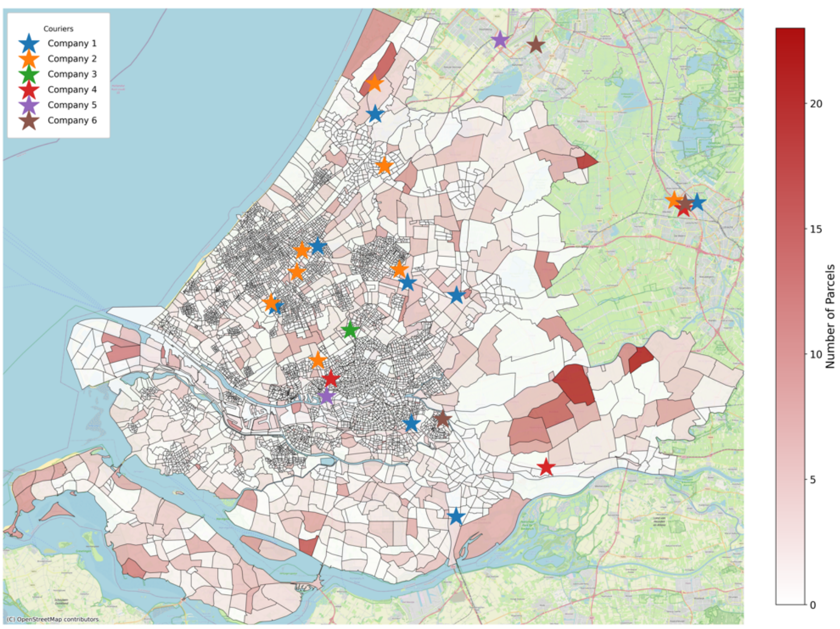
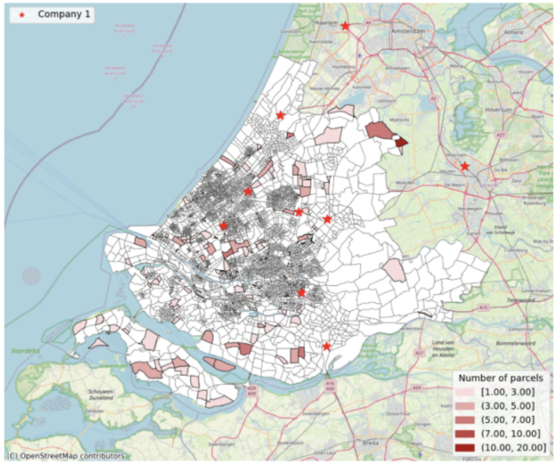
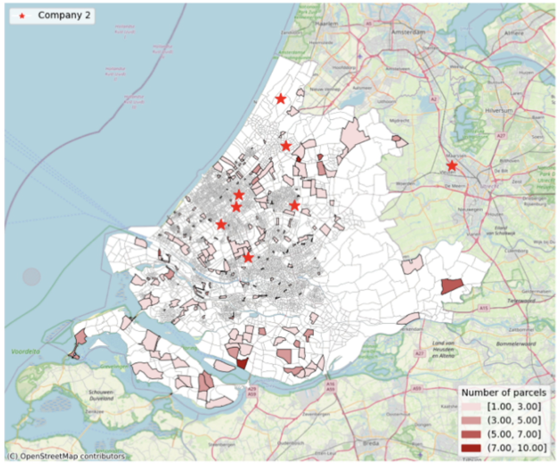


Figure 5.7: Outlier parcel distribution in the network, for all LSPs

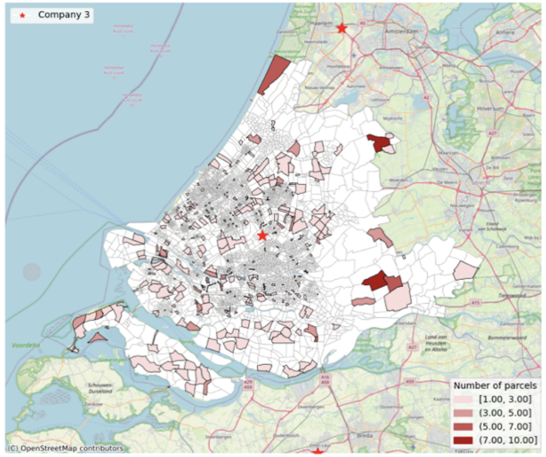
Figure 5.8 (a-f) provides a detailed representation of the outlier parcels per courier. As shown, Company 1 and Company 2 have 9 and 8 depots in the region, respectively. The main reason for comparing these two couriers is their dense distribution centre structure. A common feature of the outlier parcels is that they typically appear away from the depot locations, particularly in the southern part of the network. However, the distribution of outliers is dispersed across the network. Potential reasons for this include market coverage, delivery density at destination locations, and operational strategy differences between the two couriers. Figures 5.8 d and f show the distribution of outlier parcels for Companies 4 and 6. Although the distribution of outlier parcels varies for each courier, some regions are highlighted across both couriers, possibly indicating areas with an overall high marginal cost per parcel. For instance, the southern parts of the network show a high number of outlier parcels for all the couriers. Figures 5.8 c and e illustrate the outlier parcel structure for Companies 3 and 5. These couriers exhibit a similar distribution pattern, particularly in the northern and southern parts of the network. There are also similarities in their depot locations, with one main depot in the centre and the rest positioned outside the network. As shown in Figure 5.8, the distribution of outlier parcels varies depending on several factors. Consequently, some outliers appear in the urban areas like in Companies 4-5 and 6, in other cases, they appear far away zones. This highlights that solely focusing on spatial concentration of parcels within specific geographic areas might lead to under- or overestimation of inefficient parcels and overlook company-specific attributes. Interestingly, the company-based outlier parcel distribution shows differences when analysed at the zonal level in terms of outlier parcel volume, which could encourage collaboration among couriers to handle outlier parcels.



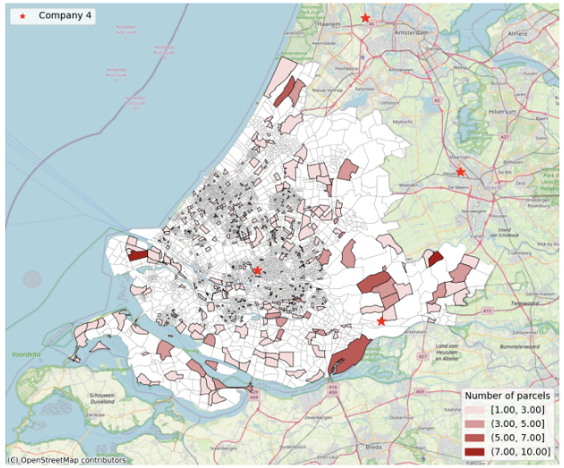
(a) Outlier parcel distribution Company 1



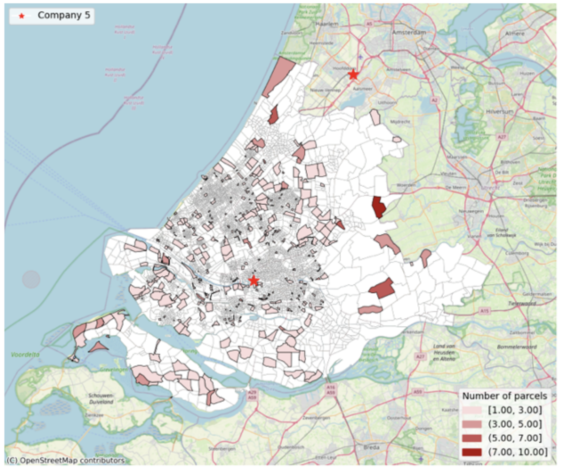
(b) Outlier parcel distribution Company 2



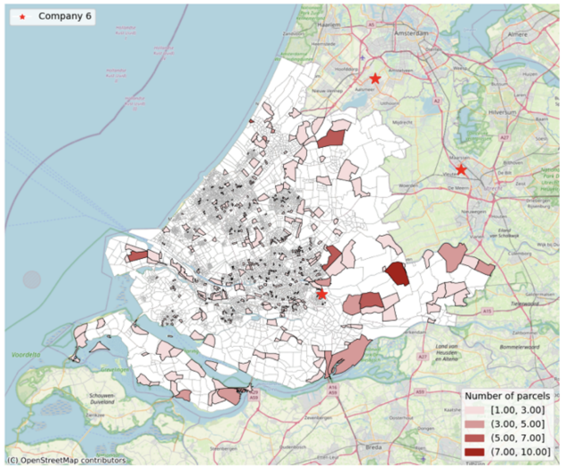
(c) Outlier parcel distribution Company 3



(d) Outlier parcel distribution Company 4



(e) Outlier parcel distribution Company 5



(f) Outlier parcel distribution Company 6

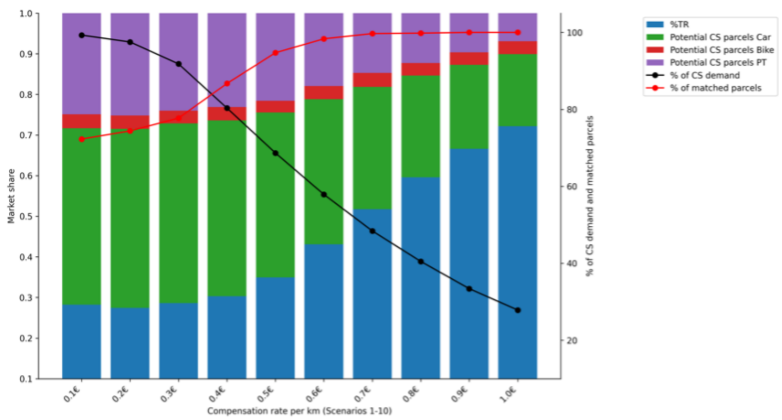
Figure 5.8: Outlier parcel distribution per courier

