MASTER

Critical success factors in implementing in-car delivery
a study on the opportunities and challenges of implementing innovation in parcel delivery

Jong, S.J.G.

Award date:
2021

TU/e supervisors:

Dr. J.M.P. (Josette) Gevers – Human Performance Management Group

Dr. S.W. (David) Lai – Operations, Planning, Accounting & Control Group

Company contact:

R. (Richard) Klomp – 2DEAL B.V.

Critical success factors in implementing in-car delivery

A study on the opportunities and challenges of implementing innovation in parcel delivery.

S.J.G. (Sander) Jong
0905435
March 2021

Colophon

Master Thesis – in partial fulfillment of the double degree Master of Science Innovation Management & Operations Management and Logistics

Critical success factors in implementing in-car delivery

A study on the opportunities and challenges of implementing innovation in parcel delivery

Keywords: in-car delivery, vehicle routing, technology acceptance, innovation resistance, customer trust, job demands, job resources, psychological safety

Publishing date: March 2021

Author: S.J.G. (Sander) Jong

First supervisor/mentor IM: Dr. J.M.P. (Josette) Gevers

First supervisor/mentor OML: Dr. S.W. (David) Lai

Company contact: R. (Richard) Klomp – 2DEAL B.V.

Department of Industrial Engineering & Innovation Sciences

Eindhoven University of Technology

Abstract

This research investigated the opportunities and challenges for in-car parcel delivery from three perspectives: logistics efficiency, customer adoption, and delivery employee safety and satisfaction. The main research question was what critical success factors could contribute to a successful large-scale implementation of in-car delivery. Several research methods were used for the different perspectives. The logistics efficiency potential was investigated by implementing two Vehicle Routing Problems in programming software and analyzing the results of running a dataset of hypothetical customers. Customer research was done by sending out a quantitative survey to potential customers, and analyzing the data with hierarchical linear regression analyses. Finally, the employee research consisted of distilling several design propositions from academic literature. The main results were that in-car delivery could yield substantial savings for logistic service providers when utilized for allowing multiple potential delivery options per customer and choosing the most efficient one. However, to benefit from these savings, it is important that customers see the added value of it compared to incumbent parcel delivery methods, that sufficient flexibility is provided, and that they trust the service. Moreover, employers of delivery employees have to provide employees with fitted job resources to cope with potential changes in their job demands as a result of in-car delivery. Concretely, it is advised that logistic service providers introduce in-car delivery as a flexible delivery method where customers can indicate several potential delivery locations other than their home address, with an associated time window. Moreover, in selling the technology to potential customers, the technology developers are advised to stress this additional flexibility and in general its value compared to other delivery methods. Finally, it is recommended that delivery employees are provided with sufficient training for them to be able to work smoothly with the new technology. Furthermore, resources such as supervisor support and extensive performance feedback are suggested for enhancing employee performance. Based on the findings, several avenues for future research are identified.

Management summary

Currently, e-commerce is growing fast, and with that, the parcel delivery market as well. The number of parcels delivered to customers every day is growing so fast, that it becomes increasingly difficult to serve all customers on time within the current network capacity, especially during peak periods. To combat this problem and sustainably increase parcel delivery network capacity, several alternative delivery methods have been examined recently. In-car delivery is one of them, and the main focus of this thesis. In-car delivery refers to delivering parcels inside the trunk of the customer's car, which could provide several advantages for both logistic service providers and customers. This thesis discusses an after-sales product enabling in-car delivery, where a key recorder and mobile application are used to provide the delivery employee keyless entry to the car. The technology was designed in such a way that it is safe and secure to use, to minimize potential harm to customer data and property.

For the logistic service provider, deliveries would not be bound to a customer's home address anymore, but can be done at any location as long as the customer's car is there. This way commuter behavior could be used to make routing more efficient, such that multiple deliveries normally taking place at different locations could be combined and done at one location, eliminating unnecessary kilometers from vehicle routes. More efficient routing can lower costs, but also create additional capacity within the current vehicle fleet, as the occupancy time of vehicles decreases. On the other hand, for customers in-car delivery could provide additional comfort as they do not have to be home to receive the parcel. Moreover, in-car delivery could enable deliveries at extra delivery hours late at night or in the early morning, when customers are asleep, as they do not have to open the door anymore to receive the parcel. For logistic service providers this could provide the advantage of extending network capacity in an additional manner, namely by extending the daily planning horizon.

However, implementing such an innovation also comes with challenges. First of all, many customers should adopt the innovation for the logistic service provider to obtain its full benefits. A big part of this is the customer's trust in the technology and the people using it, as they let a stranger enter their car to deliver the parcel. Finally, it is important to also take the employee perspective into account. When implementing in-car delivery, his or her job changes drastically because of using a new technology, leading to a new delivery routine. Moreover, he or she can experience additional pressure because of feeling a responsibility to not do harm to the customer's property. When these potentially negative effects on employees are not taken into account sufficiently, their wellbeing and productivity could decrease, and therefore the potential benefits of in-car delivery most likely not obtained either. Therefore, taking these three perspectives into account, the central research question of this thesis is:

What are critical factors to make large-scale implementation of in-car delivery a success for logistic service providers, customers and employees?

To this end, this thesis presents a three-part research. First, the potential effect of in-car delivery on vehicle routing was examined by running a tabu search heuristic on a dataset of hypothetical customers. Second, a customer research was performed by means of a survey, which examined two main parts: (1) their attitudes towards in-car delivery and willingness to adopt it, and (2) their preferred way of having access to in-car delivery after implementation. Finally, an employee research was done. A set of design propositions was proposed based on job design literature. Due to the Covid-19 pandemic, the verification of these design propositions through delivery employee interviews had to be cancelled, but these propositions still provide theoretically solid guidelines on what measures can be taken to mitigate the potentially negative effects of in-car delivery on employees.

The research results implied that all three perspectives interact and therefore should be taken into account. Logistic service providers could obtain substantial benefits from in-car delivery in the form of more efficient routing. To do this, they should offer customers multiple potential delivery options, which can be flexible in both location and delivery time window. Especially this time window flexibility proved to be very important in obtaining more efficient routes. Results showed that on the test instances, cost savings of around 30% on average could be obtained. These cost savings resulted from reductions in route distance, travel time, and waiting time caused by early arrivals at customer locations. Moreover, having multiple potential delivery options per customer reduced the number of stops per route because of combined deliveries. Customers could indicate these delivery options (location and time window) at checkout when shopping online, based on their plans for the delivery date (for instance work or social activities). If they plan to have their car at a certain location for enough time, they can indicate this as an option, whether this is at the home address or not.

The results of the scenario analysis implied that customers were willing to put in this extra effort of providing multiple delivery options at checkout, as long as there was some type of flexibility included. Therefore, this flexibility is important to consider for logistic service providers. Perceived usefulness of the service was identified as the strongest predictor of adoption intentions. Therefore, it is recommended to set up campaigns focusing on the value of this service as compared to conventional parcel delivery, to make customers enthusiastic about adopting it. Part of this should focus on the service ease of use, as this was found to significantly relate to perceived usefulness. Another significant predictor of customer adoption intentions was initial trust in the technology and the parties using it. To enhance this trust, customers should be made aware of the functioning and the safety measures of the technology. A recommendation was to explain and trial the service with well-known, trusted persons or institutions, who can provide a third-party guarantee of the service's trustworthiness.

Finally, the research formulated a set of design propositions acting as guidelines for implementing in-car delivery from the delivery employee perspective. Based on job design theory, it was proposed that in a situation where job characteristics and demands change because of the new technology, employees should be provided with additional resources to cope with these changed demands. Therefore, the research recommends to set up extensive training and feedback programs, such that delivery employees (1) are made familiar with the technology before starting to use it, and (2) that they receive information on their performance with the technology after starting to use it, to be able to improve their work performance. Moreover, the research considers the case in which in-car delivery is utilized to set up late night or early morning deliveries. In that case, employers are recommended to implement fast and forward rotating shift schedules, to minimize the potential negative effects on employee health when working such shifts. Additionally, it is recommended that employees get the possibility to self-schedule their shifts to some extent, such that they experience more autonomy in planning their work hours. Finally, to deal with potential unsafe situations in the work environment because of using in-car delivery, attention should be paid to the support and safety employees experience. Therefore, the research recommends to pay attention to employee psychological safety by implementing a psychological safety climate, together with extensive supervisor support. These two guidelines ensure that the employee feels enough support from a supervisor that he or she could fall back on in case of trouble, and that because of the clear policies and practices of the psychological safety climate, he or she knows what the company can do in case of an unsafe situation.

All in all, the research presents a multi-perspective overview of critical success factors for implementing in-car delivery. The (cost) savings potential for logistics service providers is high, but the research also shows that it will take effort to let sufficient customers adopt it for these benefits to be obtained fully, and that the potentially negative effects on the employees cannot be forgotten.

Foreword

This document marks the end of my dual degree Master program, combining the degrees of Innovation Management & Operations Management and Logistics. Moreover, this thesis for now marks the end of my time as a student here at Eindhoven University of Technology. This research was conducted from the university, in collaboration with 2DEAL B.V., the developers of the in-car delivery technology.

For my thesis, I wanted to do exactly that what made me choose to pursue this dual degree program a few years ago: building bridges between several disciplines that is not always done in making decisions. Too many times, I feel that only one perspective is taken into account in taking operational optimalization decisions, while these implementations never function on their own. In the current case of in-car delivery, initial literature focuses solely on its potential benefits of more efficient routing. However, my thoughts were that this savings potential can never be obtained if customers are not adopting the service. Therefore, I wanted to understand what drives customers in adopting such a technological innovation, but also what makes them resist such innovations. Due to the nature of the technology, I also wondered what the explicit role of trust would be in this process, since it would involve strangers entering the customer's car. Finally, I wanted to take the employee into account. My strong conviction is that one can design the most efficient operational systems in the world, but they will only function if the employees can work with it. Therefore, I wanted to investigate the potential (negative) effects of in-car delivery on employees, and how these can be mitigated to ensure their wellbeing and performance.

Just as in the rest of the world, the Covid-19 pandemic did have its impact on my thesis. Instead of working from a company, or even the university, most of the time I have worked on this thesis from home, coming with its ups and downs. Mentor meetings were online, almost from the very start of the project until the end. Moreover, the pandemic made this thesis topic more urgent than ever before, as online shopping skyrocketed because of the (partial) lockdowns all over the world. Because of this, unfortunately the delivery employees were overloaded as well, causing the employee research to be purely theoretical instead of actually going into the field to talk with them, as planned.

I want to thank my university supervisors, Josette Gevers and David Lai, for their feedback and support. Josette was my mentor from the start, and made me think and improve my work with her constructive feedback and helpful insights. David only came in during the last part of the thesis to replace my initial mentor, but in that short time helped me a lot in developing my programming skills to implement the routing algorithm. A special thanks goes to Luuk Veelenturf, who was my initial mentor for the Operations Management and Logistics program. Before leaving for the Erasmus University in Rotterdam, he helped me through my proposal, in which we formed the research set-up as it is now. Without his help and feedback, my project would not have been where it is now. Finally, I want to thank Richard Klomp from 2DEAL B.V., who acted as my company supervisor. He gave me insights into the world of parcel delivery and the in-car delivery technology that made it possible to do this project.

I want to thank my family, especially my parents, for their support during this difficult year, especially when I spent much time working on my thesis from their home. Finally, I especially want to thank my girlfriend Valentina, who has always been my primary motivation to keep going when times were rough. Even though we were far apart physically, I always felt you close to me, no matter what.

Sander Jong

Table of contents

List of figures

List of tables

Chapter 1: Introduction

Nowadays, e-commerce grows fast in the Netherlands. The Dutch Central Agency for Statistics (CBS) showed that, in the third quarter of 2019 the amount of online B2C sales in the Netherlands grew with 17,5 percent on average compared to the same period in 2018. A distinction can be made here between pure web shops (around 15 percent growth) and so-called multi-channelers, selling both online and in physical stores (around 22 percent growth). As total turnover of the Dutch business-to-consumer market grew with 3,7% in the same time period, this implies that online shopping in the Netherlands is currently growing faster than offline shopping (CBS, 2020). This, in turn, implies a growing daily package flow from companies to consumers. The most recent annual report from the Dutch Authorities on Consumer and Markets (ACM) on mail and package delivery states that in 2018 the package delivery market grew around 20 percent to a total volume of 504 million packages (ACM, 2019). A growing package flow means more income on the one hand, but increases peak pressure: growing demand during peak periods, either in business hours, or time periods like Christmas. Allen et al. (2018) found that peak pressure is a main operational factor impacting profitability. This is a challenge to overcome for logistic service providers. Another relevant challenge is sustainability. The growing amount of delivery vans also means a growing carbon footprint for package delivery. However, every day more people realize what environmental impact online shopping has (Schinkels, 2019). Finding greener ways of logistics to combat the growing demand while minimizing their environmental impact poses a big challenge to logistic service providers.

1.1 In-car delivery as a solution

Several modern solutions for solving these challenges exist, like drone delivery (Shivakumar, 2019) and in-car delivery. The latter is the focus of this research. In-car delivery uses private cars as package delivery locations, serving as a personal locker. The deliverer can enter the car mostly using an application, like Amazon Key (Amazon, n.d.). Amazon can however only use this in newer models of for instance Volvo (Volvo, 2018), and Ford (Hawkins, 2019) cars, that have a built-in in-car delivery function. Using in-car delivery that way has also been used for European pilots (Zurel, 2020). This research however focuses on a different, after-sales technology, developed by 2DEAL. 2DEAL uses a key recorder that is compatible with any car that can be opened with a remote control. Therefore, this technology enables in-car delivery for the mass market, instead of just the innovator niche market.

1.2 Research problem and fields

This research investigates the implementation of in-car delivery from three perspectives. From a logistics perspective, the impact of in-car delivery on routing efficiency is investigated by comparing situations where customers have one sole delivery location to situations where customers might have multiple potential delivery locations, depending on their car location. In-car delivery technology could enable this, since the car does not necessarily have to be at a fixed location for the parcel to be delivered. This will be investigated with the help of theory on the Vehicle Routing Problem (VRP): finding an optimal delivery route from one or more depots to several customers (Laporte, 1992). This classical approach to the VRP will be combined with a more modern variant with roaming delivery locations, where delivery locations are more dynamic (e.g. cars) instead of just static (e.g. houses) (Reyes, Savelsbergh, & Toriello, 2017).

The customer is the second perspective, and an important one for the company that developed the technology. The research investigates the factors that contribute to customer adoption of new technologies, as well as possible barriers that make customers resist them. For investigating this perspective, the Technology Acceptance Model (TAM) (Davis, 1985) is combined with theory on innovation resistance (e.g. Ram & Sheth, 1989) and consumer trust (e.g. Gefen & Straub, 2004). The integration of these concepts and theories should lead to a comprehensive insight on how to approach a large-scale implementation of this technology, and the challenges that might pop up.

The final perspective deals with the delivery employee, whose job changes by implementing in-car delivery. They would for instance deliver into cars instead of at houses, and would have to get used to working with the technology. To research the effect of changes like these on employee outcomes, such as job satisfaction and health, two main theories are consulted: the Job Demands-Resources (JD-R) model by Demerouti, Bakker, Nachreiner, & Schaufeli (2001), and psychological safety climate theory (e.g. Christian, Bradley, Wallace, & Burke, 2009). By using these theories, potential negative effects of in-car delivery on the deliverers might be mitigated, supporting their productivity and job satisfaction.

These perspectives were chosen because of their interaction in successfully implementing in-car delivery. For logistic service providers (LSPs), in-car delivery potentially allows big savings in routing efficiency by combining multiple deliveries in the same locations, as customers can be delivered in multiple locations outside their home address as long as their car is available there. Moreover, more efficient routes can contribute to a sustainable increase in network capacity as vehicles need less time to complete their routes, thereby reducing their emissions as well. However, for LSPs to be able to obtain this savings potential, enough customers should adopt it to be able to combine enough deliveries for it to be advantageous. Therefore, it is essential to learn how customers can be stimulated to adopt an innovation like in-car delivery, or why they would reject it. Finally, it is essential to take the human factor into account, as no logistical network can be utilized to its full efficiency without the employees making the deliveries. To minimize the possibility of undoing logistical efficiency gains by loss of employee productivity, it is important to look at this perspective as well.

1.3 Contributions

This research aims to contribute to theory in several ways. First, it contributes to logistics literature by adding to the young field of the VRP with Roaming Delivery Locations (VRPRDL) and improving the insights on its savings potential compared to more traditional routing problems. Second, the research contributes to customer technology acceptance theory by integrating theories on trust and customer innovation resistance into the widely studied TAM. Finally, the research contributes to theory on job design by investigating a combination of existing models in a different, more modern, job context.

This research also aims to contribute to practice in three ways. First, it gives LSPs insights into whether and how modern delivery methods can contribute to designing more efficient logistical networks. Second, the research gives 2DEAL, the developers of the technology, comprehensive insights in critical factors that should be met to increase the chances of a successful implementation. It does this by looking not just at customer acceptance, but also at why customers resist new technologies. Finally, the research shows LSPs what potential changes in-car delivery brings to deliverers' jobs, and how these affect employees' work-related outcomes. That way, they could prevent that logistics efficiency gains of in-car delivery are undone by losses in employee productivity.

1.4 Structure of this document

The rest of this document is structured as follows. Chapter 2 introduces a more extensive problem description and formulates the research questions. Next, chapter 3 presents a theoretical background on each perspective, and presents the models and hypotheses used for the analysis. Chapter 4 presents the methodology for all three analyses. Then, chapter 5 presents all analyses and results, which lead to the research conclusions in chapter 6. Chapter 7 presents a discussion and a set of practical recommendations for each stakeholder, before chapter 8 presents the final conclusions.

Chapter 2: Problem description

This chapter further describes the research problem and its context. Moreover, the opportunities and challenges of in-car delivery are discussed and research questions formulated. Section 2.1 explains the 2DEAL technology considered for the implementation of in-car delivery. Next, section 2.2 focuses deeper on the process of package delivery for a large LSP in the Netherlands. Section 2.3 then aims to integrate the technology and the process by presenting several scenarios for implementation and what impact each scenario has on the current process. Section 2.4 further discusses several opportunities and challenges that arise for each of the relevant perspectives. Finally, section 2.5 closes the chapter by formulating several research questions to be answered.

2.1: 2DEAL technology: enabling in-car delivery with key recorder and mobile app

The technology this research focuses on for in-car delivery implementation is developed by 2DEAL. It gives deliverers the opportunity to enter a customer's car in a safe and easy way to deliver packages. To achieve this, the service contains a key recorder and a mobile app. The functioning of the technology is schematically visualized in Figure 1.

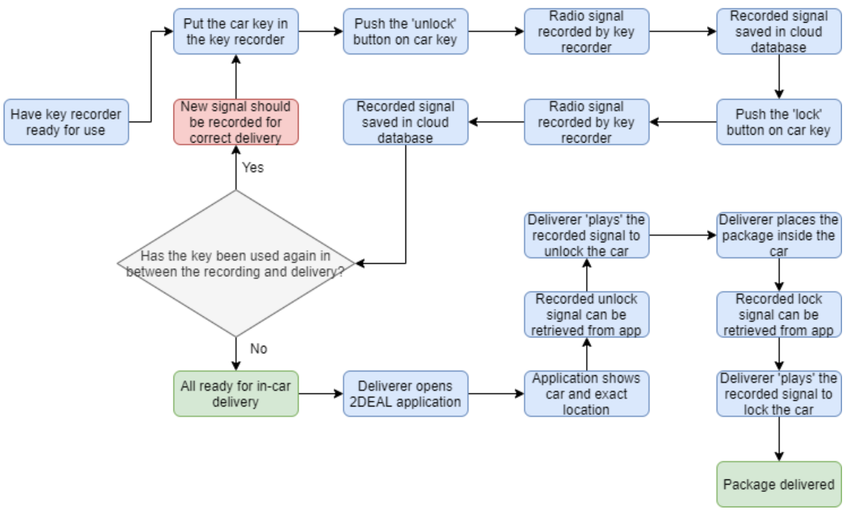

Figure 1: Schematic overview of an in-car delivery using 2DEAL technology

When shopping online, at checkout the customer enters in-car delivery as the preferred method. After parking and closing the car for the last time before receiving the package, one opens the mobile app. Now, two actions are required to prepare the in-car delivery. First, the customer enters the exact car location by pinning it onto a map, such that deliverers know where to find it. Second, the app can be used to check whether the key codes are uploaded correctly. This uploading is done with the key recorder: an isolated, transparent box in which one puts the car key. Next, the customer presses the 'open car' and 'close car' buttons one time each, in that order. Because of the isolation these signals never reach the car, but instead are recorded and safely saved to the cloud. When the deliverer arrives, he or she opens the app and checks all data: order number, timeframe, and location. If everything is correct, the deliverer accesses and plays the recorded 'open car' signal to open the car, drop the package, and close it in the same way. As the key codes are unique for each opening and closing of the car, each signal can only be used once, forming an extra security layer. Finally, the customer receives a notification through the app when the package is delivered.

2.2: Package delivery process

This section looks closer on the package delivery process, from the completion of an online purchase until a successful package delivery. The most relevant parts of this process for a large Dutch LSP are schematically visualized in Figure 2.

Upon completion of the order, the LSP receives a pre-notice from the web shop with the approximate size and weight of the package they can expect. After receiving the package, the LSP sorts and transports it to the correct regional depot for a second sorting on route number. Routes usually have a fixed base order (on postal code level), but drivers can make minor changes to them before leaving the depot, if necessary. When the driver leaves the depot, notifications with two-hour delivery timeslots are sent out to customers.

Usually neighbor delivery is the default not-at-home option. When this is not possible, the package is brought to a pick-up point. Deliverers pass by each pick-up point once a day. Therefore, all unsuccessful deliveries before passing the pick-up point are dropped there later on the route; those from later on the day are delivered the next day after passing through the depot again (step 24). It is also possible that packages are undelivered at the end of day because of time issues. These are also taken to the depot, but the next day another attempt for home delivery is made (step 23).

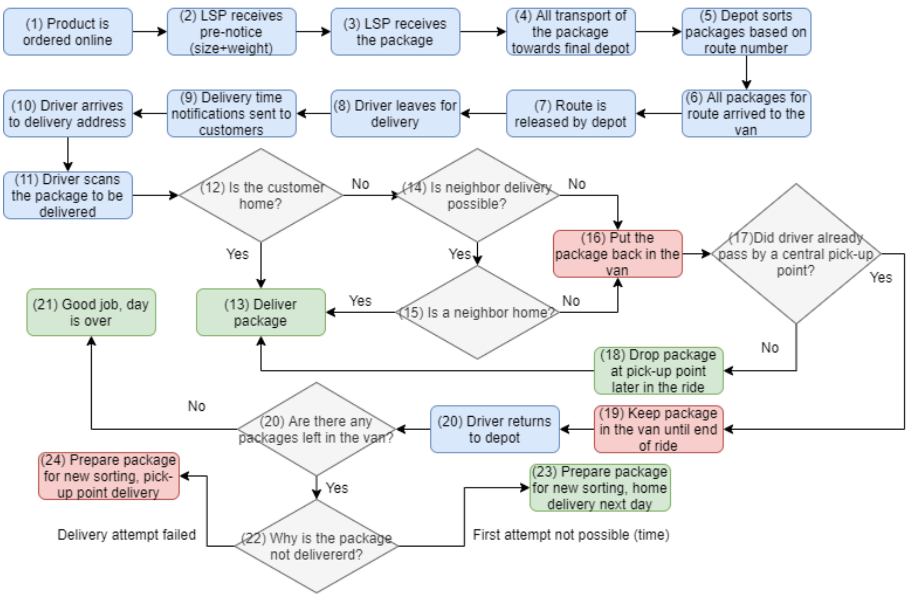

Figure 2: Schematic overview of the package delivery for a large Dutch LSP

2.3 Integrating 2DEAL technology and the delivery process

Next, the technology has to be integrated into the delivery process, which can be done in several ways. Four variants of indicating customer time and location preferences are discussed with their impact on the delivery process, as well as two variants of key recorder distribution.

2.3.1 Variants in customer delivery preference indication

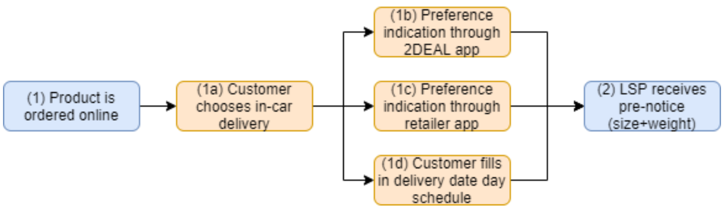

Figure 3: Schematic visualization of delivery process changes at check-out

This section presents four possible variants in which customers can indicate their in-car delivery preferences. These, together with their impacts on the process, are further explained below and schematically visualized in Figures 3, 4, and 5.