5.5.2 Crowdshipping

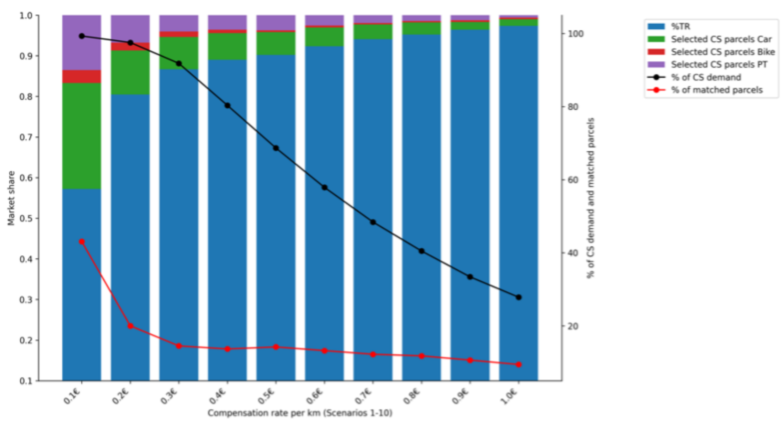
By integrating willingness-to-deliver and willingness-to-send through crowdshipping choice models, as described in Section 3.3, we assess the potential for delivering the 2,700 identified outlier parcels via a crowdshipping service. Using synthetic trip diaries from the ALBATROSS activity-based model, we match outlier parcels with existing trips of occasional carriers to evaluate the feasibility, costs, and environmental impacts under different compensation scenarios. To do this, the scenarios are run for different compensation levels per kilometre, ranging from €0.1 to €1 per kilometre. As described in Section 4, the ALBATROSS synthetic trip diaries are used which result in a pool of 16878 travellers with 19410 trips. Table 4 presents the results of the crowdshipping model for the total number of outlier parcels. As shown, because of the increase of the compensation the prices for crowdshipping increase from €2.37 to €23.66 per trip.

Scenarios (1-10)	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Compensation €/per km	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
Potential crowdshipping parcels (2700)										
Crowdshipping demand	2681	2633	2479	2169	1854	1563	1307	1093	902	752
Matched parcels	1938	1959	1927	1881	1756	1537	1303	1091	902	752
Matched parcels (%)	72.3	74.4	77.7	86.7	94.7	98.3	99.7	99.8	100	100
Traditional parcels	762	741	773	819	944	1163	1397	1609	1798	1948
Average compensation (€)	2.37	4.73	7.10	9.46	11.83	14.19	16.56	18.92	21.29	23.66
Crowdshipping platform revenue (€)	598	1223	1778	2280	2539	2444	2204	1915	1603	1359
Traditional delivery (%)	28	27	29	30	35	43	52	60	67	72
Crowdshipping (%)	72	73	71	70	65	57	48	40	33	28
Selected crowdshipping parcels (crowdshipping price <marginal delivery cost)										
Selected crowdshipping parcels	1155	527	360	297	264	207	160	129	96	71
Total traditional parcels	1545	2173	2340	2403	2436	2493	2540	2571	2604	2629
Matched parcels (%)	43.0	20.0	14.5	13.7	14.2	13.2	12.2	11.8	10.6	9.4
Average compensation	1.38	1.35	1.41	1.30	1.29	1.88	1.41	1.41	1.53	1.69
Crowdshipping platform revenue (€)	270	258	287	346	393	333	279	243	178	126
Traditional delivery (%)	57	80	87	89	90	92	94	95	96	97
Crowdshipping (%)	43	20	13	11	10	8	6	5	4	3
Crowdshipping CO_2 (tonne)	3.38	1.50	1.23	1.02	0.86	0.75	0.54	0.46	0.25	0.23
Traditional delivery CO_2 (tonne)	2.87	3.76	3.93	3.98	3.95	4.04	4.11	4.18	4.21	4.17

Considering all potential outlier parcels being crowdshipped, regardless of their costs, and allowing crowdshipping only when the crowdshipping price does not exceed the marginal delivery cost per parcel, referred to as selected parcels, lead to two distinct outcomes. Firstly, the number of matched parcels decreases marginally when crowdshipping is limited to only selected parcels. The ratio of matched parcels for crowdshipping ranges between approximately 72% and 100% across all crowdshipping simulations. This ratio drops to between 43% and 9% when only selected parcels are allowed to be crowdshipped. Secondly, the average compensation is higher in the case of all parcels being crowdshipping due to the lack of a cost constraint on the service. Interestingly, increasing the compensation rate per kilometre, and consequently the average compensation, does not positively affect the matching rate of parcels in the selected parcels. This is because the compensation is capped by the parcel delivery cost, thus limiting the effect of a larger compensation per km. A similar trend is more prominently shown in Figure 5.9. The two figures illustrate the impact of varying compensation rates on the market share and demand for crowdshipping across different transportation modes. In both cases, crowdshipping demand decreases, leading to a shift towards traditional delivery methods. The results show that the compensation rate per parcel distance directly affects the market share of car, bike and PT. In both of the cases (all parcels and cost-efficient parcels), car-based and PT-based crowdshipping become dominant. Although PT emits no CO_2, its share is very low, resulting in a negligible impact. These findings contrast with those of Zhang & Cheah (2024); Zhang et al. (2023), who found up to 20% reduction in vehicle kilometres travelled, emissions, and delivery costs. This highlights the impact of the decision rules used to define outliers, and the behavioural components influencing the willingness to send and decision to become an occasional carrier. Regarding the matching rate, since fewer parcels are sent via crowdshipping with higher compensation rates, there are enough crowdshippers to fulfil all parcel requests, resulting in higher matching rates in the all-parcels scenario. In the cost-efficient scenario, the matching rate also decreases marginally due to the relatively low compensation.



((a)) Potential crowdshipping parcels



((b)) Selected crowdshipping parcels

Figure 5.9: Market shares, CS demand and matched parcels

As can be seen from Figure 5.10, as expected, the number of parcels delivered with crowdshipping decreases quickly when the compensation increases. Both cases provides the highest crowdshipping platform revenue when the compensation per kilometre is €0.5.

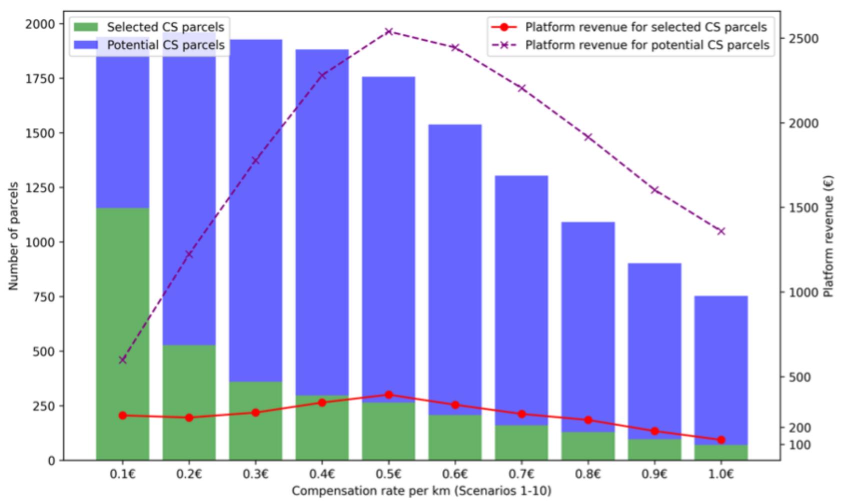


Figure 5.10: Crowdshipping platform revenue and the number of parcels delivered by CS for all and cost-efficient scenarios

When compensation is low, more parcels are crowdshipped, resulting in higher CO_2 emissions due to the large proportion of car-based crowdshipping trips similar to the results found in Tapia et al. (2023). This indicates that car-based crowdshipping is being used more frequently, which increases its environmental negative impact, similar to the findings of Simoni et al. (2020). Specifically, detours are longer compared to those in dense urban areas, leading to lower usage of bikes for crowdshipping. When compensation increases, crowdshipping flow decreases, leading to fewer trips and lower CO_2 emissions. The potential of using crowdshipping as a sustainable alternative exists only when it is economically viable, meaning that the service offers a cost-competitive price for both senders and bringers. This can positively impact emissions reduction. However, the overall impact remains limited due to the small volume of parcels that can be shared through crowdshipping. Exploring the geographical distribution of crowdshipped parcels in the network can specify potential delivery patterns. We focus on Scenario 5, as the other scenarios show similar patterns, and Scenario 5 yields the highest crowdshipping platform revenue. However, no distinct spatial pattern emerges, suggesting that crowdshipping activity is dispersed variably across regions without clear areas of concentration.

Another analysis of compensation rates and crowdshipping demand is presented through a sensitivity analysis, as shown in Figure 5.11. The elasticity curve shows that crowdshipping is sensitive to price and strongly elastic above a price of €0.7/km. This highlights the limited scalability of crowdshipping under high compensation scenarios and suggests that careful pricing strategies are essential to maintain operational and environmental sustainability.

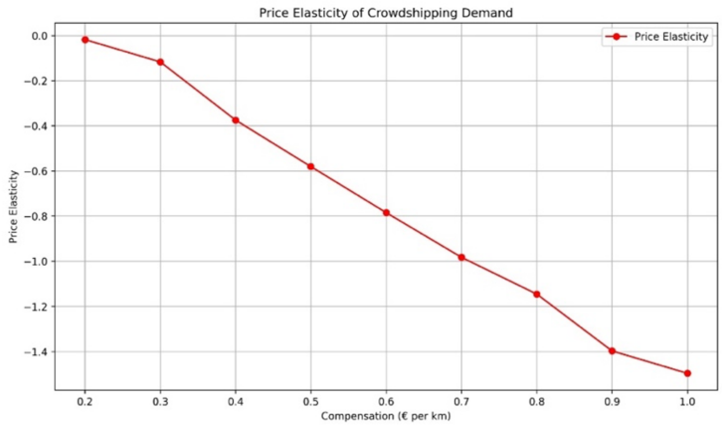


Figure 5.11: Compensation rate elasticity of crowdshipping demand

5.6 Conclusions

In this study, we introduce a cost-based outlier parcel detection mechanism using the marginal delivery cost method, applied to a simulated delivery plan from the MASS-GT simulation model. Next, we evaluate the use of crowdshipping for delivering outlier parcels—those with a high negative impact on last-mile delivery. The outlier parcels identified with a logistics-costs driven approach constitute only of 1% of the total parcel demand. Most parcels have low marginal costs, while a small fraction of outliers drives up overall delivery expenses, underlining the efficiency of last-mile delivery planning. We show in our case that while cut-off costs are similar across companies, the consequences for volumes vary widely, from less than 1% to more than 8% of all shipments in the region. While the proportion of parcels selected for crowdshipping is low within the overall network, this study provides insights into the significance of couriers' delivery networks and emphasizes that crowdshipping remains a niche market. Our findings show that while crowdshipping can help address last-mile delivery inefficiencies for only a small proportion of parcels, its economic and environmental impacts are sensitive to several factors, such as compensation rates, delivery distance, and demand availability. Given the existing low delivery costs in the last-mile market, crowdshipping might better serve customer-to-customer deliveries or more time-sensitive parcels rather than courier services. A limitation of this study is that we only include the transport related variable costs in our analysis, as data about other costs are not available. Other costs, such as vehicle insurance, and infrastructure, could influence the overall profitability of traditional last-mile delivery and, consequently, the impacts on crowdshipping. Additionally, this study evaluates crowdshipping as an alternative delivery option for LSPs. Future research could explore the integration of crowdshipping with other last-mile solutions, such as parcel lockers. Moreover, it could investigate diverse sources of parcel delivery demand, including C2C and B2C, as well as the potential of crowdshipping for handling delivery returns. Although the sustainability effects of crowdshipping alone are limited, the potential of hyperconnecting services as a chain is more promising than relying on individual services alone, which requires further investigation.

Chapter 6

Conclusion

This final chapter discusses the salient outcomes of this research and identifies opportunities for extending the research in new directions. The chapter concludes with a discussion of the implications of this research to practice and recommendations for future research in the field.

6.1 Main findings

In this section, we discuss a summary of each chapter's key findings relating them to the sub-research questions proposed in Chapter 1.

How do consumers make decisions about hyperconnected last-mile services, either as users or as suppliers, in the context of omnichannel retailing? **[Chapter 2]**

In Chapter 2, we conducted a literature review study to examine the evolving role and behaviour of consumers in the last-mile delivery ecosystem. We positioned consumers as also having the role of active producers in last-mile logistics, as also referred as prosumers, not merely recipients of services but also suppliers of services, such as delivering parcels in crowdshipping. This perspective offers insights into how the next generation of last-mile logistics influences consumer decision-making and how these decisions, in turn, can shape and potentially enhance system efficiency. The proposed conceptual framework classifies consumer decisions and system attributes that influence consumer engagement in last-mile services.

The decisions made by a citizen in last-mile logistics are classified into three main categories. These reflect their evolving role as both users and occasional providers of logistics services. First, shopping channel decisions involve choosing between online, in-store, or hybrid shopping options such as order online-pick up in store. These decisions are influenced by factors such as convenience, accessibility, delivery cost, and return policies. Second, delivery method decisions focus on selecting a mode of delivery, such as home delivery, parcel lockers, in-store pickup, or crowdshipping. These choices depend on product attributes such as parcel size and value, service characteristics such as cost, reliability, and environmental impact, and personal attributes such as prior experience, habits, and social influences. Third, decisions to become occasional carriers reflect consumers' willingness to participate as service suppliers. These decisions are shaped by factors such as compensation, trip flexibility, parcel characteristics, and trust in the platform or sender. The rise of crowdshipping highlights the potential for leveraging consumers' existing trips to improve delivery efficiency, even though its adoption requires addressing concerns around trust, remuneration, and convenience. Together, these classifications illustrate the interconnected nature of consumer decisions as a user and active supplier of delivery services.

What is the role of trust in crowdshipping service choice? **[Chapter 3]**

Having classified the choices of consumers and their role in last-mile logistics in Chapter 2, it becomes evident that consumers can actively participate in delivery services through crowdshipping. In this context, trust emerges as a critical determinant for the acceptability of crowdshipping, as consumers must feel confident in both the reliability and safety of the service. Trust influences whether individuals are willing to engage in the system, particularly given that crowdshipping involves entrusting their parcels to non-professional carriers who integrate deliveries with their own travel, theoretically.

In Chapter 3, we operationalise trust in crowdshipping service choice. Firstly, by employing trust as a situation-specific latent variable, we investigate trust's mediating role in consumer delivery choice for last-mile delivery options. Unlike previous studies that often treat trust as a static or generalised concept, this study reveals how trust mediates various service attributes directly or indirectly. We considered six attributes which might affect the level of trust towards crowdshipping namely, delivery time, delivery cost, tracking and tracing options, delivery company's reputation, insurance coverage and possibility of damage.

We find out that trust mediates the effects of most service attributes on crowdshipping service choice and fully mediates the influence of delivery company reputation and the possibility of damage. However, trust does not mediate the adoption of same-day delivery, which has a direct positive effect on crowdshipping choice. Interestingly, sociodemographic characteristics, such as education level and occupation, do not directly mediate trust but affect the likelihood of choosing crowdshipping. The study shows that service attributes such as strong company reputation and low damage risk significantly enhance trust, which in turn increases the likelihood of service adoption. Flexible delivery options and tracking and tracing also influence trust, though their effects are partially mediated. Delivery time has no measurable impact on trust, despite being an important direct determinant of adoption. These findings emphasise the complexity of building trust in crowdshipping and its role in decision-making and highlight the importance of designing crowdshipping business models that meet these diverse requirements of crowdshipping users.

When are occasional carriers willing to accept a delivery request, even if the delivery operation generates a new trip? **[Chapter 4]**

After examining how trust influences consumer acceptance of crowdshipping, which defines the system's demand, we shift focus to studying consumers' decision-making as prosumers—essentially, the suppliers of the delivery service. We explore the supply side of the crowdshipping system by investigating the willingness of occasional carriers (OCs) to deliver parcels based on two distinct scenarios: leveraging existing commute trips or creating newly generated home-based trips. The findings reveal a dual impact of crowdshipping on urban mobility: commute-based deliveries align with the original concept of leveraging existing trips, while home-based deliveries generate new, dedicated trips. Although commute-based crowdshipping minimises additional travel demand, a new home-based trip may increase urban kilometres travelled, potentially exacerbating congestion and emissions. This shows the importance of promoting crowdshipping models that align well with existing mobility patterns to maximise sustainability benefits. Additionally, the type of commuting mode used by occasional carriers plays a critical role in determining the overall sustainability of the system. For instance, deliveries integrated with eco-friendly modes such as cycling or walking contribute to significantly lower emissions compared to car-based crowdshipping.

The findings highlight a distinction between the motivations to become an OC and their implications for urban mobility and sustainability. The VoT analysis suggests that, for commute-based trips, respondents in the high-income group are willing to deviate by only about five minutes from their already planned route. In contrast, this value increases to sixteen minutes for lower-income groups, which leads to an approximate detour of 5 km by bicycle. Consequently, these short trips could also lead to additional trips, depending on the crowdshipping business model. The developed model highlights the heterogeneity in willingness to become an OC across sociodemographic characteristics. Among these, income level is the only significant attribute influencing the generation of home-based and commute-based trips. The model results indicate that low-income individuals, defined as those earning less than C2,000 per month in net income, are significantly more willing to act as OCs compared to higher-income individuals. This willingness is closely tied to their notably lower VoT, estimated to be approximately five times lower for home-based crowdshipping and three times lower for commute-based crowdshipping. These lower VoTs suggest that low-income individuals are more inclined to accept longer detours for parcel deliveries, driven by a stronger preference for the additional income crowdshipping activities provide. This economic disparity highlights the need to design crowdshipping systems and compensation strategies that consider varying income groups to optimise participation and ensure the sustainability benefits of these services.

How can the potential demand for crowdshipping be defined? **[Chapter 5]**

Building on the supply and demand characteristics, it is crucial to explore the interaction between these two components to gain a clearer understanding of the crowdshipping service coverage. To address this, the final chapter of this thesis evaluates crowdshipping as a solution for managing high-cost parcels by outsourcing them to individuals who incorporate delivery tasks into their pre-existing trips. A cost-based outlier parcel identification mechanism is introduced to enhance the efficiency of last-mile delivery by selecting parcels for CS delivery with disproportionately high marginal delivery costs.