Variant 1: non-changeable in-car delivery at check-out, use 2DEAL to indicate preferences: In this option, customers indicate their non-changeable preference for in-car delivery at check-out. Then, they provide the necessary time and car location information through the 2DEAL app. For the LSP this option is convenient since the delivery method and approximate location are known up front; the exact car location is pinned later

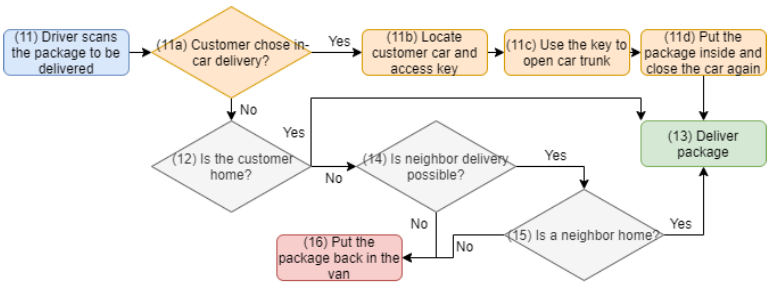

Figure 4: Schematic visualization of delivery process changes at first attempt

by the customer. However, in case of a sudden change of customer plans, an error in the uploaded car location, or when the user forgets to upload the key or the exact location, delivery immediately fails. For customers, indicating their preferences should take little effort at a convenient moment (at check-out), but there is no flexibility for changes later. Moreover, it requires customers to download the 2DEAL app, which would only add another app to the app pile for them. In Figure 3, this variant follows steps 1a and 1b, and in Figure 4 this variant follows 11a until 11d.

Variant 2: flexible in-car delivery at check-out, use 2DEAL to indicate preferences: This option also lets customers indicate their preferences at check-out, but here the option of switching later between home and in-car delivery (through the 2DEAL app) remains for the delivery date, as shown in Figure 5. An important condition for this flexibility is that the car and home address are close to each other, because planned routes cannot be changed. This option gives customers more flexibility: you can still go out (without the car) without missing the delivery, as long as the car is parked at the initially indicated address during the delivery window. Customers also need the 2DEAL app to indicate their preferences. The main advantage for LSPs is an increased chance of a successful first delivery as customers can easily switch the delivery method if they are not at home. However, when customers forget to switch or when the car is not at the indicated location during delivery, delivery is more likely to fail. In Figure 3, this variant also follows steps 1a and 1b, and in Figure 4 it follows the upper path (11a-11d) with in-car delivery and a bottom path with home delivery.

Figure 5: Introducing a flexible delivery method option

Variant 3: customers choose in-car delivery at check-out, indicate preferences through retailer app: This option is similar to the first one, but with a big difference: 2DEAL functionality would be integrated into the retailer application. This way, customers can complete all actions regarding in-car delivery directly from this app instead of having to use an additional one. For the LSP, the advantages and downsides are largely the same as in the first option. However, an extra risk might be that the integration of the 2DEAL API in the retailer application is not complete and does not function as intended. For the customers the main extra advantage compared to the first variant is that they do not have to download an additional app, as the retailer application would be sufficient to perform all required actions for in-car delivery. In Figure 3 this variant is represented by steps 1a and 1c, and in Figure 4 by steps 11a-11d.

Variant 4: customer fills in delivery date day schedule, LSP chooses delivery time and location: In this option, customers fill in a delivery date day schedule at check-out, which the LSP uses to choose the delivery method, time, and location. The advantage for the LSP is that they have very complete information up front, making route planning easier. However, a disadvantage is that customers might have to change their plans between filling out the form and actual delivery, leading to failed deliveries. For customers this variant mainly has disadvantages, since filling in the day schedule is a hassle and it restricts their day planning flexibility. However, a potential advantage could be that they could receive early delivery time notifications from the LSP, because of the more extensive information the LSP has. This variant follows steps 1a and 1d in Figure 3, while in Figure 4 it follows steps 11a-11d.

2.3.2 Variants in key recorder distribution

Variant 1: Customers have their own key recorder: In this case, each customer or household obtains their personal key recorder. This can be either by buying one personally or obtaining one via a web shop that bears (part of) the cost. The advantage is that, once obtained, the customer always has a key recorder close by to upload a key. The downside however is that this is a relative costly option: either for customers when they have to buy them, and for the involved companies to distribute them. For the companies (retailers and LSPs) it will mainly be costly when they want to make the key recorders available to their customers for free, which means that they have to bear all the costs.

Variant 2: Install central key upload stations at pick-up points: Alternatively, next to distributing personal key recorders, central key upload stations could be installed at pick-up points, comparable to OV chipcard service points in the Netherlands. Customers can visit such a station and upload their key just like they would do with a personal key recorder. The main advantage for customers is that this is much cheaper than buying your own key recorder. However, it means you always have to go out for uploading your key, thereby restricted by pick-up point opening times as well.

2.3.3 Scenario development

Combining these four variants of indicating customer delivery preferences with these two variants on key recorder distribution results in the eight scenarios listed schematically in Table 1.

	Fixed in-car delivery at check-out: use 2DEAL app	Flexible in-car delivery at check-out: use 2DEAL app	In-car delivery at check-out: use retailer's app	Fill in day schedule, LSP chooses location, method and time
Using personal key recorders only	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Using central key upload stations	Scenario 5	Scenario 6	Scenario 7	Scenario 8

Table 1: Overview of different implementation scenarios for analysis

These eight scenarios were used in the customer research to perform a scenario analysis, where respondents rated each scenario based on their preferences to discover which combinations of delivery preference indication and key recorder distribution have most potential. This research is further discussed in chapters 4 and 5.

2.4 Opportunities and challenges

After discussing the technology, the delivery process, and the integration of the two, this section discusses some implications of this integration, in the form of opportunities and challenges. These are discussed from the relevant perspectives: logistics, customer, and deliverer.

2.4.1 Logistics

Utilize commuting behavior for more efficient delivery: In-car delivery could potentially realize more efficient logistics by utilizing commuting behavior, based on the idea that delivery can take place on locations closer to the depot or other delivery locations when packages can be delivered in someone's car trunk during work time (Reyes et al., 2017). There is large savings potential for this in the Netherlands: the latest report on commuting behavior from the Dutch Central Statistics Agency (CBS) found that in 2014 the total daily commuting distance accountable to car drivers was estimated to be 172.8 million kilometers (CBS, 2016). If using in-car delivery can utilize just a part of this distance, many kilometers and costs can be saved.

Open additional delivery windows: In-car delivery could increase network capacity by making deliveries in time windows that cannot be utilized yet because someone needs to open the door. This mainly includes an early morning time window before people go to work and are still asleep, and a late night time window, when people are already asleep or less willing to open the door. Since in-car delivery only needs a car parked at a known location, these limitations are at least partly eliminated. Moreover, this could be extended to overnight deliveries, such that you order a product online and receive it in your car next morning before going to work (T. Kroeze, personal communication, 13-02-2020; R. Klomp, personal communication, 14-02-2020).

Increase the number of first time right deliveries: In-car delivery could simplify the delivery process by increasing the amount of packages successfully delivered in one attempt, thereby eliminating the need for neighbor delivery or transport to a pick-up point which occupies van space. Moreover, if key code recording and car location indication are done correctly, the probability of a fast and successful first delivery attempt increases. This is because in-car delivery should nearly always function in one attempt when these elements are in place.

2.4.2 Customers

More comfortable package delivery: For customers, a main advantage is that in-car delivery can eliminate worries about missing deliveries when shopping online. Customers could obtain more freedom in choosing where and how their package is delivered, for instance during work time. This reduces the need to adjust their daily schedule for receiving a package, which might make customers more relaxed compared to the current situation. Moreover, in-car delivery could largely eliminate the need for neighbor delivery as a not-at-home option, which bothers some people currently, for instance in the 2DEAL pilot group (Klomp, 2019). These customers would benefit greatly from in-car delivery.

Possibility to receive early morning deliveries: In-car delivery enables the delivery of online orders at more unconventional timeslots, such as in the early morning before work. This could for instance be done with groceries. A Dutch online shopping market report showed that food was the Netherlands' biggest online growth market in the first half of 2019. (Thuiswinkel, 2019). This might be exploited by offering customers the possibility to have their fresh groceries delivered in their car before going to work, such that they can take fresh food for breakfast or lunch, or can cook straight away after work.

Consumer adoption of and trust in new technology: A major challenge of in-car delivery, like other new technologies that are still unknown to the general public, is to convince consumers to try, and then repeatedly use it. Several factors can influence this process, an important one of which is consumer trust in new technology. Although a pilot group shows high customer feedback scores on trust (Klomp, 2019) and 2DEAL ensures the safety of the technology (T. Kroeze, personal communication, 13-02-2020), trust might still be an issue for the mass market. As trust is assumed to be vital for customers to adopt new technologies, this is likely to be a challenge to overcome.

2.4.3 Employees

Effect of opening someone's car on employees: In-car delivery changes the way deliverers perform their job, which might also affect them personally. Employees should be made familiar with a new technology, the way it functions and how it impacts their work routine. Moreover, opening a stranger's car can also influence an employee mentally, for instance through feelings of conscience because employees could consider it unethical to open another person's car. Additionally, opening a stranger's car could lead to feelings of unsafety, as the deliverer could be mistaken for a burglar, for instance by neighbors unfamiliar with in-car delivery. This especially applies to late night or early morning deliveries. Therefore, the challenge is to ensure that employees can work safely, receive the necessary tools to cope with changed job demands, and learn how to carefully deliver packages in customer cars.

Employee productivity in night shifts: As mentioned earlier, logistically and for customers in-car delivery enables delivery in now unconventional timeslots, such as late night or early morning. However, deliverers would start working night shifts to be able to achieve this, which might impact their productivity. Working night shifts could for instance negatively affect their sleeping rhythm, with negative health consequences such as tiredness or even sickness. Moreover, it can also be a challenge to find enough employees willing to work these shifts. Therefore, in designing the logistical networks for in-car delivery, sufficient attention should be paid to possible negative effects of working night shifts on the employee.

2.5 Research questions

To conclude this chapter, the problem analysis from the previous sections is converted into several research questions. This includes one central research question that is subsequently translated into a separate main research question and various sub-questions per perspective.

Central research question: What are critical factors to make large-scale implementation of in-car delivery a success for logistic service providers, customers, and employees?

Main research question 1: What potential impact could implementing in-car delivery have on package delivery routing efficiency?

Research sub-question 1.1: What would be the cost savings potential when customers can have multiple potential delivery locations besides their home, for instance by utilizing commuting behavior?

Research sub-question 1.2: What would be the cost savings potential when customers can be delivered within multiple different time windows?

Research sub-question 1.3: What would be the cost savings potential when customer can have multiple potential delivery locations besides their home, each with their associated time window?

Research sub-question 1.4: What would be the effect of implementing in-car delivery on distance and travel time?

Research sub-question 1.5: How could implementing in-car delivery influence the number of stops per route?

Research sub-question 1.6: How would opening extra delivery windows impact the network capacity?

Main research question 2: How can 2DEAL stimulate adoption of in-car delivery among consumers?

Research sub-question 2.1: What main factors influence the customer adoption of new technologies, and specifically in-car delivery?

Research sub-question 2.2: What role does trust play in the customer adoption of new technologies, and in-car delivery in particular?

Research sub-question 2.3: What barriers might customers experience towards adopting new technologies, and specifically in-car delivery?

Research sub-question 2.4: What would be the preferred way of access to in-car delivery for customers?

Main research question 3: What impact would the implementation of in-car delivery have on employees, both on a job and a personal level?

Research sub-question 3.1: How would implementing in-car delivery change the employee's job characteristics and work environment?

Research sub-question 3.2: What can be done to make sure employee work-related outcomes are not negatively impacted by implementing in-car delivery?

Research sub-question 3.3: What measures can be taken to let employee safely perform in-car delivery?

Chapter 3: Theoretical background

This chapter provides a theoretical background to the analysis. For all three perspectives, relevant insights from academic literature are presented, together with their relevance to the case. The structure of this chapter is as follows. First, section 3.1 focuses on the logistics perspective, with a brief introduction to the Vehicle Routing Problem (VRP) and the variants relevant to this case. Moreover, this section develops the models used for analysis in the current study. Next, section 3.2 focuses on the customer perspective. Theory on technology acceptance, innovation resistance, and consumer trust is introduced, together with the research model and the hypotheses for the current study. Finally, section 3.3 zooms in on the employee perspective, with a short overview of literature on job characteristics, demands, and resources, as well as psychological safety. Also here, the research model for the current study is developed, together with the hypotheses.

3.1 Logistics: Vehicle Routing Problem

The VRP is a well-studied problem in logistics literature that aims to find an optimal delivery route from one or more depots to a set of geographically scattered customers (Laporte, 1992). The problem originates from the fifties as a generalized version of the Traveling Salesman Problem (TSP) (Dantzig, Fulkerson, & Johnson, 1954). The TSP aims to find one single route that connects a set of locations, to minimize costs, distance, or time (Little, Murty, Sweeney, & Karel, 1963), whereas the VRP also allows a set of multiple routes to connect these locations.

Several forms of the VRP have emerged over time, with different objectives and constraints. Some common types of objectives and constraints in VRP literature are schematically shown in Figure 6. Many VRP studies focus on cost minimization, such that all customers are served in the most cost-efficient way (Garcia, Potvin, & Rousseau, 1994), either alone or combined with a cap on total distance driven (Osman, 1993). Moreover, several studies focus on travel time, where the objective becomes to find a solution that minimizes the total time needed to traverse all necessary edges once (Savelsbergh, 1992). The final common economic motive focuses on vehicles, with the goal to find a set of routes that minimizes the amount of vehicles needed to complete all routes (Kontoravdis & Bard, 1995).

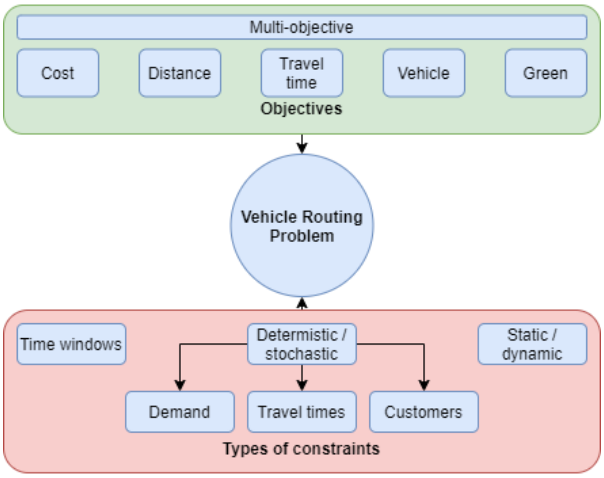

Figure 6: Schematic overview of common objectives and constraints for the VRP

While traditionally VRP objectives were driven by economics, more recently broader objectives have also emerged. A main example of this is the Green VRP, where objectives are not just economic, but also focus on social and environmental aspects. Green VRPs try to find a balance between both environmental and economic costs (Lin, Choy, Ho, Chung, & Lam, 2014). Finally, combining several objectives is also possible, in a so-called multi-objective VRP. Their big advantage is that they are more realistic, since real-life problems are often multi-objective in nature (Jozefowiez, Semet, & Talbi, 2008).

The other aspect in which VRPs can differ is in the nature of the information and the constraints. Regarding the information, two main distinctions exist. First, a VRP can be static or dynamic. In a deterministic VRP, all parameters are assumed to be known up front, while in a stochastic VRP, several parameters can still be uncertain, such as the demands, travel times, and customer locations (Gendreau, Laporte, & Séguin, 1996b). When demands are stochastic, a vehicle must meet delivery demands at several locations without knowing the exact demand per location up front (Bertsimas, 1992). Next, travel times are a common source of stochasticity, since unforeseen traffic circumstances can easily affect them. Therefore it is argued that using stochastic travel times allows for a more realistic VRP (Taş, Dellaert, Van Woensel, & De Kok, 2013). Finally, when customer locations are stochastic, the locations are known, but each customer has a probability of being present. In case a customer is absent during route execution, it has zero demand (Gendreau, Laporte, & Séguin, 1996a).

The second main information distinction is between static and dynamic VRPs. This distinction is made based on when customer information arrives. In a static VRP, each customer has a known order size up front, which has to be fulfilled by a set of vehicles (Montemanni, Gambardella, Rizzoli, & Donati, 2005). In a dynamic VRP, however, additional customer orders can come in even during route execution, or existing orders can be changed (Pillac, Gendreau, Guéret, & Medaglia, 2013).

3.1.1 Vehicle Routing Problem with Time Windows

The in-car delivery case study compares two different VRP variants. These are the VRP with time windows (VRPTW), discussed in this section, and the VRP with roaming delivery locations (VRPRDL), which will be discussed in section 3.1.2.

The VRPTW is another historically common VRP constraint, which extends the VRP with the complexity of having specific time windows within which a van should arrive at a customer location to avoid negative consequences (Solomon, 1987). Two types of time windows exist. Soft time windows allow deliveries outside the time window limits, but deliverers incur a penalty cost in case of late arrival (Taillard, Badeau, Gendreau, Guertin, & Potvin, 1997). With hard time windows this is not possible, and customers cannot be served anymore after a late arrival (Garcia et al., 1994).

In the in-car delivery case, the VRPTW model represents the situation in which it is assumed in-car delivery can only be utilized when the car is parked outside a customer's home. So far, the companies that have piloted or implemented small-scale in-car delivery have used this form, like Amazon does with Amazon Key (Amazon, n.d.), as mentioned in chapter 1.

When in-car delivery is implemented in this form, this means each customer only has one potential delivery location (his or her home address or the pick-up point he or she chose), with one time window known up front in which the car is available for delivery at that location.

3.1.1.1 VRPTW research model

This section introduces the mathematical research model for this first in-car delivery implementation variant, where the logistical problem takes the form of a VRPTW, which can be represented on graph G, with a set N of nodes and a set A with all the arcs.

Let C be the set of customers to be delivered, with individual customers $i = 1, \ldots, C$. Let V be the set of vehicles $k = 1, \ldots, K$ available for delivery, each with finite capacity Q. Let c_{ij} denote the cost it takes to travel from customer i to customer j, and let d_i denotes the demand of customer i, and t_{ij} the travel time from customer i to customer j. The customer delivery time windows are denoted by $[a_i, b_i]$, where a_i is the earliest service time of customer i and b_i the latest service time.

The problem has two decision variables. First, x_{ijk} is a binary decision variable that takes the value 1 when vehicle k travels from customer i to customer j, and 0 otherwise. The second decision variable, s_{ik} is a continuous decision variable that denotes the time when vehicle k starts serving customer i.

The mathematical problem is formulated as follows:

$$\min \sum_{i \in C} \sum_{j \in C} \sum_{k \in V} c_{ij} x_{ijk} \tag{1}$$

$subject\ to$:

$$\sum_{k \in V} \sum_{j \in C \setminus \{i\}} x_{ijk} = 1 \qquad \forall\, i \in C \tag{2}$$

$$\sum_{j \in C \setminus \{i\}} x_{ijk} = \sum_{j \in C \setminus \{i\}} x_{jik} \qquad \forall\, k \in V, \forall\, i \in C \tag{3}$$

$$\sum_{i \in C} d_i \sum_{j \in C \setminus \{i\}} x_{ijk} \leq Q \qquad \forall\, k \in V \tag{4}$$

$$\sum_{j \in C} x_{0jk} = 1 \qquad \forall\, k \in V \tag{5}$$

$$\sum_{i \in C} x_{i0k} = 1 \qquad \forall\, k \in V \tag{6}$$

$$x_{ijk}\left(s_{ik} + t_{ij} - s_{jk}\right) \leq 0 \qquad \forall\, i, j \in N, \forall\, k \in V, j \neq 0 \tag{7}$$

$$a_i \leq s_{ik} \leq b_i \qquad \forall\, i \in C, \qquad \forall\, k \in V \tag{8}$$

$$x_{ijk} \in \{0, 1\} \qquad \forall\, i, j \in C, \qquad \forall\, k \in V \tag{9}$$

Objective function 1 presents the cost minimization objective, over all customers and vehicles. Constraints 2 state that each customer should be visited exactly once by only one vehicle, and constraints 3 ensure flow conservation. Constraints 4 ensure that maximum vehicle capacity is not exceeded. Constraints 5 and 6 state that the number of vehicles leaving the depot is equal to the number of vehicles arriving to the depot. Constraints 7 make sure that when vehicle k serves customer j after customer i, it does not arrive at customer j before its earliest possible arrival moment given by the service moment of customer i and the travel time needed between customers i and j. Next, constraints 8 enforce that the service of customer i by vehicle k is performed within the time window $[a_i, b_i]$ in which customer i is available for service. Finally, constraints 9 confirm the binary status of decision variable x_{ijk}.

3.1.2 Vehicle Routing Problem with Roaming Delivery Locations

The second variant for in-car delivery implementation that was studied is the VRP with Roaming Delivery Locations (VRPRDL). While the VRPTW has already been studied for decades, the VRPRDL has only recently emerged. When in-car delivery was investigated as a potentially important new logistical opportunity, it was proposed that it would lead to a fundamentally different VRP type: the VRPRDL (Savelsbergh & Van Woensel, 2016).

The VRPRDL is a recent variation of the VRP that was introduced as such by Reyes et al. (2017). The main difference with classical VRP types is that in the VRPRDL, customer locations cannot be assumed as a given, as customers could be in several potential locations during the planning horizon. Thus, delivery locations are no longer treated as static (e.g. houses), but rather as dynamic (e.g. cars).

Since it is rather new, only a few papers have been written so far on this variant. Reyes et al. (2017) were the first to research the VRPRDL as such, solving a deterministic version of the problem with heuristics and finding significant cost savings potential, up to 65% compared to conventional VRPs. The same problem setting was tested with exact methods by Ozbaygin, Karasan, Savelsbergh, & Yaman (2017) with similar positive results. Moreover, they included a hybrid version where home and roaming delivery are both possible.

Next to these deterministic studies, studies on the VRPRDL with stochastic travel times were done by Lombard, Tamayo-Giraldo, & Fontane (2018) and Sampaio Oliveira, Kinable, Veelenturf, & Van Woensel (2019). As pointed out by the latter study, accounting for stochastic travel times in the VRPRDL improves results, but comes at the cost of increased model complexity. Finally, while all other studies studied the static VRPRDL, Ozbaygin & Savelsbergh (2019) did an attempt to research a dynamic VRPRDL. They use a situation where both customer demands and itineraries can still change during route execution. However, despite this dynamism, they do not account for stochasticity. While VRPRDL research is still scarce, all studies have in common that they show big cost savings potential for using roaming delivery locations as compared to the traditional vehicle routing models. Moreover, most of the aforementioned studies solved the VRPRDL by using exact, and thus computationally expensive, methods. To tackle this, more recently He, Qi, Zhou, & Su (2020b) initiated a research on several greedy-based construction heuristics to solve the VRPRDL. Then they also developed a metaheuristic to solve a stochastic variant of the VRPRDL, with the big advantage over the heuristic by Reyes et al. (2017) that this metaheuristic can model more real-life situations because of its stochastic component (He, Qi, Zhou, & Su, 2020a).

Finally, recent research on this type of VRP is looking to generalize the VRPRDL and the earlier Generalized Vehicle Routing Problem with Time Windows (GVRPTW) (Moccia, Cordeau, & Laporte, 2012), which had a similar idea of having multiple potential delivery options per customer. This generalization takes the form of a Vehicle Routing Problem with Delivery Options (VRPDO), where each customer request is represented by one or more delivery options, that differ in terms of location and time window (Tilk, Olkis, & Irnich, 2020). They used an exact branch-and-price algorithm to obtain optimal solutions for instances with up to 50 customers and 100 delivery options, while also improving several optimal solutions for the VRPRDL. On the other hand, Dumez, Tilk, Irnich, Lehuédé, & Péton (2020) and Dumez, Lehuédé, & Péton (2021) focus on modeling this problem in a metaheuristic for faster solutions, which is done by a large neighborhood search strategy. However, research on this new generalization is still scarce, and

3.1.2.1 VRPRDL research model

This section presents the mathematical model of the VRPRDL as used for the second scenario in the in-car delivery case, with the mathematical model from Reyes et al. (2017) used as a basis.

The problem can be seen as a complete directed graph $G = (N \cup \{0\}, A)$, where N represents the set of potential customer delivery locations, $\{0\}$ the depot, and A the set of arcs a, each with travel time t_a and cost w_a needed to traverse them. C denotes the set of all customers that need to be delivered within a finite planning horizon $[0, T]$, with a set of vehicles V, each of which has finite capacity Q. Each customer $c \in C$ that has a geographic profile $N_c \subseteq N$ specifying the set of locations in which customer c can receive deliveries. Let d_i then be the demand of the corresponding customer on node i.

Each geographic profile N_c consists of a set O of delivery options o. Each option has a location i, and an associated time window $[a_i, b_i]$, during which customer c is available for service at location i. Here, a_i denotes the earliest delivery moment and b_i the latest delivery moment. Note that in contrast to the assumption by Reyes et al. (2017) that each of these delivery options is non-overlapping, this is not the case in the current study. This is because the assumption is made that customers indicate several delivery options at checkout, and that they can adjust their final plans based on the chosen delivery option. The total number of potential delivery options is denoted by $k = |N_c|$. Another assumption by

Reyes et al. (2017) that was not followed in this study is that different customers c and c' have non-overlapping geographic profiles such that $N_c \cap N_{c'} = \emptyset$. This is because it is assumed that two customers can be within the same location cluster at the same time, for instance because two customers work in the same area.

Finally, the customer time windows satisfy two conditions. The first one is that $a_1 \geq 0,\ b_k \leq T$, which specifies that the earliest delivery moment for customer location 1 is at the start of the planning horizon or later, and the latest delivery moment for customer location k is at or before the end of the planning horizon. The second condition is that $a_l = b_{l-1} + t_{i_{l-1};i_l}, l = 2, \ldots, k$. This denotes that the delivery at location l cannot start before the vehicle traveled from its preceding location to location l, so that the vehicle is not available for delivery while traveling between locations.

To complete, the model has two decision variables. First, x_{ijv} is a binary decision variable denoting that vehicle v travels from location i to location j. The second decision variable s_{iv} denotes the time at which vehicle v starts serving customer c at location i. The objective of the program is to minimize total costs, while ensuring each customer is visited once and that time window and capacity constraints are not broken.

This leads to the following mathematical formulation:

$$\min \sum_{i,j \in N \cup \{0\}} w_{ij} x_{ijv} \tag{1}$$

$$subject\ to:$$

$$\sum_{j \in N \cup \{0\} \setminus \{i\}} x_{ijv} = \sum_{j \in N \cup \{0\} \setminus \{i\}} x_{jiv} \qquad \forall\, i \in N \cup \{0\}, \forall\, v \in V \tag{2}$$

$$\sum_{i \in N_c} \sum_{j \in N \cup \{0\} \setminus \{i\}} x_{ijv} = 1 \qquad \forall\, c \in C \tag{3}$$

$$\sum_{v \in V} \sum_{j \in N} x_{0jv} \leq |V| \tag{4}$$

$$\sum_{v \in V} \sum_{i \in N} x_{i0v} \leq |V| \tag{5}$$

$$\sum_{i \in N} d_i \sum_{j \in N} x_{ijv} \leq Q \qquad \forall\, v \in V \tag{6}$$

$$x_{ijv}\left(s_{iv} + t_{ij} - s_{jv}\right) \leq 0 \qquad \forall\, i,j \in N, \forall\, v \in V, j \neq 0 \tag{7}$$

$$a_i \leq s_{iv} \leq b_i \qquad \forall\, c \in C, \quad \forall\, v \in V \tag{8}$$

$$x_{ijv} \in \{0,1\} \qquad \forall\, i,j \in C, \quad \forall\, v \in V \tag{9}$$

The objective function minimizes the total costs. Constraints (2) conserve the flow for each location, stating that each location must have the same amount of arcs going out as there are coming in. Constraints (3) enforce that each customer is delivered exactly once. Then, constraints (4) and (5) ensure that the amount of vehicles leaving and arriving to the depot cannot exceed the amount of vehicles available, and that each vehicle leaving also returns to the depot. Constraints (6) ensure the capacity constraint for each vehicle is respected. Constraints (7) make sure that when vehicle v serves customer location j after location i, it does not arrive at location j before its earliest possible arrival moment given by the service moment at location i and the travel time needed between the two locations. Next, constraints (8) ensure that service by to customer c at location i by vehicle v starts within the time window limits of this location. Finally, constraints (9) denote the binary status of decision variable x_{ijv}.

3.2 Customers: technology acceptance, innovation resistance, and trust

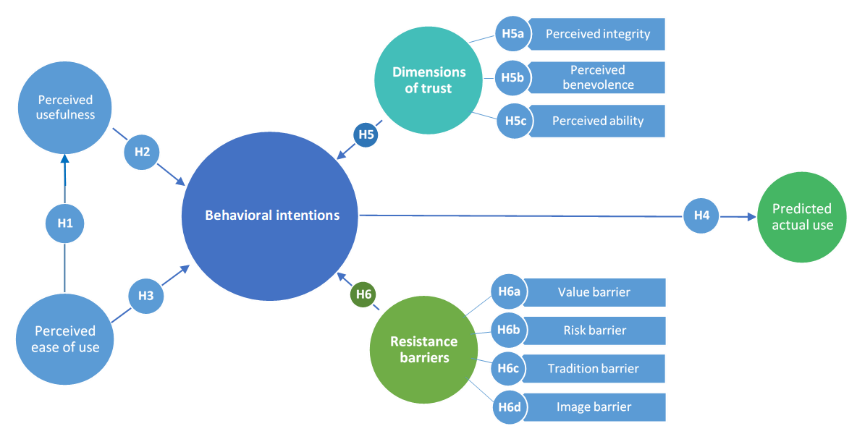

Figure 7: Conceptual framework for the customer research on in-car delivery

The research on customer adoption in this thesis aims to integrate three theoretical concepts. The base model is formed by the Technology Acceptance Model (TAM), initially developed by Davis (1985). Then, the concepts of consumer trust and consumer resistance to innovation are integrated in this model, to create a more comprehensive understanding of how consumers not only accept, but also resist innovations. The conceptual framework for the customer research is presented in Figure 7.

3.2.1 Technology Acceptance Model

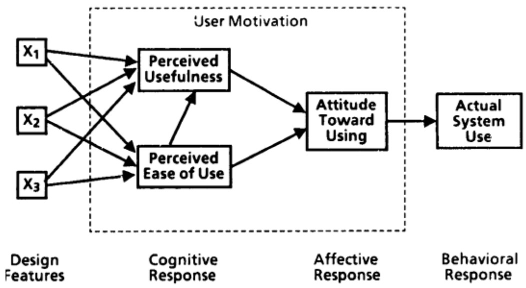

Figure 8: Initial Technology Acceptance Model as proposed by Davis (1985)

The TAM, initially developed by Davis (1985), forms the core of the research. His initial model is presented in Figure 8. The theory proposes that the user acceptance of new technologies goes in stages. TAM proposes that perceived usefulness and perceived ease of use influence attitudes or behavioral intentions that users develop towards the technology. These intentions, in turn, invoke actual technology use. Moreover, TAM proposes that perceived ease of use contributes to the perceived usefulness of a technology. Perceived usefulness is defined as the degree to which users think that using new technology will positively impact performance. Perceived ease of use is defined as the degree to which a person believes that actual use of the system is free of effort (Davis, 1989).

The validity of the model has been studied extensively since its inception, including for instance the perceived usefulness and perceived ease of use scales (Adams, Nelson, & Todd, 1992), and their predictive validity of future behavior (Szajna, 1994). Moreover, several attempts to extend the model were done by researching the influences of external factors and boundary conditions on TAM constructs. Some examples are gender (Gefen & Straub, 1997), task-technology fit (Dishaw & Strong, 1999), social influences (Malhotra & Galletta, 1999), and culture (Straub, Keil, & Brenner, 1997).

These additional insights led to a revision of TAM into an extended version: TAM2 (Venkatesh & Davis, 2000), shown in Figure 9. TAM2 keeps the original constructs and their internal relations intact, but adds external factors that help explain these constructs. These include five factors that directly influence perceived usefulness: subjective norm, image, job relevance, output quality, and result demonstrability. Moreover, it was proposed that subjective norm influences usage intentions, and that experience and voluntariness moderate the relationships between subjective norm and both perceived usefulness and usage intentions. Finally, it should be noted that also in this revised version, the original relationships between TAM constructs remain valid and therefore still form the core of the model.

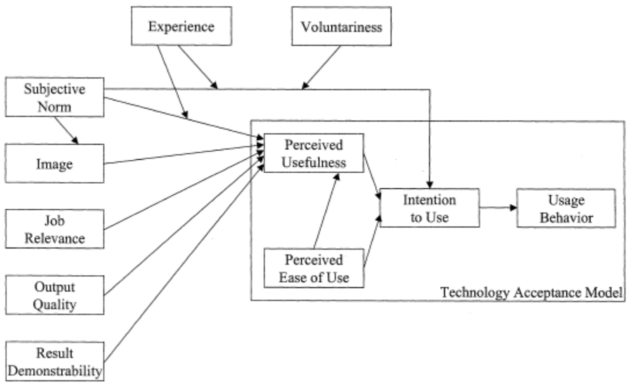

Figure 9: Revised version of the model, named TAM2, developed by Venkatesh & Davis (2000)

The large body of research on TAM over time has not only validated the core concepts, but has also seen a shift in applications. While originally TAM focused on the adoption of for instance email and text processors in the workplace, the model has also been researched in modern contexts. Some notable examples of modern applications in which TAM was valid and applicable include e-commerce (Gefen, Karahanna, & Straub, 2003), online banking (Pikkarainen, Pikkarainen, Karjaluoto, & Pahnila, 2004), mobile payments (Schierz, Schilke, & Wirtz, 2010), or adopting mobile apps in general (Yang, 2013). The fact that multiple studies have shown that the initial TAM relationships also apply on modern technologies makes it fair to hypothesize that this can also be the case for in-car delivery. Therefore, the following hypotheses are proposed:

H1: Perceived usefulness of in-car delivery is positively related to customers' behavioral intentions to adopt it.

H2: Perceived ease of use of in-car delivery is positively related to customers' behavioral intentions to adopt it.

H3: Perceived ease of use of in-car delivery is positively related to its perceived usefulness.

H4: Behavioral intentions towards using in-car delivery are positively related to its predicted actual use.

3.2.2 Consumer trust

Since in-car delivery is a new technology that has not been proven to the general public yet, people likely do not know what to expect from it since there is no historical evidence. To overcome perceived risks and actually engage in a relationship with an unknown party, trust is very important (McKnight, Choudhury, & Kacmar, 2002). Therefore, trust is integrated into the research model as important factor. Trust is defined as having confidence in the reliability and integrity of an exchange partner (Morgan & Hunt, 1994), and that one can believe that people will react in predictable ways (Gefen & Straub, 2003). In case this exchange partner is unfamiliar, where trust therefore is not based on any previous experience with that partner, it is called initial trust (McKnight, Cummings, & Chervany, 1998).

Trust and TAM

Several studies already investigated the relation between trust and TAM. For instance for online stores, trust was found to play a vital role in purchase intentions and customer acceptance of online stores

(Gefen et al., 2003). Also in the context of websites, trust plays a positive role in customers' visiting intentions (Chen & Dibb, 2010). Moreover, trust was found to positively influence perceived usefulness and perceived ease of use of a technology, while reducing perceived risk (Pavlou, 2003). Finally, trust was also found to be important in mobile contexts, as Gao & Waechter (2017) found that initial trust was needed to overcome the perceived risk of an innovation for customers.

Next to the effects of trust on behavioral intentions and user acceptance of technologies, multiple studies found antecedents to consumer trust. For instance website usability, security and privacy, product information quality (Chen & Dibb, 2010), familiarity, and disposition to trust (Gefen et al., 2003) were all found to have positive relationships with trust. Moreover, in electronic contexts the perception of social presence positively influences trust (Gefen & Straub, 2004). Other examples of antecedents to consumer trust were company reputation and satisfaction with past transactions (Pavlou, 2003), perceived integrity, perceived ability, perceived benevolence, perceived uncertainty, perceived system, information and service quality (Gao & Waechter, 2017), perceived ease of use, and perceived usefulness (Kaushnik, Mohan, & Kumar, 2020).

Trust

While trust has been investigated in relation to the TAM in multiple studies, as described above, varying dimensionalities have been used in these studies. However, three dimensions were prevailing in previous research: integrity, benevolence, and competence (or ability) (McKnight et al., 2002).

Integrity is defined as the honesty of the trustee and the extent to which this party keeps their promises (McKnight et al., 2002). Benevolence refers to whether the company behind the service actually cares about the customer and his or her interests (Gefen & Straub, 2004). Finally, the ability dimension is the customer judgment about whether the trusted party knows what they are doing, which reduces customer uncertainty about what to expect (Gefen & Straub, 2004). Apart from being the most frequent dimensions to measure trust, research also showed them to be a qualitatively good representation of trust, with significant factor loadings for all three dimensions on initial trust (Gao & Waechter, 2017).Moreover, their study found a significant positive relationship between initial trust and behavioral intentions. Combined with the idea that in general, it would be more likely for customers to start business with a party they trust, especially when it involves a service that has the risk of harming private property (the customer's car), this strengthens the hypothesis of a positive relationship between trust and behavioral intentions. Therefore, for all three dimensions a significant positive relationship with behavioral intentions is hypothesized:

H5a: Perceived integrity of 2DEAL is positively related to customer intentions towards adopting in-car delivery.

H5b: Perceived benevolence of 2DEAL is positively related to customer intentions towards adopting in-car delivery.

H5c: Perceived ability of 2DEAL is positively related to customer intentions towards adopting in-car delivery.

3.2.3 Customer resistance to innovation

Finally, it is not just interesting to look at the factors that influence the adoption of innovations, but it is just as important to look at the reasons why customers resist them (Kleijnen, Lee, & Wetzels, 2009). However, literature on resistance is scarce compared to that on innovation adoption (Szmigin & Foxall, 1998), which can be attributed to a pro-change bias in the field of innovation diffusion (Sheth, 1981). Innovation resistance can be defined as the resistance customers develop towards an innovation because it brings great changes to a satisfactory status quo, or because it conflicts with current belief structures (Ram & Sheth, 1989). One can distinguish between passive innovation resistance, where customers have a negative predisposition towards a new product before its evaluation, and active innovation resistance, where customers form negative attitudes after evaluation (Heidenreich & Spieth, 2013). Resistance can be classified into groups of resistance behavior or into resistance barriers.

Groups of resistance behavior

Innovation resistance can be classified into three groups of resistance behavior: rejection, postponement, and opposition (Kleijnen et al., 2009). Rejectors are customers who decided to not adopt an innovation at all, not now nor in the future (Laukkanen, Sinkkonen, & Laukkanen, 2008). Postponement refers to behavior where customers find an innovation acceptable, but choose not to adopt it yet (Szmigin & Foxall, 1998). However, in general they plan to eventually adopt it within one year (Laukkanen et al., 2008). Finally, opposition behavior ultimately leads to innovation rejection, but not without trying it first (Szmigin & Foxall, 1998). At first customers intend to adopt, before they try and reject it, but certainly not within one year (Laukkanen et al., 2008). Opposition can also be more active, where consumers may launch attacks against the innovation. In this case, it turns into innovation sabotage (Kleijnen et al., 2009).

Resistance barriers

The second classification of innovation resistance is into a set of resistance barriers. These can be divided into two main categories: functional and psychological barriers (Ram & Sheth, 1989).

Functional barriers

Functional barriers arise when customers perceive product attributes to be inadequate for their personal needs and expectations (Talke & Heidenreich, 2014). The main functional barriers are usage, value, and risk barriers (Laukkanen, Sinkkonen, Kivijärvi, & Laukkanen, 2007). Usage barriers arise when a customer feels an innovation is not compatible with current habits. The value barrier refers to the value an innovation offers compared to current systems, and whether it would be worth switching. Finally, the risk barrier refers to the amount of risk an innovation involves (Laukkanen et al., 2007).

Moreover, the risk barrier can be subdivided into four types of risk: physical, economic, functional, and social (Ram & Sheth, 1989). Physical risk is the risk that an innovation will harm a person or its property because of innovation characteristics. Economic risk refers to the finances: it depends on the cost of the innovation and will increase when these costs increase. Third, functional risk involves the uncertainty about how the innovation will perform. Finally, social risk means that customers resist an innovation because they do not feel it is socially acceptable to do so (Ram & Sheth, 1989).

Psychological barriers

Psychological barriers arise when innovations clash with certain norms or values, or when they are considered too risky (Talke & Heidenreich, 2014). Literature identified two main psychological barriers: tradition and image barriers (Laukkanen et al., 2007; Ram & Sheth, 1989). Tradition barriers involve the changes that an innovation brings to someone's daily routines, with this barrier likely to increase when someone puts more importance to these routines. The image barrier refers to the brand, country of origin, or product category of the innovation, putting a certain image on the innovation that might prevent people from adopting it (Laukkanen et al., 2007).

While the five barriers explained above are the most common ones in literature, other studies have identified additional barriers as well, for instance Talke & Heidenreich (2014), who identified nine functional and eight psychological barriers.

When looking at barriers that make customers resist innovations, it is appropriate to hypothesize that customer adoption intentions decrease when the experienced resistance increases. Moreover, several studies have already found significant negative relationships between each of these barriers and adoption intentions (Laukkanen et al., 2007; Laukkanen, 2016; Moorthy et al., 2017). Since the usage barrier is considered to be the opposite of perceived usefulness and ease of use, it was chosen not to test this barrier separately. Therefore, the remaining four barriers give these hypotheses:

H6a: Value barriers are negatively related to customer behavioral intentions to adopt in-car delivery.

H6b: Risk barriers are negatively related to customer behavioral intentions to adopt in-car delivery.

H6c: Tradition barriers are negatively related to customer behavioral intentions to adopt in-car delivery.

H6d: Image barriers are negatively related to customer behavioral intentions to adopt in-car delivery.

3.3 Employee: Job characteristics, demands, resources, and psychological safety

The final research perspective in this thesis considers the employee and the way that job design impacts employee outcomes. This research uses the Job Demands-Resources (JD-R) model as the core theoretical foundation, combined with theory on psychological safety climates (PSC). Taken together, this forms the conceptual research framework schematically represented in Figure 10.

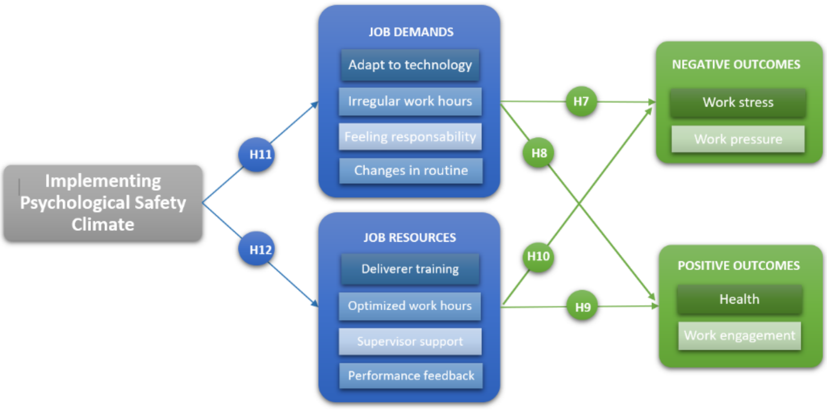

Figure 10: Conceptual framework for the employee research on in-car delivery

3.3.1 Job Demands-Resources model

The JD-R model, initially developed by Demerouti, Bakker, Nachreiner, & Schaufeli (2001), proposes that two processes contribute to employee well-being. First, an overload of so-called job demands leads to exhaustion. Secondly, a lack of job resources can make it even more difficult to cope with these job demands, leading to disengagement. Formally, job demands are those physical, organizational, or social job aspects that require sustained mental or physical efforts and might therefore exert negative influences on employee health. Job resources are defined as those

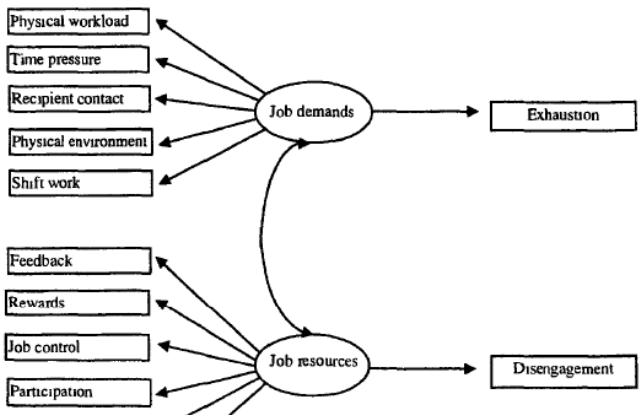

Figure 11: Job demands-resources model of burnout, by Demerouti et al. (2001)

physical, organizational, or social job aspects that may help to achieve work goals, reduce job demands and their effects, or stimulate personal growth and development. (Demerouti et al., 2001).

Figure 11 schematically shows the JD-R model. The general main proposition of the JD-R model is that multiple job resources can help buffer for multiple job demands in predicting job stress (e.g. Bakker, Demerouti, Taris, Schaufeli, & Schreurs, 2003; Xanthopoulou, Bakker, Demerouti, & Schaufeli, 2007). The general consensus is that this buffer effect exists, and that the model is robust (Llorens, Bakker, Schaufeli, & Salanova, 2006; Korunka, Kubicek, Schaufeli, & Hoonakker, 2009).

Next to providing a buffer against negative job demands, job resources can also enhance work engagement. Engaged workers have a positive state of mind regarding work, and experience vigor, dedication, and absorption. Vigor means one has high energy levels and is willing to persist in continuing their work in difficult situations. Dedication refers to feelings of enthusiasm, inspiration, pride, challenge, and significance in work. Finally, absorption means that an employee is fully concentrated in his or her job and finds it difficult (in a positive way) to detach him- or herself from the job (Bakker, Hakanen, Demerouti, & Xanthopoulou, 2007). Engagement was found to be such an important mediator between job resources and job performance that Bakker & Demerouti (2014) included it in extended JD-R theory.

The JD-R model has been researched substantially over time in different applications, such as predicting counterproductive work behavior (Balducci, Schaufeli, & Fraccaroli, 2011). Moreover, it was tested in different contexts, such as education (e.g. Hakanen, Bakker, & Schaufeli, 2006; Bakker et al., 2007), dentists (Hakanen, Bakker, & Demerouti, 2005), police officers (Wolter et al., 2019), and public sector employees (Bakker, 2015). This confirms the robustness of the JD-R model and its applicability across different contexts, making it relevant for the in-car delivery case as well.

Job demands and job resources with in-car delivery implementation

Job demands and resources of package deliverers can be influenced in several ways by in-car delivery. For instance, deliverers need to learn to use the technology, which might be difficult for some of them. Moreover, using this technology together with having to open cars instead of ringing a doorbell changes their job routines compared to home delivery. Moreover, when logistics companies use in-car delivery to offer delivery early in the morning or late at night, deliverers likely have to work more irregular schedules since these time windows are hardly used right now. Finally, mental pressure could arise from the responsibility deliverers feel when they have to open someone else's car without damaging anything.

However, these demand changes do not necessarily have to be negative. In JD-R literature, several studies have distinguished between two types of job demands: challenge demands and hindrance demands. Crawford, LePine, & Rich (2010) defined challenge demands as stressful demands that have the potential to promote personal or professional growth, which employees tend to perceive as learning opportunities. Hindrance demands, on the other hand, were defined as stressful demands that have potentially detrimental effects on this growth, and employees perceive them as barriers blocking any potential progress in the job. Both of these demand types were found to negatively relate to burnout, while the relationship between job demands and engagement depended on the demand type: challenges related positively with engagement, while hindrances related negatively with engagement (e.g. Crawford et al., 2010; Bakker & Sanz-Vergel, 2013; Tadic, Bakker, & Oerlemans, 2015).

Therefore, following JD-R theory, changed job demands because of in-car delivery are proposed to relate negatively with employee outcomes, however with the notion that there is a difference between whether the employee perceives the changes as challenges or as hindrance demands:

H7: The changed job demands as a result of in-car delivery implementation are positively related to negative employee outcomes such as work pressure and stress.

H8: The changed job demands as a result of in-car delivery implementation are negatively related to positive employee outcomes such as health and work engagement when these changes are perceived as hindrances, and positively related with these outcomes when the changes are perceived as challenges.