Outlier parcels are filtered based on a calculated cut-off cost, with parcels exceeding this cost deemed eligible for crowdshipping. Using willingness-to-send (Chapter 2) and willingness-to-bring (Chapter 3 models, the share of outliers handled by crowdsourced carriers is determined which enables comparison of crowdshipping costs with traditional delivery for economic and environmental analysis in a simulation environment. We use unique data on delivery tours of six service providers for the province of South Holland in the Netherlands. The analysis reveals that only 1% of the total parcel demand qualifies as outlier. This low proportion depicts the overall cost efficiency of current last-mile delivery networks, where the majority of parcels incur at a minimal marginal cost. However, the volume of outliers vary significantly among carriers, ranging from less than 1% to over 8% of total shipments which reflects the diversity in delivery network structures and operational dynamics. The findings indicate that while crowdshipping is feasible, only a small fraction of outlier parcels is selected for outsourcing based on cost-efficiency criteria. This variation highlights the sensitivity of crowdshipping to operational factors such as compensation rates, delivery distances, and demand availability. The study also identifies the suitability of crowdshipping for specific use cases. The proportion for crowdshipping based on their cost efficiency ranges from around 40% to 3%, depending on the scenario. Noting that the low proportion of outliers in traditional last-mile delivery, crowdshipping may be more effective for C2C deliveries or time-sensitive shipments rather than large-scale logistics operations. This aligns with the concept of crowdshipping as a supplementary rather than primary delivery model.

While crowdshipping can reduce delivery costs and emissions for high-cost parcels, its stand-alone contribution to environmental and economic sustainability is limited. The marginal gains from crowdshipping arise primarily from its ability to target inefficiencies in traditional delivery networks rather than its scalability. Nonetheless, integrating crowdshipping with other innovations, such as parcel lockers or hyperconnected logistics systems, may offer a pathway to amplify its benefits. By combining the strengths of crowdshipping with advanced logistics technologies and platforms, urban freight systems could address last-mile inefficiencies more comprehensively.

6.2 Synthesis of the results

The findings of the individual chapters converge to address the overarching research question: *How does consumer decision-making within crowdshipping impact the performance and sustainability of last-mile delivery systems?* This section integrates insights from the individual chapters and draws on relevant literature to provide an understanding of the research outcomes.

Consumers in this research is framed around their dual role in last-mile logistics both their behaviours as service users and their active participation as service providers. As highlighted in the literature (X. Wang et al., 2023; Silva et al., 2023), consumers are deeply embedded in last-mile logistics through their consumption choices and their dual role as occasional carriers or suppliers of delivery services. This dual engagement emphasise the importance of understanding both the demand and supply dimensions of crowdshipping.

By drawing on a detailed two-sided empirical analysis of demand and supply factors, this research demonstrates the interconnected nature of consumer choices in crowdshipping. The findings show that the interaction between demand-side factors, such as trust and cost sensitivity, and supply-side drivers, such as compensation and delivery time, is important to the viability of crowdshipping service. This interconnection also shows the necessity of designing a pricing mechanism that aligns consumer willingness to send a parcel with prosumer willingness to bring the parcel. Such mechanism is vital for sustaining the economic equilibrium of crowdshipping service.

A component that is not addressed in the literature is the potential for crowdshipping to disrupt or deteriorate the existing last-mile delivery landscape, similar to the concerns raised about ride-hailing services like Uber, which have, in some cases, increased traffic congestion and emissions due to newly generated trips (Tarduno, 2021; Z. Li et al., 2016). The empirical findings of this thesis provide sociodemographic trends on both the supply and demand sides of crowdshipping. On the supply side, lower-income groups are significantly more inclined to accept delivery tasks, motivated by the financial incentives crowdshipping offers. This highlights the economic appeal of the service to these groups, as well as their willingness to incorporate parcel delivery into their existing travel plans or even generate new trips. On the demand side, the estimation results on willingness to send parcels through crowdshipping emphasises the importance of education level. Individuals with a bachelor's degree or lower are more likely to adopt crowdshipping services. Together, these findings reveal the dual challenge of designing a crowdshipping service that minimise the risk of unintended externalities, such as new trip generation, while also ensuring equitable participation across diverse sociodemographic groups. Addressing these challenges is crucial for the sustainability goals in terms of economic and environmental.

After investigating the factors that influence demand and supply, it is also important to examine how these two components shape the overall market share. To achieve this, we designed a crowdshipping model that considers not only consumer decisions but also the objectives of LSPs. This approach allows for a behaviourally realistic understanding of the crowdshipping market potential and its impact. Unlike other studies in this area (Wicaksono et al., 2022; Arslan et al., 2019), our research reveals the very limited market share of crowdshipping when it is used to handle parcels that are too costly for LSPs. These findings reveal the challenges of using crowdshipping for such parcels, although further exploration of this specific market segment could yield additional insights.

6.3 Implications for practice

This research, which provides insights into the feasibility of crowdshipping as a sustainable and efficient last-mile delivery solution. Through various methods, we identified key preferences and behaviour of consumers and occasional carriers, offering actionable guidance for crowdshipping platforms, logistics service providers, and policymakers.

Crowdshipping is a relatively new service in the urban freight market, particularly in the Netherlands. The challenges faced by crowdshipping platforms attempting to enter new markets show the importance of understanding consumer preferences, local market structures, and regulatory environments. Aligning crowdshipping services with these factors is essential for consumer acceptance and participation; otherwise, such initiatives are likely to fail. This thesis primarily focuses on consumer preferences and the urban market structure in the Netherlands.

The successful implementation of crowdshipping depends on its acceptance by both consumers (demand side) and occasional carriers (supply side). Platforms must address key factors such as ease of use, reliability, and safety to encourage participation from both groups. In this regard, trust plays a critical role in driving demand for crowdshipping services. Platforms entering the market should prioritize building a strong reputation, as this is the most significant factor influencing consumer willingness to adopt the service. Strategies such as offering insurance, reliable tracking, and transparent operations can enhance trust and drive participation.

From the supplier perspective, crowdshipping platforms should focus on attracting low-income individuals as occasional carriers, as this group is more likely to participate due to the potential for supplementary income. Tailored recruitment strategies and compensation schemes that align with the needs and motivations of this demographic group can enhance platform profitability and service reliability. However, the possibility that the low-income category may generate additional trips highlights the importance of policymakers establishing clear rules and regulations to mitigate negative externalities. To this end, the Dutch government's regulatory actions on Uber-like services provide valuable lessons for crowdshipping, as both rely on non-professional participants via digital platforms. Policies should ensure that occasional carriers do not become full-time drivers, as demonstrated by UberPop's ban on unlicensed drivers (Riemsdijk, 2015), to prevent regulatory violations, guarantee passenger safety, maintain fair competition, and protect labour exploitations. Additionally, regulations such as setting maximum detour distances and promoting eco-friendly modes, particularly bicycles, can help mitigate the risk of generating new trips, similar to congestion concerns associated with ride-hailing. Ensuring fair compensation for crowdshipping carriers is also essential to avoid labour exploitation. In this context, the compensation rate should not compete directly with traditional delivery services but should be attractive enough to encourage individuals to participate as occasional carriers in crowdshipping. We find that it is difficult to find this balance and knowledge is needed of demand and supply functions. Pricing strategies—whether flexible, flat, or distance-based—are crucial components of the crowdshipping platform and play a key role in ensuring its success. Crowdshipping platforms might consider implementing dynamic pricing models that adjust rates based on real-time demand and supply to cater to varying consumer preferences.

Due to the competitive pricing of traditional LSPs, the potential of crowdshipping for handling large-scale parcel deliveries for LSPs is limited. Crowdshipping can capture between 43% and 3% of the outsourced outlier market. However, this outlier market constitutes just 1% of the total market demand. Crowdshipping platforms could however target specific niches, such as C2C deliveries or time-sensitive shipments, where flexibility and service speed are critical. These segments may offer a promising starting point for crowdshipping to establish itself as a viable and complementary delivery option.

Lastly, the findings of Chapter 6 show that the proportion of outlier deliveries ranges from 0.2% to 8%, with larger courier companies having a lower share compared to smaller companies, based on their market share in the Netherlands. Smaller couriers often face greater challenges in managing high-cost deliveries due to limited resources and economies of scale. As a result, they stand to benefit more from connecting to crowdshipping services to handle these outlier parcels cost-efficiently. Strategies for promoting crowdshipping could therefore consider supporting collaboration between crowdshipping platforms and smaller LSPs. By targeting smaller CEPs, crowdshipping initiatives can contribute to a more sustainable and cost-effective last-mile logistics ecosystem.

Beyond its operational and economic implications, this research also contributes to the broader context of sustainable urban development and the sharing economy. By investigating the demand and supply characteristics of crowdshipping, it provides insights into the conditions under which crowdshipping can be applicable and whether it is scalable in a cost-efficient way. As the sharing economy plays a marginal role in crowdshipping, this research also examines how travellers' adoption of crowdshipping is influenced by their perceived trust. Consequently, it offers insights into how crowdshipping can be leveraged to have a positive impact on sustainable urban freight, for instance, in the context of C2C deliveries and second-hand product shipments.

6.4 Recommendations for future research

This thesis is dedicated to mitigating the negative externalities of last-mile logistics by exploring and utilising a novel delivery method: crowdshipping. To achieve this goal, we have developed methodologies and presented key findings in Chapter 6.1. This section outlines several potential research directions where the outcomes of this research can be further utilised and expanded upon.

In Chapter 2, we proposed that consumers are transitioning to ”prosumers”, combining the role of passive recipients of last-mile logistics services with a role of suppliers of services. While this research focuses on crowdshipping services, future research could investigate how the dynamics of social networks—such as peer influence, community-driven feedback, or neighbourhood interactions—affect consumers' willingness to act as crowdshipping carriers. For instance, scenarios in which consumers share their experiences and feedback with peers might significantly alter their perception of and engagement with crowdshipping services, ultimately influencing their willingness to use or recommend such services and to bring parcels for delivery.

Additionally, the conceptual framework introduced in Chapter 2 emphasises the role and potential of hyperconnected networks in last-mile logistics. The implications of hyperconnectivity and its impact on delivery systems are discussed; however, there is an opportunity for future research to treat last-mile delivery services as an interconnected chain of services rather than isolated individual services. By investigating consumer acceptance of these interconnected services, researchers could gain insights into the broader role of consumers in hyperconnected logistics systems. This perspective could help in understanding how consumers' preferences and behaviours shape the feasibility and practical application of hyperconnectivity in urban freight systems.

Chapters 3 and 4 rely on stated preference experiments to explore consumer and prosumer decision-making. The findings are based on observed behaviour in hypothetical scenarios rather than revealed choice behaviour. While SP methods are widely recognised for their ability to capture preferences and predict responses to novel services, they are inherently limited by their reliance on respondents' perceptions and assumptions about hypothetical situations. Moreover, data collection issues that may have been encountered could also have influenced the modelling results. One example is the “real-time tracking and tracing” attribute, which showed a counterintuitive negative sign. Future SP designs might consider adding more detailed information and examples to the attribute descriptions and take into account respondents' familiarity with digital delivery tools. Additionally, embedding tracking as part of a bundled service (e.g., with notifications or flexible delivery slots) might better reflect its perceived value in real-world decision-making. Future research could design and implement crowdshipping delivery pilots in specific urban areas to collect revealed preference data, thereby addressing a significant gap in this study.

Crowdshipping operations vary across countries due to differences in regulations, market structure, and user preferences. This thesis examines these dynamics within the Netherlands, developing choice models in Chapters 3 and 4 and a simulation model in Chapter 5. Expanding this research to other geographical contexts with diverse market conditions could provide valuable insights and enable more generalisable conclusions regarding the economic and environmental scalability and sustainability of crowdshipping.

In Chapter 5, a cost-based outlier parcel selection mechanism was introduced to identify parcels with high negative impacts on delivery costs. Future research could explore alternative selection criteria, such as environmental impacts (i.e., CO_2 emissions), service urgency, or customer-specific preferences.

While the cost-based rule in Chapter 5 effectively identifies high-cost deliveries for outsourcing to crowdshipping, the simulation study treats these services as isolated delivery modes. Future research could extend this by modelling the concept of hyperconnectivity, examining crowdshipping within an interconnected network of urban logistics services. Occasional carriers could pick up or deliver parcels also at intermediate points, like parcel lockers. This perspective would consider how different delivery modes, service providers, and urban freight solutions could collaborate to create a cohesive, hyperconnected system, as also outlined by (Crainic et al., 2023). By simulating such networks, it is possible to explore how hyperconnectivity enhances efficiency, minimises costs, and reduces environmental impacts, while also taking consumer decision-making into account. Within this broader vision, the thesis constitutes a first step, and contributes with a prosumer-focused behavioural framework, empirical knowledge on OCs behaviour and a realistic assessment of crowdshipping potential.

Based on the results and assumptions of this thesis, we recommend further work to evaluate and sustain the feasibility of crowdshipping and sustainable urban freight. New studies that make use of appropriate behavioural models could help to design effective policy packages, in the following three directions. Firstly, policymakers play a pivotal role in shaping the growth and sustainability of crowdshipping services. To facilitate its integration into urban logistics systems, regulatory mechanisms should be explored to create a supportive environment. For example, tax incentives could be offered to individuals participating as crowdshipping carriers, particularly those using low-emission delivery modes such as bicycles or public transport. In addition, establishing standardised regulations that define liability insurance, data privacy, and safety requirements would help build trust among users while ensuring reliable operations. Secondly, effective market segmentation is critical for the successful implementation of crowdshipping. In an already highly cost-competitive market like last-mile logistics, it is essential to determine the market potential for crowdshipping. From a cost perspective, pricing strategies should be designed to attract occasional carriers to the system without encouraging them to become dedicated drivers. These strategies should strike a balance, offering sufficient incentives to carriers while maintaining affordability and operational viability. Demographic variability is a third key factor, as socio-economic conditions such as income levels and education significantly influence participation as occasional carriers or users. Furthermore, analysing the relationship between crowdshipping platforms and traditional logistics providers is crucial. This analysis can reveal potential areas for collaboration or conflicts.

To conclude, implementing these recommendations could not only enhance the feasibility of crowdshipping but also contribute to creating a more sustainable urban freight.

Chapter A

Appendix - Overview of studies

Table below provides an overview of studies used in the literature review. The research spans various topics, including acceptance of innovative delivery methods such as crowdshipping, parcel lockers, and self-collection services. Methodologies range from regression models and structural equation modelling (SEM) to simulations and focus groups. The studies explore decisions related to shopping channels, delivery methods, and the willingness to act as service suppliers. Data sources predominantly involve surveys, highlighting the reliance on consumer perspectives to understand emerging trends and preferences in urban freight and logistics systems.

Author (s)	Research objective(s)	Method(s)	Estimation model	Data source	Decision(s)				
					Shopping channel	Delivery method			Becoming a service supplier
						Product	Service	Personal	
Millioti et al. (2020)	To identify the acceptance of consumers on click-and-collect service	Regression	Binary logit	Survey			✓		
Gatta et al. (2021)	To study the difference in preferences for delivery channel choices	SPE	Multinomial logit	Survey			✓		
Tang et al. (2021)	To investigate consumer satisfaction with the smart parcel locker services	Regression Confirmatory factor analysis	–	Survey			✓	✓	
Bidoni and Montreuil (2021)	To model consumer behaviour for new urban parcel logistics services.	Simulation	–	Historical data				✓	
Wang et al. (2021c)	To explore the fairness perspective of logistics services about self-collection service	SEM	–	Survey				✓	
Vakulenko et al. (2018)	To understand consumers changing attitudes towards parcel lockers	Focus group	–	–			✓	✓	
Schaefer and Figliozzi, (2021)	To analyse the location and accessibility of parcel lockers for different population groups	Cluster analysis	–	Open access data			✓		
Devari et al. (2017)	To test the effect of crowdshipping by using consumer's friends or acquaintances for delivering the parcels	Simulation		Survey				✓	
Akeb et al. (2018)	To study a crowdshipping based on neighbour relay as a solution to diminish delivery failure	Simulation	–	–				✓	
Gatta et al. (2018)	To understand and evaluate the environmental and economic impacts of a crowdshipping platform	SPE	Multinomial logit	Survey			✓		
Chen et al. (2018)	To investigate consumer's intention to use parcel lockers	Partial least squares SEM	–	Survey				✓	
Bhukya and Paul (2023)	To provide an overview of the literature on social influence in consumer behaviour	Review	–	–				✓	
Giglio and Maio (2022)	To study the determinants of crowdshipping adoption in university cities	SEM	–	Survey			✓	✓	
Zhou et al. (2020)	To test the influence of psychological factors on consumers' behavioural intention to adopt self-service parcel delivery services	SEM	–	Survey			✓	✓	
Mahdi Zarei et al., 2020	To identify consumer's last mile logistics beliefs in an omni channel environment	Descriptive analysis	–	Survey	✓			✓	
Wicaksono et al. (2022)	To explore how demand and supply side for bicycle crowdshipping meet in a parcel delivery market	SPE	Multinomial logit	Survey			✓		✓
Buldeo Rai et al. (2021)	To identify which type of consumer is interested in crowd logistics	Descriptive analysis Cluster analysis	–	Survey			✓	✓	
Edrisi and Ganjipour (2022)	To identify the factors impacting the adoption of sidewalk autonomous delivery robots	Partial least squares SEM	–	Survey			✓	✓	
Cebeci et al. (2023)	To explore the effect of trust on crowdshipping from the users' perspective	SPE	Hybrid choice	Survey			✓		✓
Felch et al. (2019)	To study consumer acceptance of alternative delivery services	Regression	Linear regression	Survey			✓	✓	