The potential negative effects of changed job demands, especially when perceived as hindrance demands, can be mitigated by providing sufficient resources, as employees with limited resources are also more prone to experience job demands as hindrances (Van den Broeck, De Cuyper, De Witte, & Vansteenkiste, 2010). Management has multiple options to provide such resources. They could for instance provide training for employees to get familiar with the technology and the new routines. Also, logistics companies can put effort in optimizing work schedules such that negative effects of irregular work hours are minimized. These schedules could be set up for instance in cooperation with the deliverers. Another example could be to set up a feedback scheme where supervisors, colleagues, and customers can provide extensive feedback to deliverers on their performance after in-car delivery is implemented. Finally, extensive supervisor support can be set up for employees that have difficulties with the changes or come across other problems in their job. JD-R theory proposes that providing these resources positively influence employee outcomes, leading to the following hypotheses:

H9: Providing additional job resources after in-car delivery implementation is negatively related to adverse employee outcomes such as work pressure and stress.

H10: Providing additional job resources after in-car delivery implementation is positively related to beneficial employee outcomes such as health and work engagement.

3.3.2 Psychological safety climate

The final theory to be discussed is about creating a psychological safety climate (PSC) in the workplace. A PSC is defined as the individual perceptions of safety-related policies, practices, and procedures that affect personal well-being at work (Christian, Bradley, Wallace, & Burke, 2009).

Next to the job demands and resources from the previous section, these conditions can also influence employee engagement. When employees feel psychologically safe, they feel they can employ themselves in their job without having to fear negative consequences (Kahn, 1990). This is connected to feelings of psychological meaningfulness and availability: one would ask oneself how meaningful it is to bring in a certain performance, how safe it is to do so, and whether one is available to do so or not (May, Gilson, & Harter, 2004). Both studies found these conditions to positively impact engagement.

PSC and the JD-R model

Several studies on the combination of PSC and the JD-R model have been performed as well. This integration was first proposed by Dollard & Bakker (2010). When integrated in the JD-R model, PSC acts as an additional job resource that helps alleviate pressure from job demands (Idris & Dollard, 2011). This is because when managers design jobs to have high PSC, they are more likely to ensure enough resources for employees to perform well (Dollard & McTernan, 2011).

So far, research on establishing a PSC in the context of the JD-R has shown positive results. When employees perceive their job to have high PSC levels, the negative impact of risk perceptions (that lead to additional job demands) on job satisfaction is lower than with low-PSC jobs (Nielsen, Mearns, Matthiesen, & Eid, 2011). Moreover, employees experiencing higher PSC levels are less likely to develop complaints like burnout or depression (Hall, Dollard, Winefield, Dormann, & Bakker, 2013), and daily recovery can boost employee engagement more than in low-PSC environments (Garrick et al., 2014). Therefore, it is hypothesized that implementing a PSC can lower the perceived change in job demands and increase the perceived change in job resources in the in-car delivery case as well:

H11: Implementing a PSC is negatively related to the perceived level of job demands for package deliverers after implementing in-car delivery.

H12: Implementing a PSC is positively related to the perceived level of job resources for package deliverers after implementing in-car delivery.

Chapter 4 – Methodology

This chapter describes the methodologies used to perform the analysis for the different researches. Section 4.1 discusses the methodology for the research on logistics efficiency, the composition of the dataset and the algorithms used to solve the VRP in the two different scenarios. Next, section 4.2 zooms in on the customer research, the setup of the survey, the methods to reach the target group, and the statistical methods used to analyze the data. Finally, section 4.3 does the same, but then for the employee research.

4.1 Logistics efficiency

The logistics research was performed by testing two scenarios on a theoretical dataset of hypothetical customers, modeled after real-life geographical data from the Eindhoven region in the Netherlands. Then, this dataset was tested on a mathematical model, implemented in programming software. This section describes the methods used for constructing the dataset, and for solving the problem. The rest of this section is structured as follows. First, section 4.1.1 discusses the dataset construction. Then, section 4.1.2 goes deeper into the choice of solution methodology. Finally, section 4.1.3 discusses the implementation in Python and analysis set-up.

4.1.1 Dataset construction

This section discusses the dataset construction. The dataset spanned 55 zip code areas in Eindhoven and its surroundings, all in postal area 5600. Moreover, the nearest depot from a big Dutch LSP, located in Tilburg, was chosen as the only depot from which these customers were served. The center of each zip code area in Google Maps represented the cluster of all customers in that zip code, and these locations were used for the calculations.

Distance and time matrices

The first part of the dataset was a distance matrix, computed by planning the routes between each pair of zip codes in Google Maps and taking the distance in kilometers for the matrix. Here it was assumed that these distances were symmetrical, i.e. the distance from zip code A to B is the same as from B to A. This distance matrix was also used as the basis for the corresponding travel time matrix.

As some locations are in or near the inner city, where traffic is usually slow, and others are smaller villages (partially) connected by highways, the zip codes were divided into nine zones. Within each zone, as well as for each combination of zones, several routes were computed through Google Maps and a time factor was calculated by dividing travel time by distance. Then, for each (combination of) zone(s), an average time conversion factor was calculated, and each distance in the distance matrix was multiplied with the appropriate time conversion factor to obtain the travel time matrix.

Customer demands, locations and time windows

Demands, locations, and time windows were randomly assigned to customers by generating them. In all cases, generator programs were built in Python. Since each customer represented a set of customers in the same zip code, multiple packages could be demanded per customer. Therefore, each customer was randomly assigned a demand from the range between 1 and 20 packages.

Each customer was randomly assigned one of the 55 zip codes as a location. For the time windows, a planning horizon of one day was used, spanning twelve hours in total (from 8:00am to 8:00pm). For the sake of simplicity it was assumed that each time window was two hours, with a new time window starting each 15 minutes. This resulted in 41 potential time windows. For each customer, through a

Python random generator program, a number of options was generated for each customer. Each option was a tuple, containing a location and a time window, both randomly generated.

4.1.2 Solving methodologies

An abundance of methods for solving the VRP exists in literature, with the two main categories are exact and (meta-)heuristic methods. While exact methods generally yield better results, they are computationally expensive and can therefore only handle small instances compared to heuristics. Moreover, heuristics are most common in practice (El-Sherbeny, 2010). Therefore, heuristic methods were chosen to perform the analyses for the in-car delivery case.

Literature was consulted to pick a suitable metaheuristic for the analyses. While for the VRPRDL literature on heuristics was still relatively scarce with only one paper using a construction and improvement heuristic (Reyes et al., 2017), more literature already existed on the VRPTW. Two main examples of successful heuristics in earlier studies are the tabu search algorithm (e.g. Garcia et al., 1994; Taillard et al., 1997; Cordeau, Laporte, & Mercier, 2001), and the GRASP algorithm (Kontoravdis & Bard, 1995).

The tabu search algorithm was shown valid and reliable with good results on theoretical instances in the aforementioned studies, while the GRASP algorithm was also tested on two large real-life data sets (Kontoravdis & Bard, 1995). However, since the tabu search algorithm had been more widely proven in literature so far in similar cases, this metaheuristic was chosen for solving both scenarios. Tabu search is a metaheuristic that tries to escape local optimality by prohibiting ('tabuing') certain moves for a number of iterations: the tabu tenure (Glover, 1986). At each iteration, the heuristic goes from a current solution to the best solution in a subset of the neighborhood which is not forbidden by the tabu tenure. This way, cycling is avoided and escaping local optima should lead to better results (Bräysy & Gendreau, 2005). The heuristic as it was implemented in this study is discussed in more detail below.

4.1.3 Implementation and analysis set-up

Analysis was done by implementing the tabu search algorithm in Python 3.9.0. 25 instances were created in total, in five groups of ascending customer size, from 10 to 50 customers per instance. Within each group, instances differed in the number of potential delivery options per customer. For each instance group, each instance had 1 to 5 potential delivery options. These delivery options differed both in locations, and in time windows.

As mentioned in section 4.1.1, each option was represented by a tuple containing a delivery location and a respective time window. At first, for each instance group (5 instances of the same size that differed in number of options) the maximum number of five options per customer was generated, after which the last option of each customer was eliminated for each smaller instance. This way, within each instance group a good comparison could be made between the different number of options and their influence on the costs for a certain number of customers.

Tabu search heuristic

The tabu search heuristic was implemented as follows. First, a stochastic insertion heuristic that randomly added each customer to one of the vehicles was used to generate an initial solution. This solution consisted of a number of routes with start and end at the depot, where each customer was visited exactly once (Moccia et al., 2012). Then, at each iteration the heuristic moved from one solution to another in the neighborhood. It was not necessary that each solution was feasible in terms of capacity and time window constraints. The infeasibility was handled by implementing a penalty cost in the cost calculation for lateness (see next section).

In each iteration, a neighborhood search was performed, in which several moves were tried to determine the best candidate solution in the neighborhood. Each move was represented by a tuple with the customer, and the vehicle number the customer should be moved to. All moves in a neighborhood search were picked from a list of legal moves. Whether a move was legal or not was determined by the tabu tenure. Whenever a customer was moved to a certain vehicle, its reinsertion in that vehicle was forbidden for a certain number of iterations: the tabu tenure. This tabu tenure should prevent cycling (Bräysy & Gendreau, 2005). Therefore, when a certain move was not blocked by this tabu tenure, it was considered a legal move. For each chosen move, that customer was inserted at each position in the associated vehicle to determine the optimal customer position in the vehicle.

All candidate solutions in the neighborhood search were then evaluated based on the cost calculation explained in the next section. Moreover, the feasibility of a candidate solution was taken into account in terms of capacity and time window constraints. If none of the candidate solutions was feasible, the least infeasible solution was picked as the best one. If one or more of the candidate solutions was feasible, the best feasible solution was chosen as the best candidate solution. The best candidate solution in the neighborhood search was saved as the current solution, providing the starting point of the next neighborhood search. Moreover, in each iteration this current solution was compared to the best solution overall, and when this current solution was better than the best overall solution, the latter was updated.

For the VRPRDL, where each customer had multiple delivery options (locations and time windows), the same procedure was followed. However, when determining the optimal customer position in the vehicle, the choice of delivery options was optimized as an additional step. This was done by trying each combination of options for the inserted customer, its predecessor, and its successor in the route at each insertion. When a customer was inserted at the first or last position of the route, only its predecessor or successor was taken into account, depending on whether the insertion was at the first or the last position of the route. Then, the best selection of customer options was kept within each neighborhood search, and the selection of customer options for the current and best solutions was stored similarly to the procedure described above for the VRPTW.

Solution quality

The solution quality was determined by a cost calculation, as was the main objective in the models in Chapter 3. Four elements were taken into account in this calculation: distance, travel time, waiting time, and lateness. The cost per kilometer was determined by estimating fuel costs at an estimated price of €1,50 per liter. The vehicle type used for package delivery was assumed to have a fuel usage of 1 in 12, making for a cost of €0,125 per kilometer. Next, travel time costs were calculated by estimating wage costs. An estimated wage of €12 per hour was assumed, or €0,20 per minute.

When a vehicle arrives early at a customer location, it has to wait until the start of the time window. To differentiate between waiting time and travel time, the waiting costs were assumed to be double those for regular travel time. This resulted in a waiting cost of €0,40 per minute. Finally, a lateness penalty of €50 per minute was implemented to let the algorithm prevail feasible solutions over infeasible solutions more quickly, as customers cannot be served after the end of the time window.

Parameter tuning and quality checks

For the tabu tenure and neighborhood size, the parameter values were chosen by picking several potential values, and then trying each combination. Next, the average parameter value of the best solutions within each instance group (instances with same customer size) was taken to develop a formula for picking the final parameter values.

Next, the routing algorithm quality was tested compared to the stochastic insertion heuristic used to create the initial solution, by running these both with the same time limit and compare the results. Here, a division was made between small instances (instances 1-10), medium-sized instances (instances 11-20), and large instances (instances 21-25). The small instances were run for 5 minutes, the medium-sized instances were run for 15 minutes, and the large instances were run for 30 minutes. These limits were chosen based on the runtimes from each instance in the first training run.

Analysis

For doing the analysis, several runs were done on a test set. This test set had the same number of instances with the same characteristics as in the training set in terms of customer sizes. However, the delivery options differing in both locations and time windows were both regenerated from scratch. Moreover, compared to the training set, two additional scenarios were implemented into the dataset. In one scenario, each customer had the same delivery location across its delivery options, but with flexible time windows. For the second additional scenario, the time window was fixed across all delivery options, but the locations differed. To obtain these additional scenarios, the fixed variable (location or time window) was fixed based on the location or time window of the first delivery option, where customers had only one location and one time window. Finally, it should be noted that all these analyses used the final parameter values from the parameter tuning.

Then, three different runs were done on this test set, with 1000 iterations on all 25 instances like in the training set. These runs were done to check what effect multiple delivery locations per customer had on routing costs, distance, travel time, waiting time, and locations. One run investigated the situation where customers had one location, but multiple time windows, the second run investigated the situation where customers had one time window, but multiple locations. Finally, the third run investigated the situation where the delivery options differed both in locations and time windows. These results could then be compared to the base scenario, the instances where customers only had one location and one time window.

Finally, two final runs were done on the test set to get an indication of the effects of extending the planning horizon because of in-car delivery. In one run, the planning horizon was extended by four hours (from 12 to 16 hours per day), and in the second run, the planning horizon was extended by eight hours (from 12 to 20 hours per day). The dataset with multiple locations and multiple time windows was taken as a basis. In this data, the locations were kept the same, but the time windows were generated from scratch again within the new planning horizon. This means all instances still had the same amount of customers, at the same locations, but with new time windows.

4.2 Customer research

The customer research was performed by means of quantitative survey study, with the results analyzed by statistical methods. The research aims to test the proposed research framework presented earlier in section 3.2.

Participants

The final sample consisted of 191 respondents, with 133 women, 53 men, and 5 people who did not report their gender. Moreover, people from all twelve Dutch provinces were represented in the sample. North Holland and South Holland were the provinces with the biggest representation (40.3% and 24.1% respectively), while Drenthe was the least represented province with only one respondent. Moreover, a large variety of ages was represented (M = 37.47, SD = 11.447), with the youngest respondent being 18 years old, and the oldest one being 71 years old. Finally, there was diversity in the sample in terms of frequency of online shopping as well (15.7% less than once a month, 78.0% between 1 and 5 times a month, and 6.3% more than once a week).

Procedure

The target group for this research consisted of people living in the Netherlands, who have experience with online shopping. The survey was constructed online using Google Forms. First it was constructed in English based on existing scales (see next section), and then carefully translated to Dutch to reach both Dutch- and English-speaking inhabitants. The survey was then distributed via several (online) channels, such as personal networks, survey exchange platforms, and by publication in several Facebook groups and on Linkedin.

Measures

The survey consisted of three main parts. First, the technology was explained by text and video, to familiarize respondents with the context. Next, several pages of statements were presented to measure different model constructs. Each statement was measured on a five-point scale ranging from 1 (totally disagree) to 5 (totally agree). The full set of survey statements is in Appendix 1.

Perceived usefulness, ease of use, behavioral intentions, and predicted actual use were measured by a set of statements adapted from Wu & Wang (2005). Perceived ease of use was measured by 5 items (α = 0.952), such as *"Using in-car delivery would improve my online shopping experience".* Next, perceived ease of use was measured by 3 items (α = 0.792), like "*I think it would be easy to become skillful at in-car delivery".* Third, behavioral intentions were measured by 2 items (α = 0.930), such as "*Assuming I had access to in-car delivery, I would have the intention to use it".* Finally, predicted actual use was measured by asking respondents the question how often they thought they would use in-car delivery if available. Here, respondents answered on a scale of 1 (never) to 5 (at every purchase).

Measures for consumer trust dimensions were adapted from Gefen & Straub (2004), who used four-item scales for perceived integrity, benevolence, and ability. In that study, two items were already dropped (one for integrity and one for ability), so these were not included in the adapted scales for this study either. Therefore, perceived integrity was measured by 3 items (α = 0.838), such as "*I do not doubt the honesty of the involved companies"*. Next, perceived benevolence was measured by 4 items (α = 0.867), like "*I expect that I could count on the involved companies to consider how their actions would affect me as a consumer*". Finally, perceived ability was measured by 3 items (α = 0.873), of which "*I believe that the involved companies are competent to develop a good in-car delivery service"* is an example. After performing a factor analysis, it was decided to combine the three trust dimensions into one, which lead to a 10-item, highly reliable construct (α = 0.927).

Finally, measures for the resistance barriers were taken from Laukkanen et al. (2007). Of their five barriers only the usage barrier was not considered in the current study. Items from the aforementioned study were adapted to measure the other four barriers in the current research. Value barrier was measured by three items (α = 0.801), of which "*In my opinion, in-car delivery would NOT offer any advantage compared to other package delivery methods*" was one. Next, risk barrier was initially measured by three items, but these were not considered reliable (α = 0.441). By removing one item reliability went up to an acceptable level (α = 0.651), so risk barrier was measured by two items, like "*I fear that while using in-car delivery, I might make mistakes in uploading the car key codes and location information*". Next, tradition barrier was measured by two items, but because of their lack of reliability (α = 0.135), this barrier was discarded from the research. Finally, image barrier was measured by two items (α = 0.794), of which "*In my opinion, new technology is often too complicated to directly be useful to me*" was an example. As a result of factor analysis, risk and image barriers were combined into one risk and difficulty barrier (α = 0.742), which resulted in a final set of two barriers to be tested: value, and risk and difficulty barriers. Appendix 2 presents the full results of this factor analysis.

Hypothesis testing

The final set of hypotheses was tested by means of three regression analyses in R. First, a multiple regression analysis with behavioral intentions as the dependent variable was used to test perceived usefulness, perceived ease of use, trust, value barrier, and risk and difficulty barrier as predictors of behavioral intentions. Next, the relationships between perceived ease of use and perceived usefulness, and the relationship between behavioral intentions and predicted actual use were tested by means of two simple linear regressions. To make sure that results were valid for interpretation, multicollinearity was tested by calculating the VIF scores of predictors, and Breusch-Pagan tests for heteroskedasticity were performed before testing the hypotheses.

Scenario analysis

The last part of the questionnaire was a scenario analysis, in which respondents reviewed eight possible implementation forms on a scale of 1 (not attractive) to 5 (very attractive).

Scenarios were first compared by looking at the means and standard deviations. As the answer scale went up based on increasing attractiveness, scenario attractiveness increased with a higher mean. Moreover, the histograms of the answer distributions were compared to see the variety in answers.

Finally, a series of t-tests was done to check which differences in mean scores were statistically significant, and thus, which scenarios were rated significantly higher or lower than others. First, each scenario was tested against the scale mean of 3 (the 'neutral' score), to see which scenarios were rated significantly attractive or unattractive. Next, the two scenario groups, distinguished by the method of key recorder distribution, were tested against each other. This was done on a group (average of all scenarios in the group), as well as individual level (each scenario in one group tested against its counterpart in the other group). Finally, each combination of scenarios, both within and between the two groups, was tested for statistical significant differences. All of these t-tests were performed in R.

4.3 Employee research

Due to COVID-19 circumstances, it was not feasible to empirically test the employee research hypotheses. Therefore, the employee research was done in a more theoretical way, by building design propositions upon literature, for which the literature review and conceptual framework in section 3.3 formed the basis.

Design science research

This way of doing research is built on the design science paradigm, where design knowledge is developed that can be used in finding solutions to problems (Van Aken, 2004). To logically structure this prescriptive design knowledge, the design propositions were built following the context-intervention-mechanism-outcome (CIMO)-logic (Denyer, Tranfield, & Van Aken, 2008). CIMO-logic dictates that whenever in a certain problem context C, one wants to achieve outcome O, this could be achieved by using intervention type I. To provide more body to these propositions and to clarify why outcome O could be achieved by performing intervention I, it was encouraged by Denyer et al. (2008) to include general mechanisms (M). These mechanisms are usually concepts and processes derived from theory that can explain why this outcome can be expected (Pilbeam, Alvarez, & Wilson, 2012). This logic for developing design propositions has been used in several contexts, such as supply chain resilience (Kochan & Nowicki, 2018) and its network governance (Pilbeam et al., 2012), sustainability-oriented innovation (Watson, Wilson & MacDonald, 2020), and literature reviews on accelerating innovation processes (Ellwood, Grimshaw, & Pandza, 2017), therefore making it a reliable method across contexts to use in this study.

The literature review and conceptual framework of section 3.3 formed the basis for the development of the design propositions. Apart from the papers used in that review, additional papers were used, both those already found through the literature review as well as new ones, especially to make the design propositions more intervention-specific.

Chapter 5: Results

This chapter presents the results of the various analyses that were explained in the previous chapter. The rest of this chapter is structured as follows. First, section 5.1 presents the results of the logistics research. Then, section 5.2 goes deeper into the results of the customer research and finally, in section 5.3 the employee research results are presented.

5.1: Results logistics research

This section discusses the logistics research and its results. The remainder of this part is structured as follows. Section 5.1.1 shortly discusses the design and implementation of the heuristic and the first runs on the training set to do some parameter tuning. Afterwards, section 5.1.2 compares the quality of the routing algorithm to that of the method for obtaining the initial solutions. Finally, section 5.1.3 discusses the analyses of the instances on a test set with the final parameters.

5.1.1 Implementing the metaheuristic

This first section discusses the design and implementation of the metaheuristic. As mentioned in Chapter 4, a tabu search algorithm was chosen to perform the analyses on logistics efficiency. In this section its functioning is explained, together with the first runs on a training set to tune parameters.

Functioning of the metaheuristic

As Chapter 4 explains, the tabu search heuristic is a type of metaheuristic that intends to avoid local optima by blocking several possible candidate solutions for a certain amount of time, the tabu tenure. Its aim is to prevent cycling and therefore get better quality results. (e.g. Glover, 1986; Cordeau et al., 2001; Bräysy & Gendreau, 2005) From the initial solution, each iteration a customer was moved to another position, either in the same or in another vehicle. To determine which move was made in each iteration a neighborhood search was performed. In this search, several legal moves were tried and evaluated. During the neighborhood search the best candidate solution was stored and that move was performed in the end. From that solution, the next move was performed, and so on.

Instance	Number of customers	Options per customer	Vehicles	Initial solution time	Initial solution cost	Number of iterations	Size of neighborhood	Tabu tenure	Runtime	Final solution cost	Final solution iteration
1	10	1	1	1s	€4343,49	1.000	7	5	0m02s	€156,20	9
2	10	2	1	1s	€20.093,76	1.000	4	6	0m09s	€63,11	924
3	10	3	1	1s	€34.155,04	1.000	4	7	0m17s	€53,29	18
4	10	4	1	1s	€75.957,54	1.000	3	6	0m34s	€51,54	204
5	10	5	1	1s	€27.243,24	1.000	4	6	1m11s	€47,58	312
6	20	1	3	1s	€151.470,30	1.000	30	20	0m06s	€228,85	412
7	20	2	3	1s	€109.663,00	1.000	30	20	0m56s	€138,94	163
8	20	3	3	1s	€124.816,78	1.000	40	20	3m53s	€138,48	255
9	20	4	3	1s	€115.353,93	1.000	30	20	6m30s	€125,76	158
10	20	5	3	1s	€115.984,03	1.000	20	20	8m36s	€117,66	452
11	30	1	3	1s	€197.455,75	1.000	40	30	0m18s	€176,31	714
12	30	2	3	1s	€316.865,11	1.000	50	40	10m48s	€213,40	216
13	30	3	3	1s	€247.875,84	1.000	50	30	11m07s	€181,38	267
14	30	4	3	1s	€202.523,73	1.000	40	30	19m37s	€162,39	287
15	30	5	3	1s	€188.563,28	1.000	40	30	39m08s	€174,73	739
16	40	1	5	1s	€273.032,83	1.000	50	80	0m23s	€298,56	954
17	40	2	5	1s	€196.084,70	1.000	60	80	5m22s	€272,63	279
18	40	3	5	1s	€278.336,45	1.000	50	80	10m34s	€277,09	697
19	40	4	5	1s	€191.423,39	1.000	60	80	29m00s	€229,44	420
20	40	5	5	1s	€267.337,60	1.000	60	80	57m04s	€220,93	502
21	50	1	6	1s	€377.829,71	1.000	70	80	0m45s	€349,16	571
22	50	2	6	1s	€442.759,79	1.000	70	120	6m23s	€349,95	206
23	50	3	6	1s	€247.001,99	1.000	60	100	18m45s	€331,88	448
24	50	4	6	1s	€307.696,93	1.000	70	100	50m34s	€304,59	940
25	50	5	6	1s	€299.683,76	1.000	70	100	1h26m35s	€285,21	647

Table 2: Results of 1000 iterations on the training set with best parameter values for neighborhood size and tabu tenure

Parameter tuning

Using this heuristic meant that several choices needed to be made. An important choice was to decide the parameter values for both the tabu tenure and the neighborhood size for each instance. To determine this, a parameter tuning was performed on a training set of the instances as described in Chapter 4, with 25 instances varying in number of customers, and number of options per customer.