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Cai et al., (2021)	To understand consumer's usage behaviour of logistics technologies: buy-online-and-pickup-in-store, smart locker and drone delivery	SEM	–	Survey			✓	✓	
Hagen, Scheel-Kopeinig, (2021)	To examine acceptance and willingness-to-pay for last mile micro depot	Regression	Probit regression	Survey			✓	✓	
Kapser Abdelrahman, (2020)	To investigate the users' acceptance of ADVs in last mile delivery	SEM	–	Survey			✓		
Koh et al. (2023b)	To explore how consumer health concerns can affect consumers' subjective views and their decisions to use CL	SEM	–	Survey			✓		✓
Koh et al. (2023)	To investigate the factors influencing consumer acceptance of drone delivery	SEM	–	Survey		✓			
Hübner et al. (2016)	To analyse the challenges and opportunities of last mile fulfillment and distribution in omnichannel grocery retailing	Review	–	–			✓		
Yuen et al. (2018)	To explore consumers' intention to use self-collection points	Regression	Hierarchical regaression analysis	Survey			✓	✓	
Meuter et al. (2005)	To explore the factors influencing consumers trial behaviour about innovative delivery modes	Regression	Multiple regression Logistics regression	Survey				✓	
Wang et al. (2018)	To study the behaviour of consumers towards automated parcel stations	SEM	–	Survey				✓	
Wang et al. (2020)	To investigate consumers' motivation of adopting self-collection service for e-commerce delivery	Latent class model Confirmatory factor analysis	–	Survey				✓	
Tsai and Tiwasing, 2021	To investigate determinants of consumers' intention to use smart lockers.	Partial least squares SEM	–	Survey			✓		
Yuen et al. (2019)	To analyse the determinants of consumers' intention to use smart lockers for last mile deliveries	SEM	–	Survey			✓		
Buldeo Rai et al. (2018)	To explore to which extent consumers are willing to adopt last mile options	Conjoint analysis	–	Survey			✓		
Merkert et al. (2022)	To investigate consumer preferences about parcel lockers and unmanned aerial delivery drones	SPE	Mixed logit model	Survey		✓	✓		
Bjerkan et al. (2020)	To study demographic characteristics, travel behaviour and last mile practices for pick-up points and home delivery	RPE	Descriptive analysis	Survey		✓			
Cauwelier et al. (2023)	To characterize personal shopping mobility and weight categories of online purchases	RPE	Descriptive analysis	Survey		✓			
Derhami et al. (2021)	To study the product availability under uncertain demand and in the presence of consumer substitution and inventory transshipment	A data driven model	–	–		✓			
Nguyen et al. (2019)	To study the changing preferences towards online retailing based on different product segments	Conjoint analysis Cluster anaylsis	–	Survey		✓			
Titiyal et al. (2022)	To investigate the impact of e-fulfillment on consumer loyalty across different product types	Least squares SEM	–	Survey		✓			
Madlberger and Sester (2005)	To analyse the last mile services in B2C e- commerce by focusing on consumer decisions	Interviews	Non-parametric test	survey		✓			
Wang et al. (2023)	To investigate consumer preferences for parcel delivery	Regression	Multinomial logit	Survey		✓			✓
Halibas et al. (2023)	To investigate the evolution and trends of the research and channel shopping behaviours	Review	–	–	✓				

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Polydoropoulou et al. (2022)	To study the perceptions of Greek end-users/consumers, regarding the introduction of innovative delivery services.	SPE	Mixed logit	Survey	✓		✓		
Levin et al. (2003)	To invetigate how to combine online and offline services in the most complementary way for different product categories	Averaging model	–	Survey	✓				
Rossolov et al. (2021)	To assess the purchasing behaviours of end-consumers for online or in-store shopping	RPE	Binomial logit	Survey	✓				
Aziz et al. (2021)	To assess both consumers'habits to buy groceries and their potential behaviour change	SPE	Multinomial logit	Survey	✓		✓		
Haridasan and Fernando, (2018)	To compare online and in-store shoppers motivations based on product type.	Means-end approach Interview	–	–	✓				
Chatterjee and Kumar (2017)	To examine differences in consumer willingness to pay for online purchases of functional and expressive products	Regression	Parametric tests	Open access data	✓				
Marcucci et al (2021)	To estimate market shares for e-grocery, distinguishing between home deliveries and clickpick, using the in-store option as a reference	SPE	Multinomial logit and Latent class	Survey	✓		✓		
Hsiao (2019)	To explore how consumers evaluate the time and cost attributes of physical store and e-shopping.	SPE	Binary logit	Survey	✓				
Wieland, (2021)	To identify the main drivers of store choice on the basis that both in-store, online and cross-channel shopping are available.	RPE	Conditional logit-Nested logit	Survey		✓			
Maltese et al. (2021)	To explore the willingness to e-grocery, and delivery preferences	SPE	Multinomial logit	Survey	✓		✓		
Mohri et al. (2023)	To present a comprehensive and timely review of the crowdshipping (CS) literature	Review	–	–					✓
Le and Ukkusuri (2019)	To understand the acceptability of crowdshipping	SPE	Mixed logit	Survey			✓		✓
Le et al. (2021)	To design and evaluate different pricing and compensation schemes for crowdshipping		Matching and routing model	Real-world data					✓
Serafini et al. (2018)	To analyse the willingness to act as a crowdshipper	SPE	Multinomial logit	Survey					✓
Miller et al. (2017)	To measure the potential willingness of individuals to become occasional carrier	SPE	Multinomial logit	Survey					✓
Upadhyay et al (2022)	To explore motivational factors that influence participate in crowdshipping	SEM	–	Survey					✓
Zhang et al. (2023)	To explore the impact of prioritizing outlier parcels in a crowdshipping initiative	Optimisation model	–	–					✓
Raviv and Tenzer (2018)	To introduce a logistics business model that utilizes crowd-shipment	Optimisation model	–	–					✓
Di Febbraro et al. (2018)	To better exploit the supply capacity, a shared mobility service is proposed in this paper for both people and freights	Optimisation model	–	–					✓
Marcucci et al (2017)	To analyse the feasibility and behavioural levers that might facilitate the diffusion of crowdshipping in urban areas.	Regression	Multinomial logit	Survey			✓		✓

Chapter B

Appendix - Survey Design: Chapter 3

Introduction

Dear respondent,
We invite you to participate in a study titled *"The level of trust towards crowdshipping from the user's perspective."* The purpose of this study is to understand how trust in crowdshipping services influences adoption for last-mile deliveries. Crowdshipping is a new delivery system where packages are delivered by non-professional individuals already making trips for personal purposes. Like Uber for people, services like Nimber and PiggyBee offer last-mile delivery via individuals. Your participation is voluntary, anonymous, and valuable. The survey takes about 10 minutes and includes six sections.

I have read the above information
I am above 18 years of age
I live in the Netherlands

Do you agree with the above statements?
☐ Agree ☐ Disagree

Awareness about Crowdshipping

Do you use ride-hailing services (such as Uber, BlaBlaCar)?
Please indicate your answers based on the pre-pandemic situation

☐ No, I am not familiar with these services
☐ No, I've never used it
☐ Yes, rarely
☐ Yes, monthly
☐ Yes, weekly
☐ Yes, daily

Have you sent any item with crowdshipping service before? (such as Nimber, PiggyBee)
Please indicate your answers based on the pre-pandemic situation

☐ No, I am not familiar with these services

☐ No, I’ve heard about the service but I have never used it
☐ I have heard about the service but I didn’t know it is called as crowdshipping
☐ I have used the service

Online Shopping Experience

How often do you use Internet to shop online?
Please indicate your answers based on the pre-pandemic situation

☐ I don’t use online shopping
☐ 1–5 times a year
☐ 6–10 times a year
☐ Once in a month
☐ Couple of times a month

Which option represents the amount that you spend on average per month for online shopping in Euros?
Please indicate your answers based on the pre-pandemic situation

☐ 0–50
☐ 51–100
☐ 101–200
☐ 201–300
☐ 301–400
☐ 401–500
☐ 500+

What was the last item that you bought online?
☐ Electronics / Technological product
☐ Fashion item (clothes, accessories etc.)
☐ Second-hand product
☐ Book / Music album
☐ Other: ________________________

How much did the item cost in Euros?
☐ 0–50
☐ 51–100
☐ 101–150
☐ 151–200
☐ 201–250
☐ 251–300
☐ 301–350
☐ 351–400
☐ 401+

Stated Preference Scenarios Imagine the last item that you bought online. The shop (website) provides two alternatives to deliver your package to your intended location with the following features.

In this specific case:

- It is assumed that you don't need the product urgently.
- It is assumed that you have to be at your predefined location to collect the package.
- Imagine that you can only reach out to the transportation company for your claims in case of a damaged or wrong delivery.

Feature	Explanation
Delivery time	Refers to same day or next day delivery options.
Delivery cost	Represents the cost of the service.
Tracking and tracing options	Indicates whether tracking and tracing is available.
Delivery company's reputation	Refers to the credibility and rating of the company/app.
Insurance coverage	Shows the insurance limits for the delivery option.
Possibility of damage	Represents the chance that the item gets damaged or lost.

1. From the available delivery options below, select the one that fits your preference most)

Features	Crowdshipping	Traditional Delivery
Delivery time	**Same day** delivery	**Next day** delivery
Delivery cost	**10€**	**10€**
Tracking and tracing options	Only **main steps** can be seen in the app/website	Only **main steps** can be seen in the app/website
Delivery company's reputation	★★★★	★★★
Insurance coverage	Up to **1000€**	Up to **750€**
Possibility of damage	1 in 30 damaged delivery **(3%)**	1 in 25 damaged delivery **(4%)**

Would you consider making use of this crowdshipping service?
☐ Yes ☐ No (I would use traditional delivery)

Based on the above mentioned scenario, how much would you trust crowdshipping?
☐ Strongly distrustful ☐ Distrustful ☐ Neutral ☐ Trustful ☐ Strongly trustful

2. From the available delivery options below, select the one that fits your preference most)

Features	Crowdshipping	Traditional Delivery
Delivery time	**Next day** delivery	**Next day** delivery
Delivery cost	**12€**	**10€**
Tracking and tracing options	Only **main steps** can be seen in the app/website	Only **main steps** can be seen in the app/website
Delivery company's reputation	★★	★★★
Insurance coverage	Up to **500€**	Up to **750€**
Possibility of damage	1 in 30 damaged delivery **(3%)**	1 in 25 damaged delivery **(4%)**

Would you consider making use of this crowdshipping service?
☐ Yes ☐ No (I would use traditional delivery)

Based on the above mentioned scenario, how much would you trust crowdshipping?
☐ Strongly distrustful ☐ Distrustful ☐ Neutral ☐ Trustful ☐ Strongly trustful