In the parameter tuning procedure, several combinations of parameter values were tried for each instance group. All instances were run with each combination of parameter values to check which yielded the best solution. From these best parameter values a formula for determining the final parameter values was constructed. Table 2 presents the best results for each instance with the corresponding parameter values, after running each instance for 1000 iterations.

Determining the final parameters

Finally, the final parameter values were determined by constructing a formula using the best parameter values from the parameter tuning procedure. Instances 1-5 were excluded from this formula as those instances were the only ones with parameter values less than the number of customers in the instance. This would skew the formula, and therefore the parameter values of the other instances, too much. Moreover, since almost all parameter values yielded the same result in those instances, the most common parameter values were chosen for those instances.

The formula for the other instances was derived by taking the average value of each parameter between each group of five instances that had the same number of customers. Then, the intercept and gradient were calculated with the number of customers in the instance as dependent variable. Table 3 presents the average parameter values for the two parameters, as well as the final parameter values as calculated from the following formulae, with x being the number of customers:

$$\text{Neighborhood size: } 30 + \frac{38*(x-20)}{30}$$

$$\text{Tabu tenure: } 20 + \frac{8*(x-20)}{3}$$

Instances	No. of customers	Average neighborhood size	Formula neighborhood size	Average tabu tenure	Formula tabu tenure
6-10	20	30	30	20	20
11-15	30	44	43	33	47
16-20	40	56	55	80	73
21-25	50	68	68	100	100

Table 3: Average and final parameter values for each instance group after parameter tuning

5.1.2 Quality of the routing heuristic

Although using a heuristic does normally yield good results, one cannot be sure that these solutions are always optimal, as would be the case with using an exact method. However, while optimality cannot be ensured, it can be checked whether the chosen heuristic gives better quality solutions than other methods. This section discusses the quality checks performed in comparing the tabu search heuristic with a simple stochastic insertion heuristic used to obtain an initial solution.

As Chapter 4 describes, this analysis was done by running each instance twice during the same amount of time. One time, solutions were generated and evaluated using the stochastic insertion heuristic, and the second time solutions were generated and evaluated using the tabu search heuristic. For this purpose, the instances were grouped into small, medium-, and large-sized instances, with each group getting its own runtime limit.

Table 4 presents the full results of this analysis. In all cases, the solutions delivered by the tabu search heuristic were of better quality than the stochastic insertion heuristic. It can also be seen that the number of iterations by the stochastic insertion heuristic is much higher than in the tabu search heuristic. This implies that although the tabu search heuristic makes longer iterations, these iterations are more efficient and result in better quality solutions than using the stochastic insertion heuristic.

Instance	Customers	Options	Vehicles	Initial solution cost	Initial solution iterations	Final solution iteration	Iterations algorithm	Run-time	Routing solution cost	Final solution iteration
1	10	1	1	€4343,49	12902190	1	250738	5m00s	€161,03	9
2	10	2	1	€1104,15	8706002	40	54561	5m00s	€63,11	7
3	10	3	1	€186,33	9520175	89437	17305	5m00s	€57,28	1543
4	10	4	1	€63,23	8820559	63745	7632	5m00s	€52,34	483
5	10	5	1	€62,82	9073794	3267982	4097	5m00s	€49,25	108
6	20	1	3	€11185,58	7442132	6335346	46626	5m00s	€228,85	2759
7	20	2	3	€4897,99	4973096	3319024	5666	5m00s	€143,26	972
8	20	3	3	€473,14	4968197	2649927	1745	5m00s	€137,88	589
9	20	4	3	€763,23	4876122	4257903	740	5m00s	€127,38	169
10	20	5	3	€580,31	4904058	1271278	394	5m00s	€119,66	99
11	30	1	3	€77823,40	14982282	7261173	47974	15m00s	€197,69	11273
12	30	2	3	€39512,98	9611910	2372462	5123	15m00s	€225,64	3991
13	30	3	3	€29257,15	9881573	3214922	1753	15m00s	€217,46	1726
14	30	4	3	€27595,23	9846805	7218762	745	15m00s	€217,13	62
15	30	5	3	€20073,75	10299978	9202469	397	15m00s	€208,16	192
16	40	1	5	€78875,49	10955713	3366935	34229	15m00s	€294,24	10429
17	40	2	5	€68696,64	5745062	2484479	1336	15m00s	€304,33	1184
18	40	3	5	€72807,29	3110706	1293096	477	15m00s	€272,84	241
19	40	4	5	€50546,34	3259849	1418732	212	15m00s	€262,20	138
20	40	5	5	€55636,25	3356277	2460217	137	15m00s	€246,98	81
21	50	1	6	€110335,78	18358419	6576458	43379	30m00s	€331,76	27873
22	50	2	6	€72139,84	12912763	3987940	5085	30m00s	€321,31	3175
23	50	3	6	€43644,01	13032502	11751334	1537	30m00s	€346,01	651
24	50	4	6	€62064,38	12858038	11088558	680	30m00s	€319,35	193
25	50	5	6	€69220,38	12363251	8266539	348	30m00s	€305,04	96

Table 4: Results of the quality checks comparing the stochastic insertion heuristic with the tabu search heuristic

5.1.3 Analyses on the test set

To do the final analyses, a different set of instances was used: the test set. The composition of this test set was exactly the same as in the training set in terms of size and number of customer options. However, the exact customers within each instance were generated from scratch just as for the training set. Furthermore, this time only the final parameter values as presented in section 5.1.1 were used for all analyses.

First analysis: potential cost reductions by having multiple options per customer

The first analysis step was to run 1000 iterations on the test set for three main scenarios. First, customer delivery options had fixed time windows, but multiple locations, in the second scenario they had fixed locations, but multiple time windows, and in the third, they had multiple locations and multiple time windows. These three scenarios were then compared to the base case of each customer having one location with its associated time window. Tables 5-10 present the results of these three runs and the potential cost reductions per scenario compared to the base scenario (everything fixed).

Tables 5 and 6 show that only allowing customers to have multiple potential locations with only one fixed time window hardly influenced the routing costs in these runs. The biggest cost saving obtained was in the instances with 30 customers, reporting a decrease of 24% compared to the base scenario. However, this is the positive exception, since the other four instance sets reported only reported potential savings between 2,4 and 14,1%.

On the other hand, when locations are fixed but customers can have multiple time windows to be delivered at that location, the savings potential substantially increases. Tables 7 and 8 show that the minimum savings potential reached in these runs was 14,8 percent, when 20 customers each had 3 potential time windows. The other customer sets all showed potential savings between 24,1 and 50%, which is more than any customer set in the first scenario (with fixed time windows). The average savings potential of having multiple time windows with fixed locations was around 30%.

Finally, Tables 9 and 10 show the results of the test run where customers had both multiple locations and time windows. These results showed that none of the customer sets scored worse in this scenario than in one of the scenarios where one (or both) of the variables were fixed. This implies that the most efficient way of obtaining cost savings through in-car delivery is by allowing customers to have multiple locations, each with their associated time window. Furthermore, the results showed that the flexibilization of the time windows contributed more to this savings potential than flexibilization of the locations, since the individual savings potential of time window flexibilization was much higher than the individual savings potential of location flexibilization.

Instance	Number of customers	Options per customer	Vehicles	Initial solution time	Initial solution cost	Number of iterations	Size of neighborhood	Tabu tenure	Runtime	Final solution cost	Final solution iteration
1	10	1	2	1s	€65.158,53	1.000	4	6	0m01s	€147,26	993
2	10	2	2	1s	€62.870,71	1.000	4	6	0m03s	€137,06	154
3	10	3	2	1s	€70.575,00	1.000	4	6	0m10s	€134,36	534
4	10	4	2	1s	€66.286,85	1.000	4	6	0m21s	€128,90	547
5	10	5	2	1s	€69.105,30	1.000	4	6	0m43s	€126,50	719
6	20	1	3	1s	€58.367,68	1.000	30	20	0m09s	€146,21	578
7	20	2	3	1s	€108.196,88	1.000	30	20	0m59s	€146,25	927
8	20	3	3	1s	€63.871,84	1.000	30	20	3m00s	€143,89	650
9	20	4	3	1s	€115.240,49	1.000	30	20	6m50s	€139,11	308
10	20	5	3	1s	€109.705,06	1.000	30	20	13m05s	€137,76	871
11	30	1	4	1s	€154.679,23	1.000	43	47	0m18s	€276,41	985
12	30	2	4	1s	€176.260,48	1.000	43	47	2m18s	€251,26	399
13	30	3	4	1s	€156.532,73	1.000	43	47	7m13s	€271,66	213
14	30	4	4	1s	€194.747,53	1.000	43	47	17m00s	€227,83	598
15	30	5	4	1s	€157.101,41	1.000	43	47	31m49s	€210,05	185
16	40	1	4	1s	€333.511,79	1.000	55	73	0m36s	€294,50	956
17	40	2	4	1s	€333.858,76	1.000	55	73	4m31s	€374,53	800
18	40	3	4	1s	€342.705,78	1.000	55	73	14m18s	€339,50	152
19	40	4	4	1s	€289.593,89	1.000	55	73	33m04s	€402,35	710
20	40	5	4	1s	€337.039,06	1.000	55	73	1h07m43s	€287,36	594
21	50	1	5	1s	€405.519,83	1.000	68	100	0m52s	€383,91	890
22	50	2	5	1s	€426.081,61	1.000	68	100	6m51s	€422,56	944
23	50	3	5	1s	€348.590,70	1.000	68	100	22m15s	€385,69	450
24	50	4	5	1s	€450.466,34	1.000	68	100	53m53s	€459,44	936
25	50	5	5	1s	€448.920,69	1.000	68	100	1h43m09s	€337,36	391

Table 5: Results of 1000 iterations of the tabu search heuristic on the test set with fixed time windows and multiple locations

Instances	Customers	Vehicles	Cost one option per customer	Cheapest number of options	Cost cheapest no. of options	Cost difference (%)
1-5	10	2	€147,26	5	€126,50	14,1
6-10	20	3	€146,21	5	€137,76	5,8
11-15	30	4	€276,41	5	€210,05	24,0
16-20	40	4	€294,50	5	€287,36	2,4
21-25	50	5	€383,91	5	€337,36	12,1

Table 6: Summary of potential cost savings on the test set with fixed time windows and multiple locations

Instance	Number of customers	Options per customer	Vehicles	Initial solution time	Initial solution cost	Number of iterations	Size of neighborhood	Tabu tenure	Runtime	Final solution cost	Final solution iteration
1	10	1	2	1s	€65.158,53	1.000	4	6	0m01s	€147,26	993
2	10	2	2	1s	€38.416,09	1.000	4	6	0m05s	€80,80	138
3	10	3	2	1s	€18.109,06	1.000	4	6	0m11s	€74,18	174
4	10	4	2	1s	€34.232,61	1.000	4	6	0m22s	€75,53	547
5	10	5	2	1s	€26.454,96	1.000	4	6	0m41s	€73,63	670
6	20	1	3	1s	€58.367,68	1.000	30	20	0m09s	€146,21	578
7	20	2	3	1s	€90.592,14	1.000	30	20	0m59s	€147,43	340
8	20	3	3	1s	€95.850,16	1.000	30	20	2m58s	€124,64	713
9	20	4	3	1s	€145.161,04	1.000	30	20	6m46s	€128,88	740
10	20	5	3	1s	€104.180,63	1.000	30	20	12m57s	€126,16	270
11	30	1	4	1s	€154.679,23	1.000	43	47	0m18s	€276,41	985
12	30	2	4	1s	€193.657,98	1.000	43	47	2m07s	€228,94	73
13	30	3	4	1s	€157.515,08	1.000	43	47	6m57s	€191,34	317
14	30	4	4	1s	€283.208,55	1.000	43	47	16m08s	€190,15	478
15	30	5	4	1s	€137.997,68	1.000	43	47	31m01s	€188,56	502
16	40	1	4	1s	€333.511,79	1.000	55	73	0m36s	€294,50	956
17	40	2	4	1s	€300.652,23	1.000	55	73	5m03s	€344,53	593
18	40	3	4	1s	€363.330,84	1.000	55	73	16m05s	€233,16	261
19	40	4	4	1s	€363.635,88	1.000	55	73	35m29s	€204,84	248
20	40	5	4	1s	€283.985,68	1.000	55	73	1h06m05s	€206,55	264
21	50	1	5	1s	€405.519,83	1.000	68	100	0m52s	€383,91	890
22	50	2	5	1s	€284.157,28	1.000	68	100	6m41s	€352,93	635
23	50	3	5	1s	€345.102,21	1.000	68	100	21m38s	€350,70	315
24	50	4	5	1s	€385.218,98	1.000	68	100	50m57s	€315,06	356
25	50	5	5	1s	€426.591,79	1.000	68	100	1m34m58s	€291,18	548

Table 7: Results of 1000 iterations of the tabu search heuristic on the test set with fixed locations and multiple time windows

Instances	Customers	Vehicles	Cost one option per customer	Cheapest number of options	Cost cheapest no. of options	Cost difference (%)
1-5	10	2	€147,26	5	€73,63	50,0
6-10	20	3	€146,21	3	€124,64	14,8
11-15	30	4	€276,41	5	€188,56	31,8
16-20	40	4	€294,50	4	€204,84	30,4
21-25	50	5	€383,91	5	€291,18	24,1

Table 8: Summary of potential cost savings on the test set with fixed locations and multiple time windows

Figures 12-16 graphically show the effect of different flexibilization options on routing costs. In each graph, the first instance on the horizontal axis represents the base scenario where each customer has only one fixed location and time window. The next instances on the horizontal axis each represent one additional option per customer, so either an additional location, time window, or both. The blue line labeled FLEXLOCS represents the scenario where time windows are fixed and locations are not. The orange line labeled FLEXTIME represents the scenario where locations are fixed, but time windows are not. Finally, the grey line labeled FLEXBOTH represents the scenario where neither of the two is fixed.

Instance	Number of customers	Options per customer	Vehicles	Initial solution time	Initial solution cost	Number of iterations	Size of neighborhood	Tabu tenure	Runtime	Final solution cost	Final solution iteration
1	10	1	2	1s	€65.158,53	1.000	4	6	0m01s	€147,26	993
2	10	2	2	1s	€42.908,65	1.000	4	6	0m03s	€81,03	867
3	10	3	2	1s	€54.417,09	1.000	4	6	0m09s	€74,26	279
4	10	4	2	1s	€71.759,26	1.000	4	6	0m21s	€75,66	865
5	10	5	2	1s	€66.283,90	1.000	4	6	0m43s	€66,06	284
6	20	1	3	1s	€58.367,68	1.000	30	20	0m09s	€146,21	578
7	20	2	3	1s	€80.045,93	1.000	30	20	1m01s	€136,26	308
8	20	3	3	1s	€89.907,66	1.000	30	20	3m13s	€126,71	200
9	20	4	3	1s	€137.371,53	1.000	30	20	7m18s	€125,76	299
10	20	5	3	1s	€85.781,64	1.000	30	20	12m53s	€122,30	276
11	30	1	4	1s	€154.679,23	1.000	43	47	0m18s	€276,41	985
12	30	2	4	1s	€196.782,66	1.000	43	47	2m25s	€200,84	717
13	30	3	4	1s	€152.149,51	1.000	43	47	7m23s	€192,88	386
14	30	4	4	1s	€163.677,96	1.000	43	47	17m45s	€189,54	995
15	30	5	4	1s	€157.171,96	1.000	43	47	31m42s	€188,64	251
16	40	1	4	1s	€333.511,79	1.000	55	73	0m36s	€294,50	956
17	40	2	4	1s	€302.849,90	1.000	55	73	5m01s	€337,44	265
18	40	3	4	1s	€344.326,74	1.000	55	73	15m04s	€260,30	582
19	40	4	4	1s	€327.650,39	1.000	55	73	35m15s	€198,64	556
20	40	5	4	1s	€332.310,55	1.000	55	73	1h07m19s	€195,95	650
21	50	1	5	1s	€405.519,83	1.000	68	100	0m52s	€383,91	890
22	50	2	5	1s	€405.658,03	1.000	68	100	8m03s	€388,60	959
23	50	3	5	1s	€390.452,89	1.000	68	100	24m00s	€357,26	793
24	50	4	5	1s	€382.436,73	1.000	68	100	55m25s	€281,44	510
25	50	5	5	1s	€444.235,19	1.000	68	100	1h46m14s	€267,03	373

Table 9: Results of 1000 iterations of the tabu search heuristic on the test set with multiple locations and multiple time windows

Instances	Customers	Vehicles	Cost one option per customer	Cheapest number of options	Cost cheapest no. of options	Cost difference (%)
1-5	10	2	€147,26	5	€66,06	55,1
6-10	20	3	€146,21	5	€122,30	16,4
11-15	30	4	€276,41	5	€188,64	31,8
16-20	40	4	€294,50	5	€195,95	33,5
21-25	50	5	€383,91	5	€267,03	30,4

Table 10: Summary of potential cost savings with multiple locations and multiple time windows

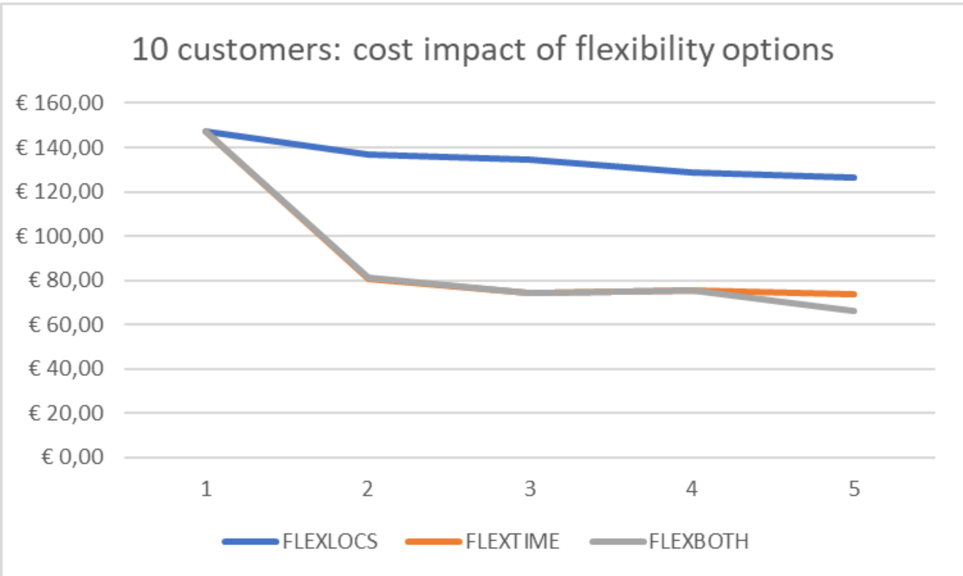

Figure 12: Impact of different flexibility options on routing costs for the 10-customer set

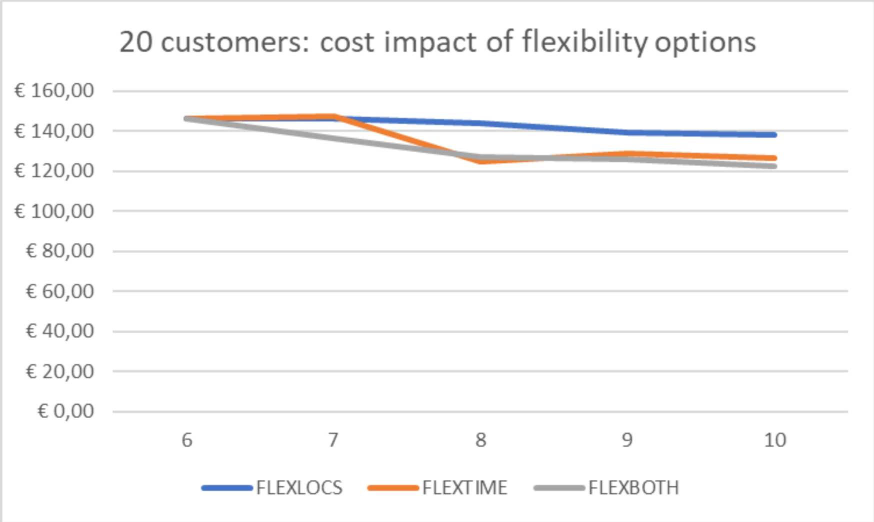

Figure 13: Impact of different flexibility options on routing costs for the 20-customer set

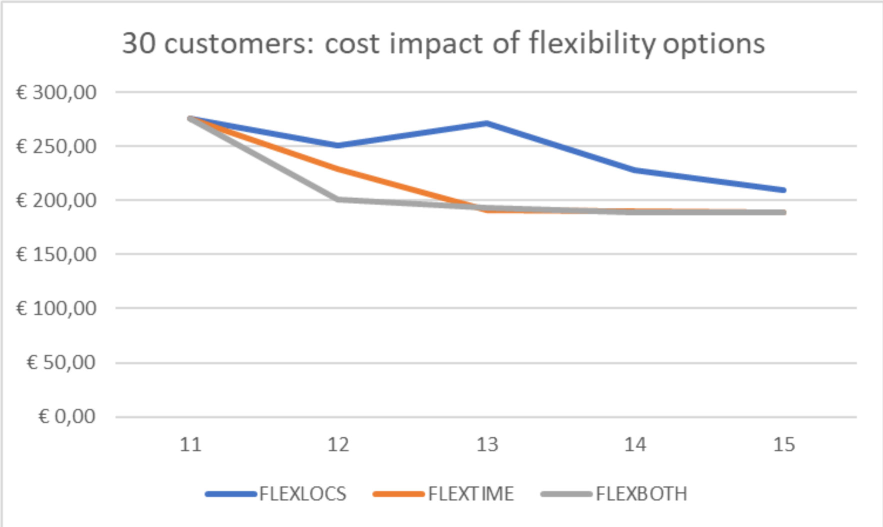

Figure 14: Impact of different flexibility options on routing costs for the 30-customer set

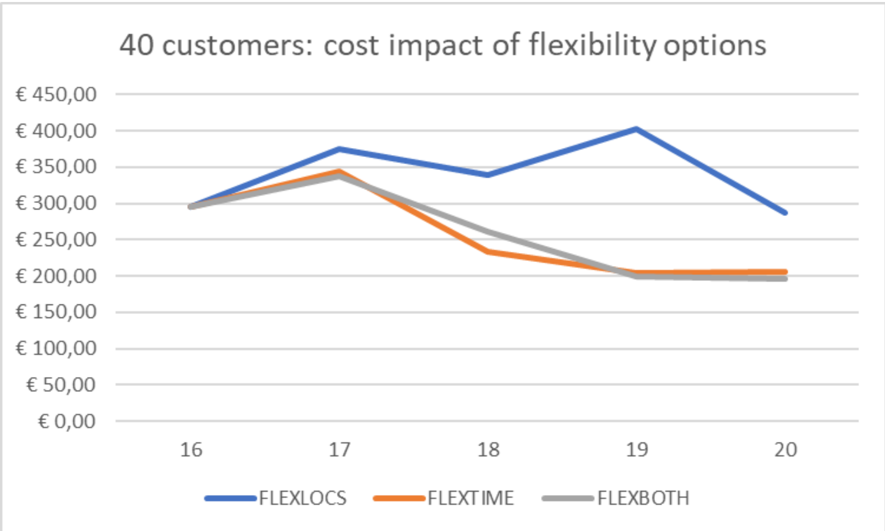

Figure 15: Impact of different flexibility options on routing costs for the 40-customer set

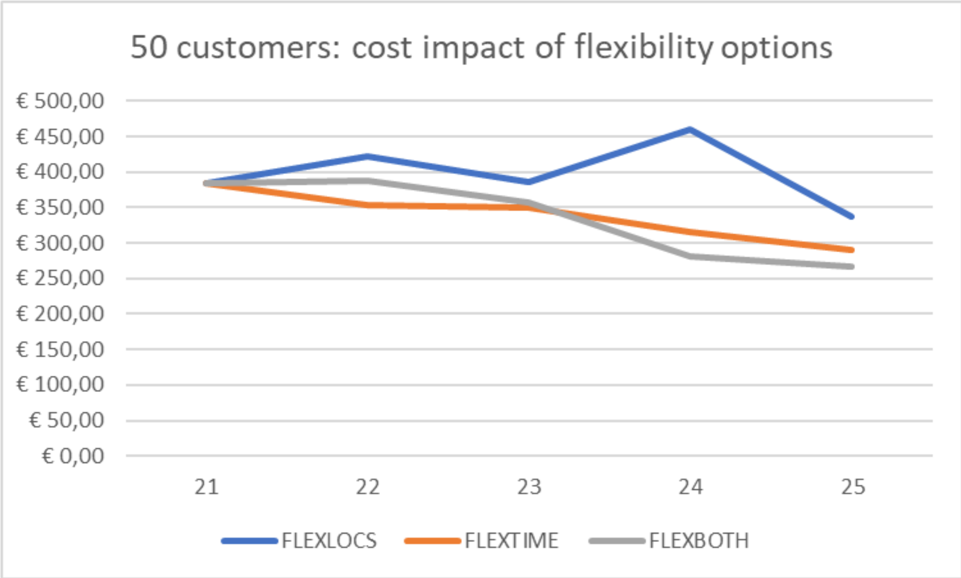

Figure 16: Impact of different flexibility options on routing costs for the 50-customer set

Maps and routing analysis

To gain more insight into how these cost differences occur, and what impact the different flexibility options had on routing, the routes were analyzed in more detail. Tables 11-13 present the distances, travel and waiting times, number of unique locations and stops (per route) for two instances of each customer set. The first one represents the scenario of fixed locations and fixed time windows, and the second represents the best instance of having multiple options (locations, time windows, or both). Figures 17-20 present a series of maps with the routing of the 40-customer set to give an idea on the routing differences.

Tables 11-13 provide three main insights. First of all, only allowing for multiple locations while keeping the time window fixed did not eliminate waiting time (almost) completely, while allowing for multiple time windows did, both on its own and in combination with multiple locations. As waiting time has a higher cost than regular travel time because of its unwantedness, this reduced potential savings. Moreover, the worst example of this insight was for the 50-customer set, where allowing for multiple locations increased the waiting time with 446%.

The second main insight is that allowing for multiple locations mostly reduced the number of unique locations visited as compared to the base scenario. However, the number of stops was mostly lower in the scenarios with multiple time windows. The difference between the two was that unique locations looked at all the routes (i.e. when one location appeared in two routes it was counted as one unique location), while the number of stops was counted per route (i.e. when that same location appeared in two different routes, two stops had to be made there). The main insight from this was that while allowing for multiple locations on its own reduced the number of unique locations visited, these could not be utilized sufficiently for combined deliveries because of different time windows. By allowing for multiple time windows, customers that could potentially be delivered at the same location at different moments during the day could be combined more easily if multiple customers had overlapping time windows. These combined deliveries, by delivering multiple customers at the same location and the same time, provide the biggest savings potential for in-car delivery, as these combined deliveries save distance, travel time, and therefore costs.

Finally, this analysis confirmed the image of the first graphs (Figures 12-16) that allowing for multiple time windows was the biggest contributor to routing efficiency gains in all areas. One example here is the waiting time mentioned before, that got practically eliminated with allowing multiple time windows, but not with multiple locations on its own. However, distance and travel time data generally showed the same image. For instance in the 40-customer set, allowing for both multiple locations and time windows the savings potential was up to 25,9% in distance, and 30,7% in travel time. However, when reviewing multiple locations with a fixed time window, this saving was only 3,9% in distance and 1,0% in travel time, while for the fixed location with multiple time windows these savings were 22,1% and 27,5%, respectively. This indicated the relative importance of time window flexibilization as a contributor to savings potential as compared to just allowing for multiple locations.

Inst. (size)	Dis-tance (km)	Time (mins)	Wait (mins)	Diff. locs	Total stops	Avg. stops per route	Distance gain (km)	Time gain (mins)	Wait gain (mins)	Stops p/ route gain
1 (10)	221,3	392	103	10	10	5	-	-	-	-
5 (10)	253,6	372	51	9	9	4,5	+32,3 (+14,6%)	20 (-5,1%)	52 (-50,5%)	0,5 (-10%)
6 (20)	387,3	489	0	18	18	6	-	-	-	-
10 (20)	346,9	472	0	16	18	6	40,4 (-10,4%)	17 (-3,5%)	-	-
11 (30)	539,3	837	104	20	29	7,25	-	-	-	-
15 (30)	501,2	691	23	20	28	7	38,1 (-7,1%)	146 (-17,4%)	81 (-77,9%)	0,25 (-3,4%)
16 (40)	647,2	978	45	31	40	10	-	-	-	-
20 (40)	622,1	968	40	32	39	9,75	25,1 (-3,9%)	10 (-1,0%)	5 (-11,1%)	0,25 (-2,5%)
21 (50)	944,9	1303	13	32	49	9,8	-	-	-	-
25 (50)	714,9	1098	71	28	44	8,8	230 (-24,3%)	205 (-15,7%)	+58 (+446%)	1 (-10,2%)

Table 11: Potential gains in several routing parameters in the case of multiple locations and fixed time windows

Inst.	Dis-tance (km)	Time (mins)	Wait (mins)	Diff. locs	Total stops	Avg. stops per route	Distance gain (km)	Time gain (mins)	Wait gain (mins)	Stops p/ route gain
1 (10)	221,3	392	103	10	10	5	-	-	-	-
5 (10)	198,6	244	0	10	10	5	22,7 (-10,3%)	148 (-37,8%)	103 (-100%)	-
6 (20)	387,3	489	0	18	18	6	-	-	-	-
8 (20)	321,9	420	1	17	17	5,67	65,4 (-16,9%)	69 (-14,1%)	+1 (N/A)	0,33 (-5,5%)
11 (30)	539,3	837	104	20	29	7,25	-	-	-	-

15 (30)	487,7	638	0	20	25	6,25	51,6 (-9,6%)	199 (-23,8%)	104 (-100%)	1 (-13,8%)
16 (40)	647,2	978	45	31	40	10	-	-	-	-
19 (40)	504,3	709	0	31	35	8,75	142,9 (-22,1%)	269 (-27,5%)	45 (-100%)	1,25 (-12,5%)
21 (50)	944,9	1303	13	32	49	9,8	-	-	-	-
25 (50)	713,4	1010	0	32	44	8,8	231,5 (-24,5%)	293 (-22,5%)	13 (-100%)	1 (-10,2%)

Table 12: Potential gains in several routing parameters in the case of fixed locations and multiple time windows

Inst.	**Dis-tance (km)**	**Time (mins)**	**Wait (mins)**	**Diff. locs**	**Total stops**	**Avg. stops per route**	**Distance gain (km)**	**Time gain (mins)**	**Wait gain (mins)**	**Stops p/ route gain**
1 (10)	221,3	392	103	10	10	5	-	-	-	-
5 (10)	181,3	217	0	8	9	4,5	40 (-18.1%)	175 (-44,6%)	103 (-100%)	0,5 (-10%)
6 (20)	387,3	489	0	18	18	6	-	-	-	-
10 (20)	320,8	411	0	16	17	5,67	66,5 (-17,2%)	78 (-16%)	-	0,33 (-5,6%)
11 (30)	539,3	837	104	20	29	7,25	-	-	-	-
15 (30)	475,5	646	0	21	25	6,25	63,8 (-11,8%)	191 (-22,8%)	104 (-100%)	1 (-13,8%)
16 (40)	647,2	978	45	31	40	10	-	-	-	-
20 (40)	479,6	678	1	24	31	7,75	167,6 (-25,9%)	300 (-30,7%)	44 (-97,8%)	2,25 (-22,5%)
21 (50)	944,9	1303	13	32	49	9,8	-	-	-	-
25 (50)	638,6	934	1	36	45	9	306,3 (-32,4%)	369 (-28,3%)	12 (-92,3%)	0,8 (-8,2%)

Table 13: Potential gains on several routing parameters in the case of multiple locations and multiple time windows

The same influences were seen when analyzing the routing structures on a map, as Figures 17-20 show for the 40-customer set as an example. Figure 17 shows the map for the base scenario, where each customer had a fixed location and time window for delivery. As the map shows, this resulted in a rather messy routing structure, where some routes were making a lot of back-and-forth detours. Especially the red route showed this behavior, going back and forth several time between the north(-west) and south(-east) of the map. The main problem with this was that these detours were mostly between subsequent customers, so hardly any deliveries were made on the way. This resulted in unnecessary travel time and kilometers driven. Figure 18 showed that when the customers were allowed multiple locations, but within their fixed time window, the situation hardly changes. The routing structure was still chaotic, although the flexibilization of locations did seem to make a change in adjusting several customer locations at the outside of the map. For instance, Figure 17 showed one delivery location in the northern village of Breugel and four in the southeastern village of Geldrop. However, in Figure 18, of these locations only one in Geldrop remained, while the other delivery locations changed.

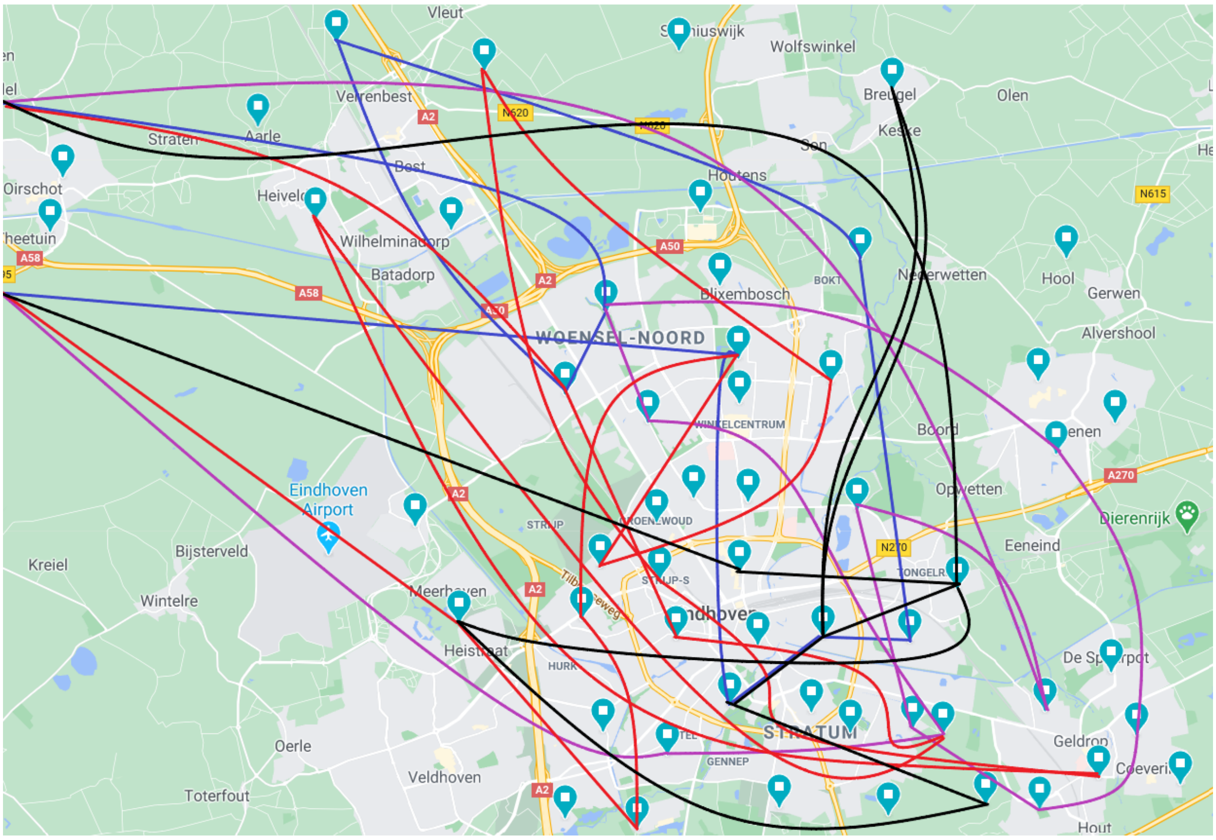

Figure 17: Map of the routing structure of the 40-customer set with fixed locations and fixed time windows

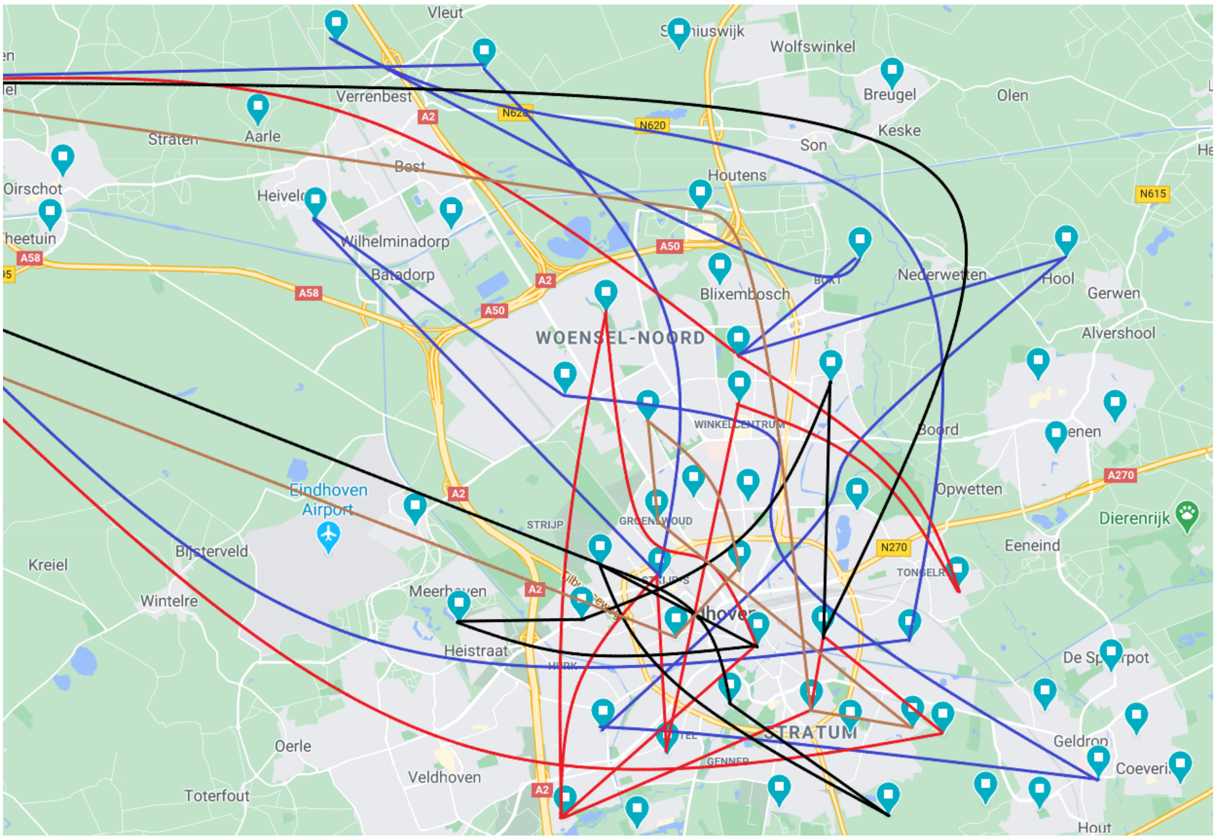

Figure 18: Map of the routing structure of the 40-customer set with multiple locations and fixed time windows

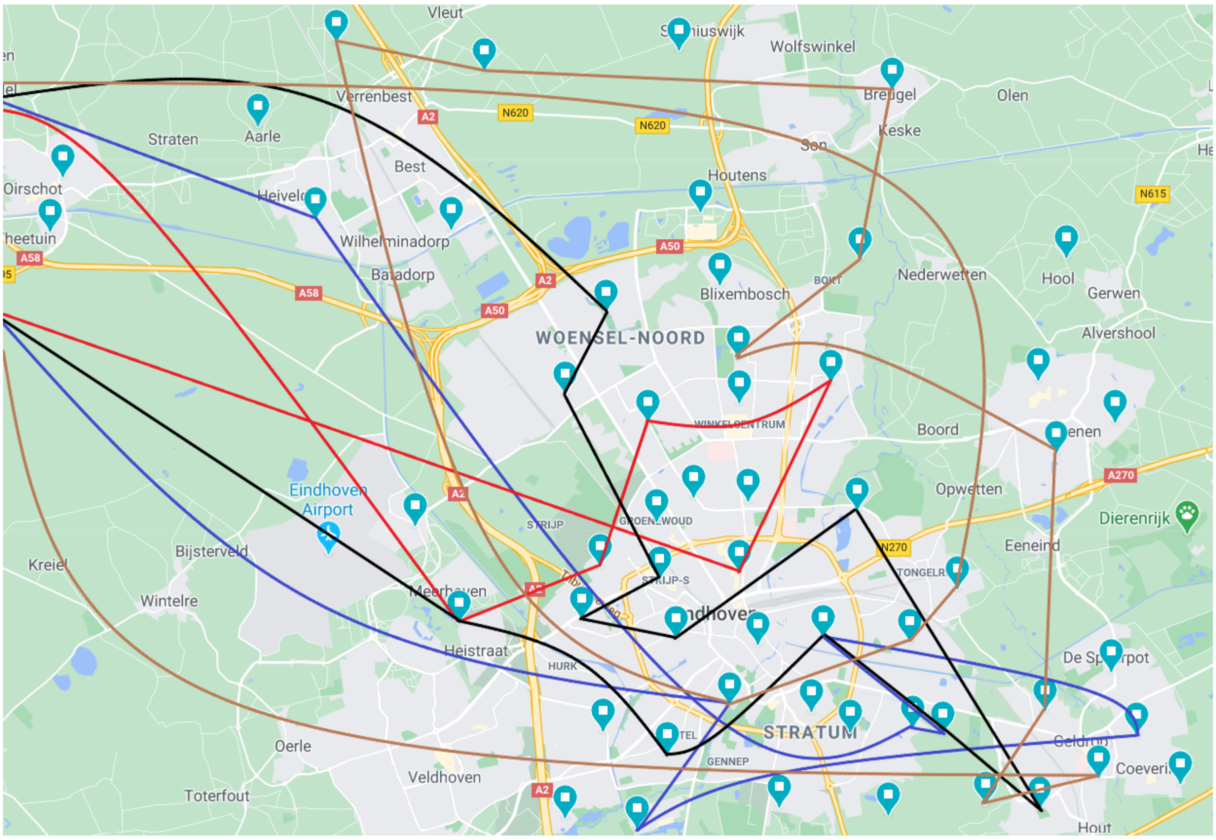

Figure 19: Map of the routing structure for the 40-customer set with fixed locations and multiple time windows

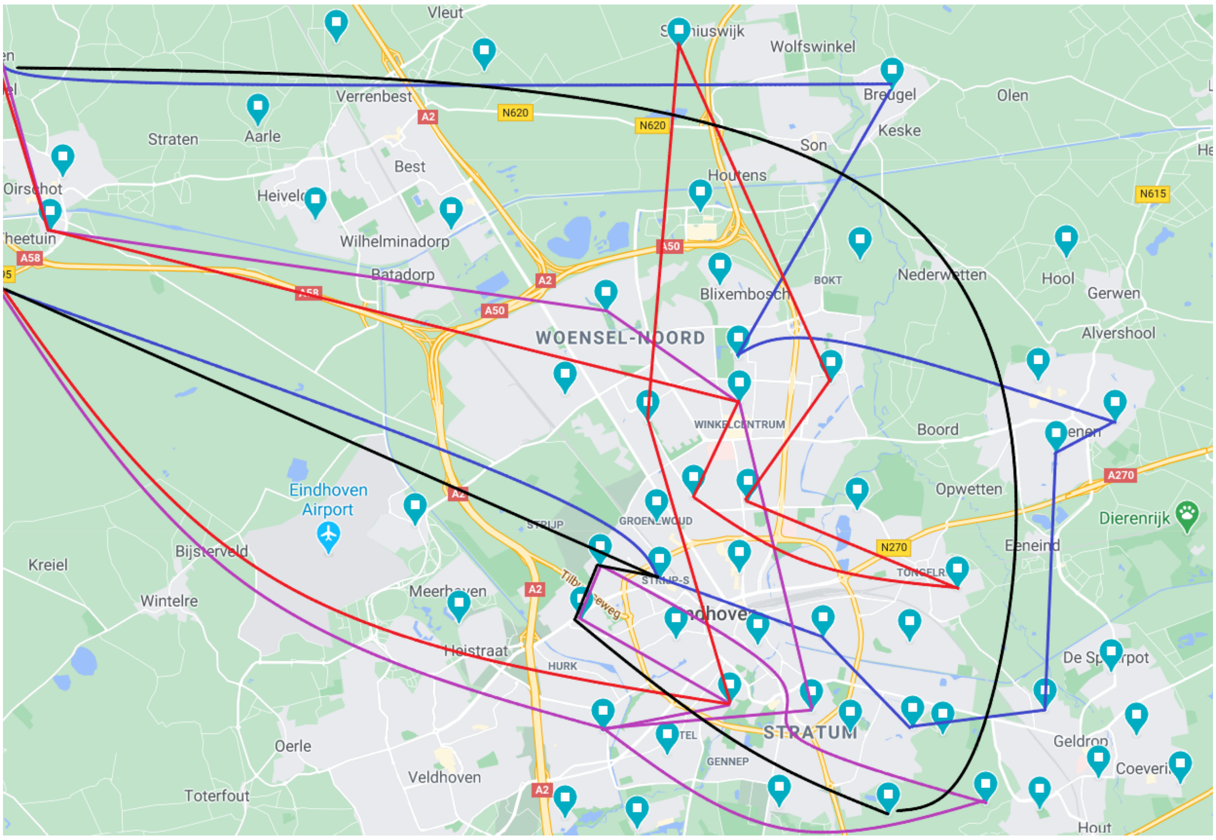

Figure 20: Map of the routing structure for the 40-customer set with multiple locations and time windows

The image changed when allowing for multiple time windows, such as in Figure 19. There, the same number of customers was delivered, but the routing structure seems much less chaotic than in the first two maps. The example showing the main difference between the two types of routing structures is the brown route in Figure 19. While this route still went all over the map, serving customers in multiple areas of the map, the difference with the first two maps was that this route served multiple customers on its way. The different locations were thus combined in a smarter way, such that the vehicle better utilized its time on the road going from one side of the area to the other, with shorter distances between the different customers. Finally, Figure 20, where both locations and time windows were flexible, showed a similarly clean image, where distances between subsequent customers were relatively shorter than in the first two scenarios. This allowed for more efficient routes. The fact that the last two maps, where time windows were flexible, showed more efficient routing than in the first two maps where these windows were fixed, confirmed the image that allowing for multiple time windows made a larger contribution to more efficient routing than just allowing for multiple locations.

Extending the planning horizon

The second research question dealt with whether in-car delivery could potentially increase network capacity by opening up additional delivery windows. Therefore, two additional runs of the test set were done: one with an additional four hours of delivery windows (so 16 hours in total) and one with an additional eight hours of delivery windows (with a total of 20 hours). As Chapter 4.1 describes, for each customer in both scenarios the locations were kept the same, but all time windows were regenerated from scratch with the new planning horizon. Moreover, these additional runs were only done for the situation with multiple locations and multiple time windows, labeled as delivery options.

Tables 14 and 15 show the results of both runs. Both scenarios showed a similar pattern where costs decreased with the number of potential delivery options per customer.