3. From the available delivery options below, select the one that fits your preference most)

Features	Crowdshipping	Traditional Delivery
Delivery time	**Next day** delivery	**Next day** delivery
Delivery cost	**10€**	**10€**
Tracking and tracing options	**Real time** driver tracking by the app/website	Only **main steps** can be seen in the app/website
Delivery company's reputation	★★	★★★
Insurance coverage	Up to **500€**	Up to **750€**
Possibility of damage	1 in 20 damaged delivery **(5%)**	1 in 25 damaged delivery **(4%)**

Would you consider making use of this crowdshipping service?
☐ Yes ☐ No (I would use traditional delivery)

Based on the above mentioned scenario, how much would you trust crowdshipping?
☐ Strongly distrustful ☐ Distrustful ☐ Neutral ☐ Trustful ☐ Strongly trustful

4. From the available delivery options below, select the one that fits your preference most)

Features	Crowdshipping	Traditional Delivery
Delivery time	**Next day** delivery	**Next day** delivery
Delivery cost	**5€**	**10€**
Tracking and tracing options	**Real time** driver tracking by the app/website	Only **main steps** can be seen in the app/website
Delivery company's reputation	★★	★★★
Insurance coverage	Up to **1000€**	Up to **750€**
Possibility of damage	1 in 30 damaged delivery **(3%)**	1 in 25 damaged delivery **(4%)**

Would you consider making use of this crowdshipping service?
☐ Yes ☐ No (I would use traditional delivery)

Based on the above mentioned scenario, how much would you trust crowdshipping?
☐ Strongly distrustful ☐ Distrustful ☐ Neutral ☐ Trustful ☐ Strongly trustful

5. From the available delivery options below, select the one that fits your preference most)

Features	Crowdshipping	Traditional Delivery
Delivery time	**Same day** delivery	**Next day** delivery
Delivery cost	**7€**	**10€**
Tracking and tracing options	**Real time** driver tracking by the app/website	Only **main steps** can be seen in the app/website
Delivery company's reputation	★★★★	★★★
Insurance coverage	Up to **500€**	Up to **750€**
Possibility of damage	1 in 30 damaged delivery **(3%)**	1 in 25 damaged delivery **(4%)**

Would you consider making use of this crowdshipping service?
☐ Yes ☐ No (I would use traditional delivery)

Based on the above mentioned scenario, how much would you trust crowdshipping?
☐ Strongly distrustful ☐ Distrustful ☐ Neutral ☐ Trustful ☐ Strongly trustful

6. From the available delivery options below, select the one that fits your preference most)

Features	Crowdshipping	Traditional Delivery
Delivery time	**Same day** delivery	**Next day** delivery
Delivery cost	**5€**	**10€**
Tracking and tracing options	Only **main steps** can be seen in the app/website	Only **main steps** can be seen in the app/website
Delivery company's reputation	★★★★	★★★
Insurance coverage	Up to **500€**	Up to **750€**
Possibility of damage	1 in 20 damaged delivery **(5%)**	1 in 25 damaged delivery **(4%)**

Would you consider making use of this crowdshipping service?
☐ Yes ☐ No (I would use traditional delivery)

Based on the above mentioned scenario, how much would you trust crowdshipping?
☐ Strongly distrustful ☐ Distrustful ☐ Neutral ☐ Trustful ☐ Strongly trustful

7. From the available delivery options below, select the one that fits your preference most)

Features	Crowdshipping	Traditional Delivery
Delivery time	**Next day** delivery	**Next day** delivery
Delivery cost	**7€**	**10€**
Tracking and tracing options	Only **main steps** can be seen in the app/website	Only **main steps** can be seen in the app/website
Delivery company's reputation	★★	★★★
Insurance coverage	Up to **1000€**	Up to **750€**
Possibility of damage	1 in 20 damaged delivery **(5%)**	1 in 25 damaged delivery **(4%)**

Would you consider making use of this crowdshipping service?
☐ Yes ☐ No (I would use traditional delivery)

Based on the above mentioned scenario, how much would you trust crowdshipping?
☐ Strongly distrustful ☐ Distrustful ☐ Neutral ☐ Trustful ☐ Strongly trustful

8. From the available delivery options below, select the one that fits your preference most)

Features	Crowdshipping	Traditional Delivery
Delivery time	**Same day** delivery	**Next day** delivery
Delivery cost	**12€**	**10€**
Tracking and tracing options	**Real time** driver tracking by the app/website	Only **main steps** can be seen in the app/website
Delivery company's reputation	★★★★	★★★
Insurance coverage	Up to **1000€**	Up to **750€**
Possibility of damage	1 in 20 damaged delivery **(5%)**	1 in 25 damaged delivery **(4%)**

Would you consider making use of this crowdshipping service?
☐ Yes ☐ No (I would use traditional delivery)

Based on the above mentioned scenario, how much would you trust crowdshipping?
☐ Strongly distrustful ☐ Distrustful ☐ Neutral ☐ Trustful ☐ Strongly trustful

Demographic Information

- **What is your gender?**
  ☐ Male ☐ Female ☐ Non-binary / third gender ☐ Prefer not to say
- **What is your age?**
  ☐ 18–25 ☐ 26–33 ☐ 34–41 ☐ 42–49 ☐ 50–57 ☐ 58–65 ☐ Above 65
- **What is your current occupation?**
  ☐ Working full time ☐ Working part time ☐ Student ☐ I have no work at the moment ☐ Volunteer work ☐ Retired
- **What is your highest, or current, level of education?**
  ☐ VMBO (MAVO) ☐ HAVO ☐ VWO ☐ MBO ☐ Bachelor ☐ Master ☐ PhD ☐ Other: _______________
- **What is your individual net monthly income in Euros?**
  ☐ Less than 500 ☐ 501–1000 ☐ 1001–1500 ☐ 1501–2000 ☐ 2001–2500 ☐ 2501–3000 ☐ 3001–3500 ☐ More than 3500 ☐ I prefer not to answer this

Chapter C

Appendix - Survey Design: Chapter 4

Introduction

The amount of deliveries in the world is increasing, and we need to find new and more clever ways to deliver and save the world at the same time. Crowdshipping can become a possible way to reduce the impact of deliveries. The parcels would be carried by existing passenger trips so they would emit less and be cheaper. Crowdshipping consists of two parties: senders and bringers. The senders are the ones willing to send a parcel through crowdshipping, while the bringers are commuters that are going in the same direction as the parcel is and take the parcel with them.

The objective of this survey is to understand what drives bringers to accept delivering a parcel during their commute. In this survey, we will ask you to be in the role of a possible bringer and answer the scenarios as if you were considering picking up a parcel on your way to work/university. The survey is expected to take you 10 minutes approximately.

Socio-demographic Questions

What is your monthly net income?
☐ Less than €1,000
☐ €1,000 – €1,499
☐ €1,500 – €1,999
☐ €2,000 – €2,999
☐ €3,000 – €3,999
☐ €4,000 – €4,999
☐ More than €5,000

What is your highest level of education achieved?
☐ VMBO (MAVO)
☐ HAVO
☐ VWO
☐ MBO
☐ Bachelor

☐ Master
☐ Doctorate
☐ Other (please state)

In which city do you currently reside?

____

Mobility Characteristics

What is your main commuting activity?
☐ Work
☐ Study
☐ Shopping
☐ Leisure

How many times per week do you go to work/study?
☐ Never
☐ Once a week
☐ 2–3 times a week
☐ 4–6 times a week
☐ Every day

How long is your commute?
☐ $<$ 5 minutes
☐ 5–15 minutes
☐ 16–25 minutes
☐ 26–35 minutes
☐ 36–45 minutes
☐ $>$ 45 minutes

How do you normally commute?
☐ Car
☐ Bicycle
☐ Walking
☐ Public Transport

Vehicles available
☐ Car
☐ Bicycle

*Online Shopping Patterns

How often do you shop online?
☐ I don't use online shopping
☐ 1–5 times a year
☐ 6–10 times a year
☐ Once a month
☐ A couple of times a month

Which option represent the amount that you spend on average per month for online shopping
☐ €0–50
☐ €51–100
☐ €101–200
☐ €201–500
☐ > €500

What was the last item you ordered online?
☐ Electronics / Technological product
☐ Fashion item (clothes, accessories, etc.)
☐ Second-hand product
☐ Book / Music album

Do you sell items online?
☐ Yes
☐ No

What do you sell online?
☐ Second-hand products
☐ For my business
☐ Other (please specify): ____________________

Do you use ride-hailing services (e.g. Uber, BlaBlaCar)?
☐ Never
☐ Sometimes
☐ Often
☐ Always

Have you used crowdshipping service before? (such as Nimber, Uber Eats, Deliveroo.nl)

Have you ever heard of crowdshipping before?
☐ Never
☐ Sometimes
☐ Often
☐ Always

Part 1
For the following questions, please think of the trip that you replied earlier: you travel to work for 5 - 15 minutes by bike.

Each question is a different scenario where you will be asked whether:

- you would make your trip as usual,
- you would like to pick up parcels **before** your activity,
- or you would like to pick up parcels **after** your activity.

Each situation is characterized by:

- **Number of parcels to pick up and deliver**
- **Expected total travel time:** total time travelled, including the pickup and delivery
- **Delivery point:**
  - a parcel locker (always available and accessible), or
  - person-to-person delivery
- **Expected travel cost**
- **Expected total remuneration**

1. Imagine that you are doing your regular work/study related commute and you receive a notification that indicates that you can carry a parcel on your way. Considering your normal trip that you replied earlier: you travel to work for 5 - 15 minutes by bike, please choose the preferred alternative:

	Normal trip	Pick up BEFORE activity	Pick up AFTER activity
Number of Parcels		1	2
Total Travel Time (minutes)	10	15	30
Delivery point			
Total Remuneration (euros)		5	20

Which of the alternatives above would you choose?