Instance	Number of customers	Options per customer	Vehicles	Initial solution time	Initial solution cost	Number of iterations	Size of neighborhood	Tabu tenure	Runtime	Final solution cost	Final solution iteration
1	10	1	2	1s	€115.612,19	1.000	4	6	0m01s	€324,50	204
2	10	2	2	1s	€108.751,75	1.000	4	6	0m03s	€101,00	391
3	10	3	2	1s	€90.938,45	1.000	4	6	0m10s	€89,51	439
4	10	4	2	1s	€139.296,80	1.000	4	6	0m24s	€75,68	333
5	10	5	2	1s	€61.959,45	1.000	4	6	0m43s	€74,15	23
6	20	1	3	1s	€190.042,03	1.000	30	20	0m10s	€216,61	485
7	20	2	3	1s	€77.564,58	1.000	30	20	1m01s	€157,44	602
8	20	3	3	1s	€176.255,01	1.000	30	20	3m02s	€134,88	250
9	20	4	3	1s	€215.514,99	1.000	30	20	6m50s	€135,68	663
10	20	5	3	1s	€160.154,94	1.000	30	20	15m03s	€124,29	666
11	30	1	4	1s	€199.934,48	1.000	43	47	0m18s	€331,01	356
12	30	2	4	1s	€232.144,69	1.000	43	47	2m17s	€286,91	415
13	30	3	4	1s	€239.253,58	1.000	43	47	7m12s	€273,73	584
14	30	4	4	1s	€209.093,38	1.000	43	47	16m54s	€240,74	922
15	30	5	4	1s	€304.936,04	1.000	43	47	32m45s	€203,80	492
16	40	1	4	1s	€468.154,95	1.000	55	73	0m37s	€399,58	610
17	40	2	4	1s	€453.539,71	1.000	55	73	4m53s	€333,54	199
18	40	3	4	1s	€453.912,74	1.000	55	73	15m31s	€371,68	534
19	40	4	4	1s	€466.612,91	1.000	55	73	35m28s	€245,20	61
20	40	5	4	1s	€676.957,35	1.000	55	73	1h08m45s	€241,85	757
21	50	1	5	1s	€569.592,79	1.000	68	100	0m52s	€481,14	188
22	50	2	5	1s	€488.996,60	1.000	68	100	7m36s	€423,51	382
23	50	3	5	1s	€561.062,44	1.000	68	100	24m02s	€406,73	723
24	50	4	5	1s	€545.572,16	1.000	68	100	55m27s	€404,80	468
25	50	5	5	1s	€724.880,58	1.000	68	100	1h44m18s	€295,64	421

Table 14: Results of running 1000 iterations of the tabu search heuristic on the 25 instances with a 16-hour planning horizon

Instance	Number of customers	Options per customer	Vehicles	Initial solution time	Initial solution cost	Number of iterations	Size of neighborhood	Tabu tenure	Runtime	Final solution cost	Final solution iteration
1	10	1	2	1s	€66.146,38	1.000	4	6	0m01s	€382,11	60
2	10	2	2	1s	€111.906,58	1.000	4	6	0m05s	€242,46	381
3	10	3	2	1s	€41.930,54	1.000	4	6	0m09s	€105,40	924
4	10	4	2	1s	€111.348,80	1.000	4	6	0m21s	€80,85	473
5	10	5	2	1s	€68.044,88	1.000	4	6	0m37s	€79,31	780
6	20	1	3	1s	€411.672,08	1.000	30	20	0m08s	€383,93	277
7	20	2	3	1s	€260.926,71	1.000	30	20	0m59s	€181.98	127
8	20	3	3	1s	€306.293,65	1.000	30	20	2m49s	€151,40	458
9	20	4	3	1s	€326.005,78	1.000	30	20	6m38s	€148,00	321
10	20	5	3	1s	€253.414,09	1.000	30	20	12m48s	€150,48	868
11	30	1	4	1s	€558.527,56	1.000	43	47	0m18s	€481,99	86
12	30	2	4	1s	€446.765,03	1.000	43	47	2m17s	€446,84	426
13	30	3	4	1s	€402.960,30	1.000	43	47	7m10s	€330,23	360
14	30	4	4	1s	€422.592,59	1.000	43	47	16m25s	€262,68	809
15	30	5	4	1s	€432.729,84	1.000	43	47	31m32s	€260,43	635
16	40	1	4	1s	€650.268,88	1.000	55	73	0m31s	€595,01	683
17	40	2	4	1s	€615.681,11	1.000	55	73	4m46s	€507,75	909
18	40	3	4	1s	€729.340,36	1.000	55	73	15m08s	€381,21	826
19	40	4	4	1s	€493.840,29	1.000	55	73	35m47s	€349,55	282
20	40	5	4	1s	€679.842,25	1.000	55	73	1h11m52s	€277,23	635
21	50	1	5	1s	€911.025,90	1.000	68	100	0m48s	€551,95	173
22	50	2	5	1s	€903.425,51	1.000	68	100	7m11s	€672,58	441
23	50	3	5	1s	€670.016,20	1.000	68	100	25m19s	€498,86	569
24	50	4	5	1s	€691.494,54	1.000	68	100	57m01s	€417,60	699
25	50	5	5	1s	€1025544,30	1.000	68	100	1h52m26s	€402,64	327

Table 15: Results of running 1000 iterations of the tabu search heuristic on the 25 instances with a 20-hour planning horizon

The main difference that was observed compared to the original 12-hour planning horizon is that costs generally went up by opening these additional delivery windows. However, at the same time the cost savings of having multiple delivery options per customer were generally higher than in the original scenario, as Tables 16 and 17 show. Figures 21-25 represent this idea graphically, where it can also be seen that within each set of instances with similar size, the costs of the three planning horizons converged as the number of potential delivery options per customer increased.

Instances	Customers	Vehicles	Cost one option per customer	Cheapest number of options	Cost cheapest no. of options	Cost difference (%)
1-5	10	2	€324,50	5	€74,15	77,1
6-10	20	3	€216,61	5	€124,29	42,6
11-15	30	4	€331,01	5	€203,80	38,4
16-20	40	4	€399,58	5	€241,85	39,5
21-25	50	5	€481,14	5	€295,64	38,6

Table 16: Summary of potential cost reductions for the scenario with a planning horizon extended to 16 hours

Instances	Customers	Vehicles	Cost one option per customer	Cheapest number of options	Cost cheapest no. of options	Cost difference (%)
1-5	10	2	€382,11	5	€79,31	79,2
6-10	20	3	€383,93	4	€148,00	61,4
11-15	30	4	€481,99	5	€260,43	46,0
16-20	40	4	€595,01	5	€277,23	53,4
21-25	50	5	€551,95	5	€402,64	27,1

Table 17: Summary of potential cost reductions for the scenario with a planning horizon extended to 20 hours

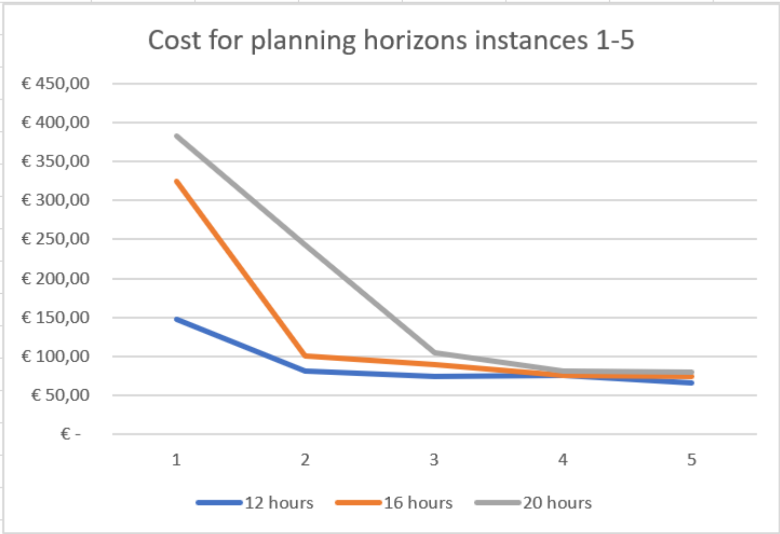

Figure 21: Cost comparison of all planning horizons for instances 1-5 (10 customers)

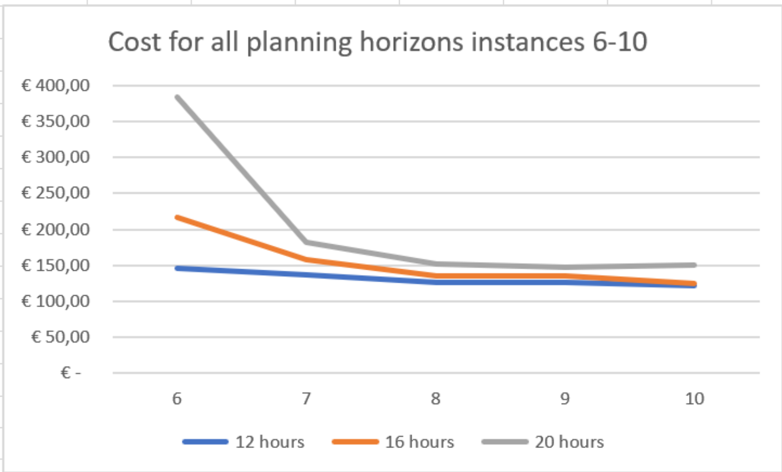

Figure 22: Cost comparison of all planning horizons for instances 6-10 (20 customers)

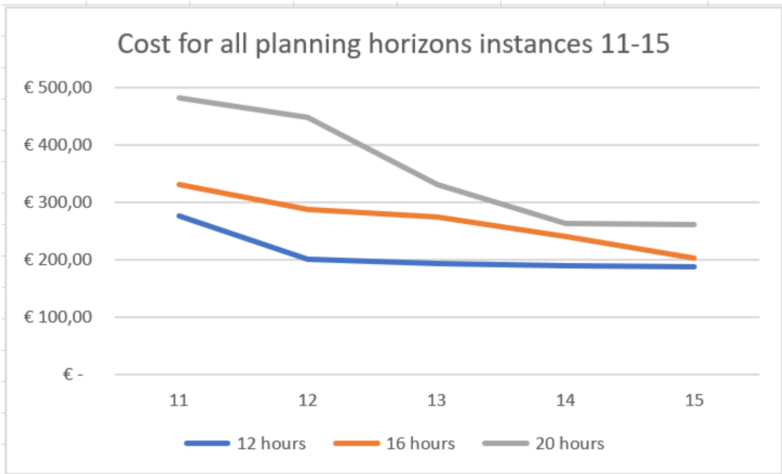

Figure 23: Cost comparison of all planning horizons for instances 11-15 (30 customers)

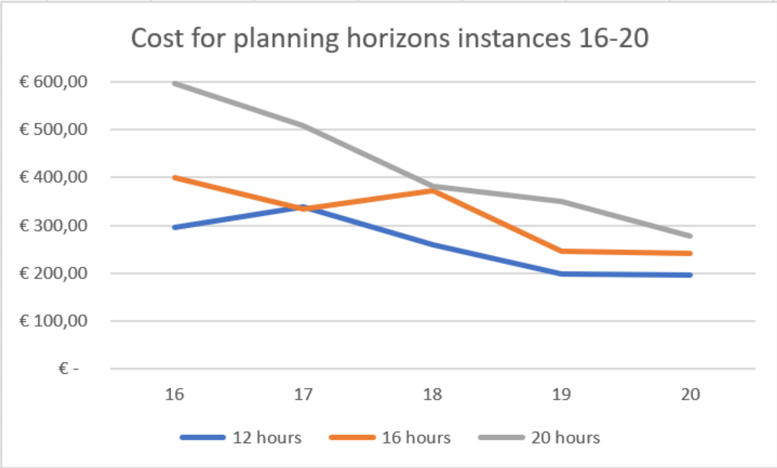

Figure 24: Cost comparison of all planning horizons for instances 16-20 (40 customers)

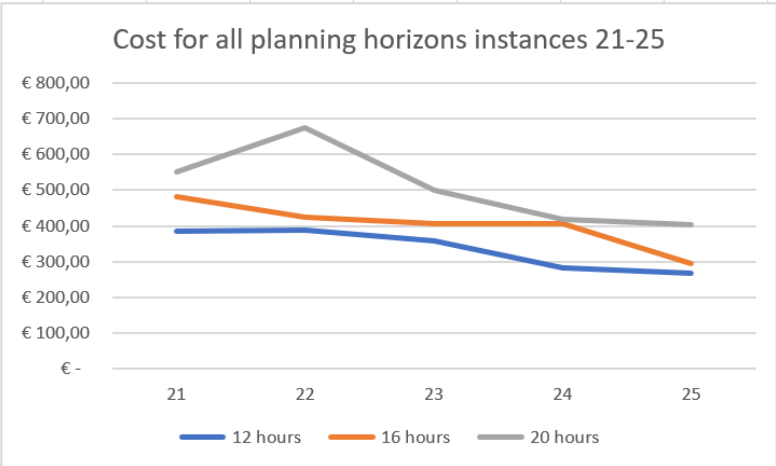

Figure 25: Cost comparison of all planning horizons for instances 21-25 (50 customers)

In general, all customer sets and planning horizons confirmed the earlier idea of decreasing costs with multiple potential delivery options per customer. One exception was instance 22, where customers each had 2 delivery options. Apparently, in this specific instance the algorithm had some trouble finding a better solution. Another observation was that in general, it seemed that for all planning horizons the biggest gains were made between 1 and at most 4 delivery options per customer. In most cases, the additional savings of having five instead of four delivery options per customer were small compared to the savings obtained before reaching four options per customer.

Potential impact on network capacity

With instances as small as these, an exact impact of extending the length of the daily planning horizon on network capacity could not be determined accurately. However, an indication was made as a basis for further research on the topic. This was done by looking at the minimum number of vehicles that were needed to perform all routes of each instance. By looking at the depot departure and arrival times in the final solutions for each instance, it was checked which routes could be performed by the same vehicle in each planning horizon scenario. It was assumed this was the case if one route started from the depot after another one was finished. Table 18 shows these results.

The main observation from Table 18 was that extending the planning horizon from the original 12 hours to 16 or even 20 hours did not negatively impact the number of vehicles needed to serve all customers in our instances. In 10 of the 25 instances (40%), extending the planning horizon did not influence the number of vehicles needed to serve all customers. In the other 15 instances (60%), extending the planning horizon resulted in needing at least one vehicle less to perform all routes as compared to the original horizon. This saved vehicle could then be used to serve additional customers. This implies that additional network capacity could be created without adding extra vehicles to the fleet. Therefore, even though hard conclusions about the cause and generality of this effect could not be made from this small research, it provided a first indication that it might be possible to extend network capacity for LSPs by using in-car delivery to extend the daily planning horizon.

Instance	Customers	Options	Routes	Vehicles needed 12-hour horizon	Vehicles needed 16-hour horizon	Vehicles needed 20-hour horizon
1	10	1	2	1	1	1
2	10	2	2	1	1	1
3	10	3	2	1	1	1
4	10	4	2	2	1	1
5	10	5	2	1	1	1
6	20	1	3	1	1	1
7	20	2	3	2	1	1
8	20	3	3	2	2	1
9	20	4	3	2	2	1
10	20	5	3	2	2	1
11	30	1	4	2	2	2
12	30	2	4	2	2	2
13	30	3	4	3	3	3
14	30	4	4	3	2	2
15	30	5	4	3	2	2
16	40	1	4	2	2	2
17	40	2	4	3	2	2
18	40	3	4	4	3	3
19	40	4	4	4	3	2
20	40	5	4	4	3	3
21	50	1	5	3	3	2
22	50	2	5	4	3	3
23	50	3	5	4	4	4
24	50	4	5	4	4	4
25	50	5	5	5	4	4

Table 18: Minimum number of vehicles needed to perform all routes in each planning horizon scenario

5.2 Results customer research

This section discusses the results of the customer research. First, section 5.2.1 elaborates on predicting customer intention to use in-car delivery. Next, section 5.2.2 discusses customer preferences regarding the form of implementing in-car delivery.

5.2.1 Predicting customer intentions to use in-car delivery

Table 19 reports the descriptive statistics and intercorrelations of all study variables in the customer research. The descriptive statistics in Table 19 reveal that most variables received quite positive scores. However, some interesting things were noted as well. First, the central construct in the model, behavioral intentions, and its predictor perceived usefulness received positive scores, but with high variance. This implies that respondents were still divided on whether or not they perceive in-car delivery as useful and are intending to use it once it becomes available. Respondents seemed to be even more divided on the step towards actual use, with predicted use receiving the lowest mean score with the highest variance. However, it should be noted that perceived ease of use was not a problem since it received the highest mean score with relatively low variance.

The descriptive statistics also revealed that respondents had relatively high initial trust in the technology and the companies using it, as all trust variables received high scores where low variance indicated relative unity amongst respondents. Finally, the barriers received relatively lower scores with low to average variance, indicating that at this point, respondents did not seem to experience these barriers to be the biggest problem.

Variable	*N*	*M*	*SD*	1	2	3	4	5	6	7	8	9	10
1. Perceived usefulness	191	3.20	1.22	1									
2. Perceived ease of use	191	3.79	0.97	.628**	1								
3. Behavioral intentions	191	3.14	1.35	.847**	.610**	1							
4. Predicted use	191	2.66	1.31	.792**	.518**	.835**	1						
5. Perceived integrity	191	3.61	0.86	.459**	.471**	.489**	.415**	1					
6. Perceived benevolence	191	3.72	0.87	.398**	.349**	.450**	.407**	.713**	1				
7. Perceived ability	191	3.77	0.87	.387**	.401**	.391**	.350**	.702**	.699**	1			
8. Trust	191	3.70	0.78	.460**	.447**	.495**	.437**	.886**	.918**	.880**	1		
9. Value barrier	191	2.97	1.10	-.820**	-.565**	-.787**	-.763**	-.410**	-.408**	-.357**	-.438**	1	
10. Risk and difficulty barrier	191	2.79	0.92	-.013	-.186**	-.095	.033	-.030	-.013	-.026	-.024	.076	1

* *p* <.05, ** *p* <.01

Table 19: Correlation table with means and standard deviations for the final constructs in the customer research

Table 19 reveals a fair amount of association between the different constructs as various significant correlations appear. As most significant correlations between constructs not directly related in the model were of moderate strength, no severe problems were found with the distinction of constructs. One exception is the high, unpredicted correlation between value barrier and perceived usefulness (r = -0.820, p < 0.001). This suggests these two constructs are each other's opposites.

Predictor variable	**VIF score**
Perceived usefulness	3.607
Perceived ease of use	1.849
Trust	1.354
Value barrier	3.148
Risk and difficulty barrier	1.066

Table 20: VIF scores for predictors of behavioral intentions

Before testing the hypotheses, some additional multicollinearity checks were done by calculating the VIF scores for each predictor in the multiple regression (see Table 20). As Table 20 shows, perceived usefulness and value barrier have higher VIF scores than the other predictors. However, these were still well below the recommended cut-off values that require strong model changing actions (Hair Jr., Black, Babin, & Anderson, 2010). Moreover, heteroskedasticity was tested by performing a Breusch-Pagan test, which showed some signs of heteroskedasticity (*BP* = 11.447(5), p = 0.043). Therefore, heteroskedasticity-corrected error terms were used to make the results valid for interpretation. These heteroskedasticity tests were also performed on the two simple linear regressions. The relationship between perceived ease of use and perceived usefulness had no problems with heteroskedasticity (*BP* = 0.123(1), p = 0.726). However, the relationship between behavioral intentions and predicted actual use did show signs of heteroskedasticity (*BP* = 14.989(1), p

< 0.001), so heteroskedasticity-corrected error terms were used to make results valid for interpretation.

Test of hypotheses

The final hypotheses of the customer research model were tested by the three multiple regression analyses, with the results presented in Table 21.

Hypotheses 1 to 4 tested the TAM model and posit that perceived ease of use positively relates to perceived usefulness (H1), that these constructs both positively relate to behavioral intentions (H2 and H3 respectively), and that behavioral intentions relate positively to predicted actual use (H4). The regression analyses confirmed that perceived ease of use related positively to perceived usefulness (β = 0.629, p < 0.001), thereby supporting H1. Moreover, perceived usefulness related positively and significantly with behavioral intentions (β = 0.561, p < 0.001), supporting H2. However, the relationship between perceived ease of use and behavioral intentions was not significant (β = 0.066, p = 0.298), therefore not supporting H3. Finally, the relationship between behavioral intentions and predicted use was significant and positive as expected (β = 0.834, p < 0.001), supporting H4.

Dependent variable: behavioral intentions					
Predictors	**B**	**Standard error**	***β***	***t*-value**	***p***
Intercept	1.267	0.597		2.122	0.035*
Perceived usefulness	0.621	0.092	0.561	6.730	< 0.001**
Perceived ease of use	0.092	0.088	0.066	1.043	0.298
Trust	0.173	0.081	0.100	2.149	0.033*
Value barrier	-0.296	0.091	-0.242	-3.247	0.001**
Risk and difficulty barrier	-0.080	0.059	-0.055	-1.347	0.180
R^2 = 0.760, adjusted R^2 = 0.754, F(5,185) = 117.2, *p* < 0.001					
Dependent variable: perceived usefulness					
Predictors	**B**	**Standard error**	***β***	***t*-value**	***p***
Intercept	0.204	0.279		0.733	0.465
Perceived ease of use	0.791	0.071	0.629	11.106	< 0.001**
R^2 = 0.395, adjusted R^2 = 0.392, F(1,189) = 123.4, *p* < 0.001					
Dependent variable: predicted actual use					
Predictors	**B**	**Standard error**	***β***	***t*-value**	***p***
Intercept	0.122	0.094		1.300	0.195
Behavioral intentions	0.809	0.036	0.834	22.170	< 0.001**
R^2 = 0.697, adjusted R^2 = 0.656, F(1,189) = 435.1, *p* < 0.001					
*** p < 0.01, * p < 0.05*					

Table 21: Results of the three regression analyses to test hypotheses 1 through 6

As the various dimensions of trust were combined into one single dimension, its relationship with behavioral intentions (H5a-c) was tested with trust as one single hypothesis. The hypothesis 5 proposed this relationship to be positive, which the data supported (β = 0.010, p = 0.033). Finally, the hypotheses 6a and 6b tested two resistance barriers. The data supported H6a by showing a significantly negative relationship between value barrier and behavioral intentions (β = -.242, p = 0.001). However, H6b was not supported, as the risk and difficulty barrier and behavioral intentions did not relate significantly (β = -.055, p = 0.180).

Figure 26 shows the final research model with all hypotheses and their path coefficients. Note that this model differs from the one presented in Chapter 3 in the sense that only the hypotheses that were actually tested are included. Moreover, the variable names are adjusted to the in-car delivery context.

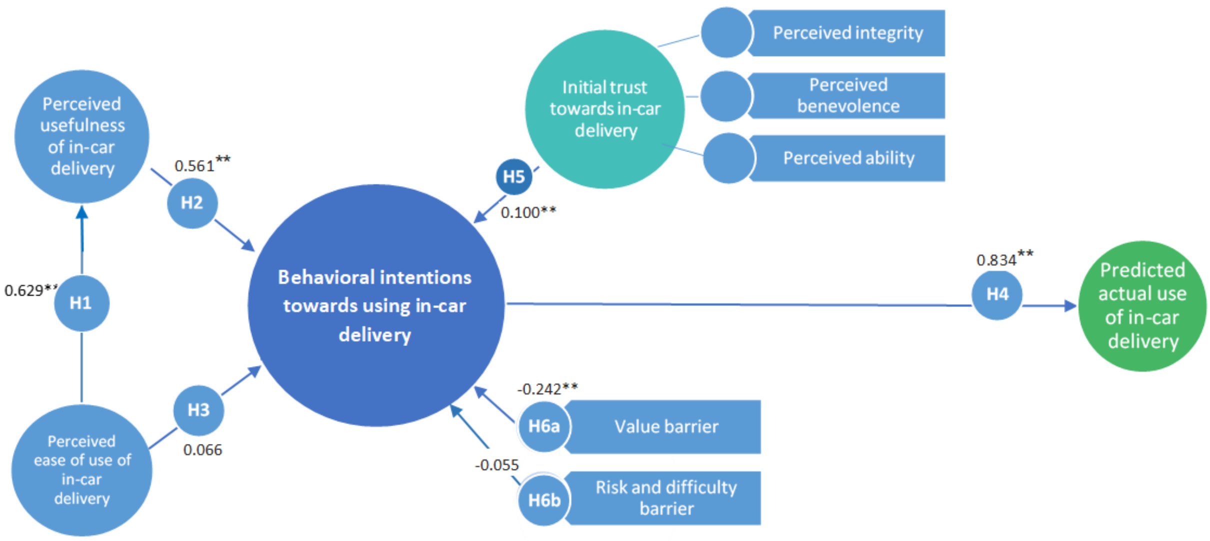

Figure 26: Final research model with path coefficients, adjusted to the in-car delivery context

When projecting the mean scores of the current sample on the research model in Figure 26, it could be predicted that implementing in-car delivery has the potential to be a success. The predictors perceived usefulness and ease of use received high scores on average, indicating that overall, respondents see potential value in in-car delivery as compared to conventional delivery methods. However, these scores came with high standard deviations, indicating that respondents were divided on this and that there is a lot of uncertainty. Moreover, given the high mean scores of the trust concepts and all of its dimensions, with relatively low standard deviations, the respondents seemed to have quite some trust in the technology, which would increase the chances of a successful introduction based on the research model. However, the big issue would probably be getting customers to take the step from having positive behavioral intentions to actually adopting the service, as the average score for predicted actual use was much lower than for predicted actual use.

5.2.2 Examining customer preferences towards in-car delivery

The second part of the customer research was a scenario analysis in which respondents rated the attractiveness of eight different implementation scenarios for in-car delivery.

Descriptive statistics

Table 22 presents the means and standard deviations for each of the scenarios.

First, these means and standard deviations were compared. Respondents rated each scenario on a scale of 1 (not attractive) to 5 (very attractive), so a higher mean score generally indicates a higher attractiveness of the scenario to respondents.

Table 22 shows that all mean scores fell in the range from 2.61 to 3.30. This means each scenario scored relatively close to the scale mean 3, which is the 'neutral' score. Three scenarios scored lower than this, indicating the scenario was slightly unattractive to the respondents. The other five scenarios scored higher, indicating the relative attractiveness of the scenario to the respondents.