☐ Do not pick up any parcels
☐ Pick up and deliver the parcels before the activity
☐ Pick up and deliver the parcels after the activity

2. Imagine that you are doing your regular work/study related commute and you receive

a notification that indicates that you can carry a parcel on your way. Considering your normal trip that you replied earlier: you travel to work for 5 - 15 minutes by bike, please choose the preferred alternative:

	Normal trip	Pick up BEFORE activity	Pick up AFTER activity
Number of Parcels		1	2
Total Travel Time (minutes)	10	15	30
Delivery point			
Total Remuneration (euros)		5	20

Which of the alternatives above would you choose?

☐ Do not pick up any parcels
☐ Pick up and deliver the parcels before the activity
☐ Pick up and deliver the parcels after the activity

3. Imagine that you are doing your regular work/study related commute and you receive a notification that indicates that you can carry a parcel on your way. Considering your normal trip that you replied earlier: you travel to work for 5 - 15 minutes by bike, please choose the preferred alternative:

	Normal trip	Pick up BEFORE activity	Pick up AFTER activity
Number of Parcels		1	2
Total Travel Time (minutes)	10	15	30
Delivery point			
Total Remuneration (euros)		5	20

Which of the alternatives above would you choose?

☐ Do not pick up any parcels
☐ Pick up and deliver the parcels before the activity
☐ Pick up and deliver the parcels after the activity

4. Imagine that you are doing your regular work/study related commute and you receive a notification that indicates that you can carry a parcel on your way. Considering your normal trip that you replied earlier: you travel to work for 5 - 15 minutes by bike, please choose the preferred alternative:

	Normal trip	Pick up BEFORE activity	Pick up AFTER activity
Number of Parcels		1	2
Total Travel Time (minutes)	10	15	30
Delivery point			
Total Remuneration (euros)		5	20

Which of the alternatives above would you choose?

☐ Do not pick up any parcels
☐ Pick up and deliver the parcels before the activity
☐ Pick up and deliver the parcels after the activity

5. Imagine that you are doing your regular work/study related commute and you receive a notification that indicates that you can carry a parcel on your way. Considering your normal trip that you replied earlier: you travel to work for 5 - 15 minutes by bike, please choose the preferred alternative:

	Normal trip	Pick up BEFORE activity	Pick up AFTER activity
Number of Parcels		1	2
Total Travel Time (minutes)	10	15	30
Delivery point			
Total Remuneration (euros)		5	20

Which of the alternatives above would you choose?

☐ Do not pick up any parcels
☐ Pick up and deliver the parcels before the activity
☐ Pick up and deliver the parcels after the activity

6. Imagine that you are doing your regular work/study related commute and you receive a notification that indicates that you can carry a parcel on your way. Considering your normal trip that you replied earlier: you travel to work for 5 - 15 minutes by bike, please choose the preferred alternative:

	Normal trip	Pick up BEFORE activity	Pick up AFTER activity
Number of Parcels		1	2
Total Travel Time (minutes)	10	15	30
Delivery point			
Total Remuneration (euros)		5	20

Which of the alternatives above would you choose?

☐ Do not pick up any parcels
☐ Pick up and deliver the parcels before the activity
☐ Pick up and deliver the parcels after the activity

Part 2
For the following questions, please imagine that you are at home. For each of the scenarios you will be asked whether you would stay at home or you would leave the house and pick up and deliver parcels.

1. Imagine you are home and you get a notification that you can pick up and deliver some parcels:

	Deliver parcels by Car	Deliver parcels by Bike
Number of Parcels	1	1
Mode		
Total Travel Time (minutes)	15	30
Delivery point		
Travel Cost (euros)	1	0
Total Remuneration (euros)	3	3

Would you:

☐ Stay home and do not pick up any parcels
☐ Pick up and deliver the parcels by bike
☐ Pick up and deliver the parcels by car

2. Imagine you are home and you get a notification that you can pick up and deliver some parcels:

	Deliver parcels by Car	Deliver parcels by Bike
Number of Parcels	2	2
Mode		
Total Travel Time (minutes)	35	40
Delivery point		
Travel Cost (euros)	3	0
Total Remuneration (euros)	14	14

Would you:

☐ Stay home and do not pick up any parcels
☐ Pick up and deliver the parcels by bike
☐ Pick up and deliver the parcels by car

3. Imagine you are home and you get a notification that you can pick up and deliver some parcels:

	Deliver parcels by Car	Deliver parcels by Bike
Number of Parcels	2	2
Mode		
Total Travel Time (minutes)	35	40
Delivery point		
Travel Cost (euros)	3	0
Total Remuneration (euros)	14	14

Would you:

☐ Stay home and do not pick up any parcels
☐ Pick up and deliver the parcels by bike
☐ Pick up and deliver the parcels by car

4. Imagine you are home and you get a notification that you can pick up and deliver some parcels:

	Deliver parcels by Car	Deliver parcels by Bike
Number of Parcels	2	2
Mode		
Total Travel Time (minutes)	35	40
Delivery point		
Travel Cost (euros)	3	0
Total Remuneration (euros)	14	14

Would you:

☐ Stay home and do not pick up any parcels
☐ Pick up and deliver the parcels by bike
☐ Pick up and deliver the parcels by car

5. Imagine you are home and you get a notification that you can pick up and deliver some parcels:

	Deliver parcels by Car	Deliver parcels by Bike
Number of Parcels	2	2
Mode		
Total Travel Time (minutes)	35	40
Delivery point		
Travel Cost (euros)	3	0
Total Remuneration (euros)	14	14

Would you:

☐ Stay home and do not pick up any parcels
☐ Pick up and deliver the parcels by bike
☐ Pick up and deliver the parcels by car

6. Imagine you are home and you get a notification that you can pick up and deliver some parcels:

	Deliver parcels by Car	Deliver parcels by Bike
Number of Parcels	2	2
Mode		
Total Travel Time (minutes)	35	40
Delivery point		
Travel Cost (euros)	3	0
Total Remuneration (euros)	14	14

Would you:

☐ Stay home and do not pick up any parcels
☐ Pick up and deliver the parcels by bike
☐ Pick up and deliver the parcels by car

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About the author

Merve S. Cebeci was born in Istanbul, Turkey. She completed her bachelor's degree in Transportation and Logistics at Istanbul University in 2017, graduating as a faculty first. Following her undergraduate studies, she was awarded the prestigious YLSY scholarship, which enabled her to pursue her master's degree in the Netherlands.

Building on this foundation, Merve continued her academic journey with a PhD at Delft University of Technology, focusing on decision-making in last-mile logistics, particularly in crowdshipping. Her research explores the role of consumers as prosumers in hyperconnected urban freight systems, integrating decision-making and simulation models.

During her PhD, she contributed to two European HORIZON 2020 research projects, namely *LEAD* and *URBANE*, where she worked on sustainable urban freight solutions and the integration of innovative crowdshipping services into urban logistics.

Publications

Journal papers

1. **Cebeci, M.S.**, de Bok, M., Tapia, R. J., Nadi, A., & Tavasszy, L. (2025). Feasibility of crowdshipping for outlier parcels in last-mile delivery. Research in Transportation Economics, 112, 101607. DOI: https://doi.org/10.1016/j.retrec.2025.101607

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5. Benus, J., & **Cebeci, M.S.** (2023). An Analysis of the Driving Behaviours of Professional Truck Drivers: A Pilot Study in Turkey. Journal of Transportation and Logistics, 7(2), 357-365.

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1. Karydis, T., Antosz, P., Gürcan, Ö., Brusset, X., ... **Cebeci, M.S.**, Tavasszy, L. (2025). The URBANE Innovation Transferability Platform. In Climate Crisis and Resilient Transportation Systems: Proceedings of the 7th Conference on Sustainable Mobility, CSuM2024, September 4–6, 2024, Plastira's Lake, Greece–Volume I: Advances in Resilience of Transportation Systems and Energy Solutions (p. 389). Springer Nature.

2. Salehi, S., **Cebeci, M. S.**, De Bok, M., Tey, M., Rinaldi, M., & Gentile, G. (2024). Is crowdshipping a sustainable last-mile delivery solution? A case study of Rome. *Transportation Research Board Annual Meeting (104)*, Washington D.C., U.S.A.

3. **Cebeci M.S.**, de Bok M., Tavasszy L. (2023). Consumer decision-making about last-mile services in the Physical Internet: a review. *World Conference on Transport Research*, Montreal, Canada.

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5. Kayikci Y., Zavitsas K., Franklin R., **Cebeci M.S.** (2023). Physical Internet-driven last mile delivery: Performance requirements across people, process, and technology. *Athens, Greece*.

6. Demirci E., **Cebeci M.S.** (2018). Economic Impacts of Highway Investments. *2nd National Congress of Transportation and Logistics*, 22-23 November, Sakarya.

7. Demirci E., **Cebeci M.S.** (2018). Integrated Analysis of University Campuses Accessibility with the Analytical Hierarchy Process and Topsis Methods: Istanbul. *Istanbul University Disability Research Conference*, 15-16 November, Istanbul.

8. Demirci E., **Cebeci M.S.** (2018). The Analysis of Increase in Accessibility to Intelligent Transportation Applications System for the Elderly and Disabled People. *Bandirma University International Conference on Intelligent Transportation Systems*, 19-21 April, Balikesir.

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