Scenario	Preference indication method	Key recorder distribution	*M*	*SD*
1	Non-flexible using a separate app	Only personal key recorders	2.61	1.17
2	Flexible using a separate app	Only personal key recorders	3.30	1.12
3	In-car delivery integrated in retailer app	Only personal key recorders	3.26	1.19
4	Fill in a delivery date day schedule	Only personal key recorders	3.22	1.22
5	Non-flexible using a separate app	Both personal and in central upload stations	2.65	1.13
6	Flexible using a separate app	Both personal and in central upload stations	3.14	1.19
7	In-car delivery integrated in retailer app	Both personal and in central upload stations	3.08	1.25
8	Fill in a delivery date day schedule	Both personal and in central upload stations	2.99	1.23

Table 22: Means and standard deviations for the eight implementation scenarios

Answer distributions

Mean scores can be obtained in different ways, so the distribution of responses among the different answer options was examined for a complete view of how respondents viewed each scenario. Especially as Table 22 showed variance to be relatively high for each scenario this is interesting to view. Figures 27-34 present this distribution in graphical form.

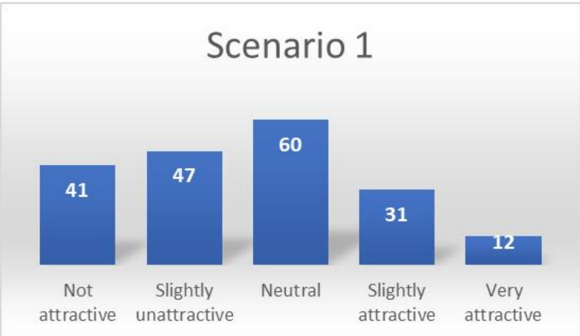

Figure 27: Answer distribution for scenario 1

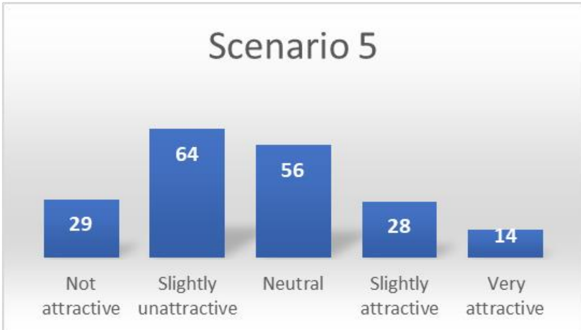

Figure 31: Answer distribution for scenario 5

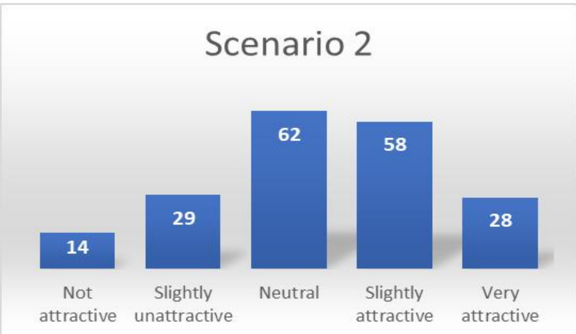

Figure 28: Answer distribution for scenario 2

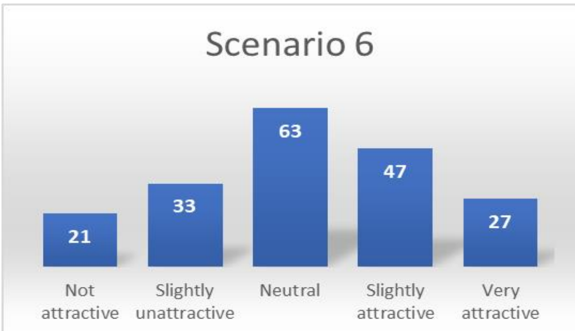

Figure 32: Answer distribution for scenario 6

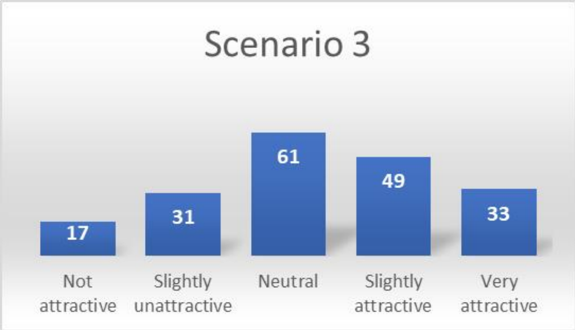

Figure 29: Answer distribution for scenario 3

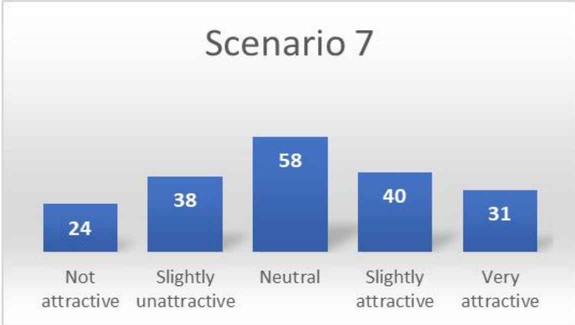

Figure 33: Answer distribution for scenario 7

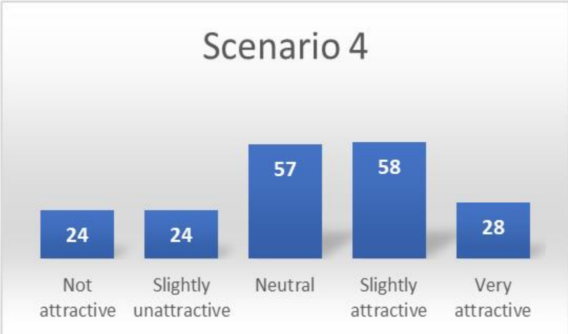

Figure 30: Answer distribution for scenario 4

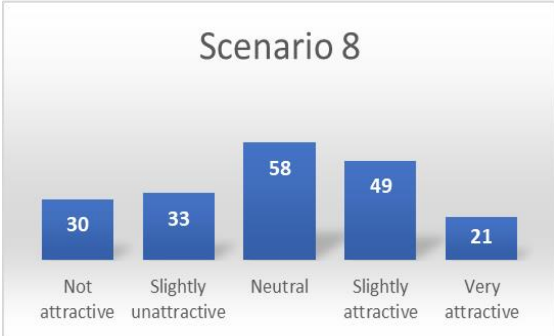

Figure 34: Answer distribution for scenario 8

Statistical differences from the neutral score

Since Table 22 showed all scenarios to score close to the neutral score, a series of t-tests was done to verify whether each mean differed significantly from this score. That indicates whether customer actually rated a scenario as attractive or unattractive. T-tests showed that this was the case for scenarios 1-5 only, whereas scenarios 6-8 did not show a statistically significant difference from the neutral score. Table 23 presents the results of this series of t-tests.

Scenario	Scenario mean	Scale mean	T-statistic	p-value
1	2.61	3	-4.566**	< 0.001
2	3.30	3	3.685**	< 0.001
3	3.26	3	3.052**	0.003
4	3.22	3	2.500*	0.013
5	2.65	3	-4.239**	< 0.001
6	3.14	3	1.583	0.115
7	3.08	3	0.927	0.355
8	2.99	3	-0.118	0.906
*** p < 0.01, * p < 0.05*				

Table 23: T-test results for each scenario against the scale mean (N = 190)

Group level analysis

The scenarios were divided in two groups for the analysis, based on the key recorder distribution method. Scenarios 1-4 formed the personal key recorder group, and scenarios 5-8 the central upload station group. Each group contained all four options of indicating in-car delivery preferences. At group level, the first group scored 3.10 on average, and the second group 2.97. While this implies that having personal key recorders only is more attractive to customers than having central upload stations, a t-test showed this difference to be non-significant (t = 1.338(190), p = 0.182). Moreover, the means of both the personal key recorder group (t = 1.489(190), p = 0.138) and the central upload station group (t = -0.463(190), p = 0.644) did not differ significantly from the neutral score.

Individual level analysis

Next, each scenario was tested against its counterpart in the other group, with the same method of indicating in-car delivery preferences. Table 24 shows that for none of these combinations a statistically significant difference was reported between the personal key recorder group and the central upload station group. Together with the group level analysis this indicates that customers in this study did not seem to prefer one key recorder distribution method over the other.

Scenario with personal key recorder	**Personal key recorder scenario mean score**	**Scenario with central upload stations**	**Central upload station scenario mean score**	**T-statistic (degrees of freedom)**	***p*-value**
1	2.61	5	2.65	-0.356 (379)	0.722
2	3.30	6	3.14	1.374 (379)	0.170
3	3.26	7	3.08	1.428 (379)	0.154
4	3.22	8	2.99	1.843 (380)	0.066
*** p < 0.01, * p < 0.05*					

Table 24: T-test results between scenarios and their counterpart in the other key recorder distribution group

Personal key recorder scenarios				***Central upload station scenarios***			
Scenario 1 (mean)	**Scenario 2 (mean)**	**T-statistic (df)**	***p*-value**	**Scenario 1 (mean)**	**Scenario 2 (mean)**	**T-statistic (df)**	***p*-value**
1 (2.61)	2 (3.30)	-5.847** (379)	< 0.001	5 (2.65)	6 (3.14)	-4.065** (379)	< 0.001
1 (2.61)	3 (3.26)	-5.381** (380)	< 0.001	5 (2.65)	7 (3.08)	-3.527** (376)	< 0.001
1 (2.61)	4 (3.22)	-4.969** (380)	< 0.001	5 (2.65)	8 (2.99)	-2.780** (377)	0.006
2 (3.30)	3 (3.26)	0.311 (379)	0.756	6 (3.14)	7 (3.08)	0.420 (379)	0.675
2 (3.30)	4 (3.22)	0.657 (377)	0.512	6 (3.14)	8 (2.99)	1.186 (380)	0.236
3 (3.26)	4 (3.22)	0.341 (380)	0.733	7 (3.08)	8 (2.99)	0.744 (380)	0.458
*** p < 0.01, * p < 0.05*							

Table 25: T-test results for scenarios within both key recorder distribution groups

Scenario 1 (mean)	**Scenario 2 (mean)**	**T-statistic (df)**	***p*-value**	**Scenario 1 (mean)**	**Scenario 2 (mean)**	**T-statistic (df)**	***p*-value**
1 (2.61)	6 (3.14)	-4.333** (380)	< 0.001	3 (3.26)	5 (2.65)	5.133** (379)	< 0.001
1 (2.61)	7 (3.08)	-3.800** (378)	< 0.001	3 (3.26)	6 (3.14)	1.035 (380)	0.302
1 (2.61)	8 (2.99)	-3.067** (379)	0.002	3 (3.26)	8 (2.99)	2.206* (380)	0.028

2 (3.30)	5 (2.65)	5.604** (380)	< 0.001	4 (3.22)	5 (2.65)	4.715** (378)	< 0.001
2 (3.30)	7 (3.08)	1.769 (375)	0.078	4 (3.22)	6 (3.14)	0.681 (380)	0.496
2 (3.30)	8 (2.99)	2.571* (377)	0.011	4 (3.22)	7 (3.08)	1.079 (380)	0.281
*** p < 0.01, * p < 0.05*							

Table 26: T-test results of the remaining combinations of scenarios not tested before

Next, different scenario combinations within each group were tested for statistically significant differences, as reported in Table 25. The main conclusion from this series of t-tests was that scenarios 1 and 5 scored significantly lower than the other scenarios within their group, while the other scenarios did not have statistically significant differences between them.

Finally, the remaining scenario combinations between the groups were tested, as reported in Table 26. The results were fairly similar to the previous tests, namely that scenarios 1 and 5 scored significantly lower than all other scenarios. Moreover, this series of t-tests showed that scenarios 2 and 3 scored significantly higher than scenario 8, making the latter the only other scenario that was significantly outranked by multiple other scenarios.

Expectations and results

Overall, the scenario analysis yielded the following conclusions. The results showed no significant differences in attractiveness between the scenarios with a personal key recorder and those with a central upload station, both on a group and an individual level. Moreover, within each of these distribution method groups, the non-flexible scenarios scored significantly lower than other scenarios. Finally, scenarios 2 and 3 significantly outranked scenario 8, making the latter the only scenario other than the non-flexible scenarios 1 and 5 that got outranked by multiple other scenarios, and scenarios 2 and 3 the only scenarios that significantly outranked other scenarios than the non-flexible ones. This made scenarios 2 and 3 the most attractive, and scenarios 1 and 5 the least attractive scenarios here.

5.3 Employee research: developing design principles for implementing in-car delivery

This final section of this chapter discusses the employee research. This section discusses the development of several design propositions based on literature, to guide companies in how to best implement in-car delivery from an employee perspective.

5.3.1 The starting point: conceptual research framework

The conceptual framework from Chapter 3 (see Figure 10) was the starting point for the design propositions. As this framework, with its proposed relationships, was the result of an extensive literature review on job design, it formed a valuable and strong basis for the design principles.

Job resources

A main insight from the literature review in Chapter 3 was that providing employees with sufficient job resources is an effective way of reducing the negative effects of high job demands. Moreover, job resources are thought to be stronger predictors of employee wellbeing, especially task and organizational commitment, than job demands (Bakker, Van Veldhoven, & Xanthopoulou, 2010).

Several job resources exist, such as social support, coaching, feedback (Bakker & Demerouti, 2014), having a good relationship with a supervisor, autonomy (Bakker, Demerouti, & Euwema, 2005), training, and rewards (Karatepe, Yavas, & Babakus, 2007). When job demands are high, which can be the case in delivering packages, especially during peak periods, having sufficient resources as a delivery employee is essential to reduce the chances of burnout (Crawford et al., 2010).

5.3.2 Provide employee training

Providing extensive training to employees would be a potentially useful job resource in this case, to familiarize them with the new technology. As having to deal with new technologies in the workplace might lead to so-called technostress and therefore higher job demands (Clark & Kalin, 1996), taking measures to mitigate this form of stress can have positive effects on for instance job satisfaction or commitment (Ragu-Nathan, Tarafdar, & Ragu-Nathan, 2008). These trainings could reduce these effects by making sure an employee knows everything about working with the technology and its safety during work.

Research showed that training could mitigate potential negative effects on employee job demands because training can enhance beliefs of self-efficacy (Schaufeli & Salanova, 2008). Self-efficacy is defined as the judgment of how well an employee thinks he or she can perform the actions required in a (work) situation (Bandura, 1982). This perceived self-efficacy is one type of personal job resource (Xanthopoulou et al., 2007), which has been tested to significantly predict work engagement (Prieto, Soria, Martínez, & Schaufeli, 2008). Following JD-R theory, this increased work engagement relates positively with work performance (Bakker & Demerouti, 2014), leading to the first design proposition:

Proposition 1: When delivery employees start working with new in-car delivery technology (C), provide extensive training to familiarize employees with the technology (I) to enhance employees' sense of self-efficacy (M), which likely relates positively to work performance (O).

5.3.3 Optimizing work hour scheduling

Training is not the only potentially useful resource in this situation. As section 5.1.3 discussed, logistic service providers could potentially utilize in-car delivery to increase network capacity without adding extra vehicles to their fleet, by opening extra delivery windows in the early morning or late night. This implies working hours for delivery employees could change as well, as these extra hours need to be worked as well. However, unusual and variable working hours, that include shift or night work, do not have a favorable effect on employees (Costa, Sartori, & Åkerstedt , 2006). These can be health effects such as deteriorated sleep patterns and associated health problems, but also in work performance since increased fatigue can increase human error during work activity (Harrington, 2001). These effects could be mitigated in several ways, such as with therapies, exercise, or by using devices or stimulants to improve wakefulness during night hours (Pallesen et al., 2010).

However, optimizing work hour scheduling would be more appropriate for this case. When this is done with shifts, three guidelines can be followed to mitigate negative effects of shift scheduling. These are using fast rather than slow shift rotation, forward rather than backward shift rotation, and increasing the amount of self-scheduling by employees (Bambra, Whitehead, Sowden, Akers, & Petticrew, 2008).

Using fast shift rotation means that all possible shifts (most likely morning, afternoon, and night) are worked by an employee within a short period of time. Its main advantage is that an employee's biological clock does not alter that much, which is positive for his or her health. However, it might lead to less predictable work schedules as shifts change rapidly (Monk, Folkard, & Wedderburn, 1996).

The direction of shift rotation can be forward (clockwise), and backward (counterclockwise). The forward shift rotation would be the preferred option here as research showed a backward rotation schedule to relate to poorer general health and greater need for recovery, while a forward rotation schedule related to less work-family conflict and better sleep quality (Van Amelsvoort, Jansen, Swaen, Van den Brandt, & Kant, 2004).

Finally, increasing self-scheduling by employees involves employees having more autonomy in deciding their own working hours. Pilot studies showed this can benefit both employee happiness and performance, although costs for the company could slightly go up as they might not follow the most efficient job scheduling (Gauderer & Knauth, 2004). Increasing this autonomy also connects to the well-known Job Characteristics Model (Hackman & Oldham, 1976), where autonomy is one of the key job characteristics to create motivating jobs. Therefore it can be seen as an important job resource to help employees cope with changed job demands. The above leads to the following design propositions:

Proposition 2: When work hours change because of the implementation of in-car delivery (C), schedule employee shifts by using a fast shift rotation schedule (I) because fast rotation has less detrimental effects on employees' biological clock than slow rotation (M), and therefore is likely to mitigate potential negative effects of changing work hours (O).

Proposition 3: When work hours change because of the implementation of in-car delivery (C), schedule employee shifts by using a forward shift rotation schedule (I) because forward rotation relates to better sleep quality and less work-family conflict than backward rotation (M), and therefore is likely to mitigate potential negative effects of changing work hours (O).

Proposition 4: When work hours change because of the implementation of in-car delivery (C), increasing self-scheduling of shifts by employees (I) enhances an employee's sense of autonomy in planning their job (M) and is therefore likely to mitigate potential negative effects of changing work hours (O).

5.3.4 Provide supervisor support and feedback

Providing extensive supervisor support and performance feedback to delivery employees would be additional resources in this case. Supervisor, or management support, refers to the extent to which employees feel that their supervisor shows concern for them and assists them in performing their job (Burke, Borucki, & Hurley, 1992). Research showed that when employees perceive this support as high, this positively relates to several personal and performance outcomes such as reduced stress and increased job satisfaction (Babin & Boles, 1996), as well as increased job performance (Shanock & Eisenberger, 2006). The idea underlying these positive relationships is that perceived supervisor support mitigates the negative effects of additional stressors by helping employees to better cope with these stressors (Schreurs, Van Emmerik, Günter, & Germeys, 2012). The latter is also reflected in the findings that supervisor support was especially important in high-demand work situations (Bakker & Demerouti, 2007; Harris, 2020), with a lot of stressors.

As in-car delivery drastically changes the current way of parcel delivery this certainly could provide additional stressors, especially with extended work hours. Therefore, it is recommended that LSPs focus on providing sufficient supervisor support for delivery employees working with in-car delivery. This could for instance be done by training (see proposition 1), but also by simply being there for employees when problems occur, or when they need help to improve their work performance. This lead to the following design proposition:

Proposition 5: When delivery employees get to work with in-car delivery technology (C), provide extensive supervisor support (I) as this support helps employees to better cope with additional or changed job demands (M), and is therefore likely to relate positively with employee performance (O).

Next to supervisor support, providing extensive performance feedback is an important resource. Feedback was identified as one of the core job dimensions in the JCM, where it was defined as the degree to which the employee receives direct and clear information about his or her performance in work activities (Hackman & Oldham, 1976). This feedback could both be coming from a co-worker or supervisor and from using the technology itself in the job (Hackman & Lawler, 1971). Either way, this theory posits that receiving sufficient feedback invokes the critical psychological state related to knowledge of results, which makes employees learn and as such, can improve performance and satisfaction (Hackman & Oldham, 1976), also by employee adaptation to work with the technology. The important role of feedback in predicting job performance was extended as such into the JD-R model, as the JCM job characteristics closely resemble the job resources in the JD-R model (Bakker et al., 2003). Indeed, feedback as a job resource was found to buffer for high job demands (Bakker et al., 2005). Moreover, Bakker et al. (2005) argued that feedback could improve the perceived employee-supervisor relationship, stressing the important role of performance feedback on its own, but also in relation to supervisor support. This lead to the following design proposition:

Proposition 6: When delivery employees start working with in-car delivery technology (C), provide regular and extensive performance feedback (I) as receiving sufficient feedback invokes a critical psychological state that facilitates employee learning and adaptation (M), and will therefore likely have a positive relationship with employee performance (O).

5.3.5 Implementing a psychological safety climate

Finally, logistic service providers should consider employee psychological safety when implementing in-car delivery. As Chapter 3 showed, this can be done by building a psychological safety climate (PSC). This PSC is defined as the individual perceptions of safety-related policies, practices, and procedures that affect personal well-being at work (Christian, Bradley, Wallace, & Burke, 2009). Research has shown that implementing a PSC can act as an additional type of job resource, to help employees to reduce the negative impact of changed or increased job demands on wellbeing or performance (Idris & Dollard, 2011). This can already have a positive effect because managers are likely to ensure more resources for their employees in general when they design high-PSC jobs (Dollard & McTernan, 2011).

It is important that logistic service providers consider this when implementing in-car delivery, as deliverers could be confronted with uncomfortable situations, especially in potential late night or early morning deliveries. An example would be a neighbor treating the deliverer badly during delivery because he or she is unfamiliar with in-car delivery and mistakes the deliverer for a car burglar. This could cause additional pressure or fear to the deliverer which can interfere with work performance. Moreover, deliverers could feel additional pressure to not do any harm to a customer's property and feel extra risk in doing their work. When in such cases the deliverer believes to job to have a high level of PSC, the negative impact of risk perceptions (leading to additional job demands) on job satisfaction and performance is lower than without this PSC (Nielsen et al., 2011).

The development of a PSC is comprised of four main areas: senior management involvement and commitment, management priority to psychological health and safety, good organizational communication, and organizational participation and involvement (Hall, Dollard, & Coward, 2010). Therefore, these are also the areas in which interventions can be taken to increase PSC levels in the delivery job. An earlier intervention, increasing supervisor support, also applies here, as investing in the employee-supervisor relationship increases the feeling of psychological safety (May et al., 2004). However, the key intervention to achieve high levels of PSC in the job is extensive involvement and commitment by senior managers and developing clear and easy procedures, policies, and practices (Dollard & Bakker, 2010). Then, if deliverers have concerns they can feel the freedom to discuss their problems within the company, such that fast action can be taken to resolve the problems (Nguyen, Teo, Grover, & Nguyen, 2017). This lead to the final design proposition:

Proposition 7: When employees get to work with in-car delivery technology (C), establish clear policies and procedures regarding employee psychological safety with full commitment from management (I) to increase an employee's sense of psychological safety within their work environment (M), which is likely to positively relate to employee wellbeing and performance (O).

Chapter 6: Research conclusions

This chapter presents the most important research conclusions from the previous chapter, structured along the research questions from Chapter 2. First, section 6.1 discusses the conclusions from the logistics research, before section 6.2 does the same for the customer research. Finally, section 6.3 presents the main conclusions from the employee research.

6.1 Conclusions logistics

This section presents the most important conclusions from the logistics research by answering the six research questions for this part. The logistics research implemented a VRP in programming software to evaluate 25 customer instances in terms of several routing indicators, such as costs, distance and travel time to answer these research questions.

The first research question was what the savings potential of allowing multiple delivery locations per customer could be. The results indicated that there was savings potential, although it was rather small in general. The positive exception was a 24% cost reduction in the 30-customer set, while the other four customer sets reported cost savings potentials between 2,4% and 14,1%.

The second research question asked the same, but then for allowing multiple delivery time windows. In this scenario the cost savings potential was more substantial than in the first scenario, with an average cost savings potential of around 30%. The two smallest customer sets reported the biggest (50%) and smallest (14,8%) savings, while the three biggest customer sets (30, 40, and 50 customers) all scored around the average, with potential savings of 31,8%, 30,4%, and 24,1%, respectively.

The third research question looked at the combined scenario, where customer delivery options differed both in location and time window. This scenario reported the biggest cost savings potential, with an average saving of 33,4%. The image was similar to the second scenario, in that the smallest customer sets reported the biggest (55,1%) and smallest (16,4%) savings, while the three largest customer sets all scored around the average with potential savings of 31,8%, 33,5%, and 30,4%, respectively. Moreover, combining the results of these three scenarios lead to the conclusion that flexibilization of the delivery time windows, on its own and combined with flexibilization of delivery locations, contributed more to savings potential than just allowing for multiple delivery locations.

The fourth research question examined the same three scenarios, but for distance and travel time. This showed a similar savings potential image. Having multiple locations with fixed time windows had the lowest potential, with an average distance saving of 6,2% and time saving of 8,5%. The opposite scenario, with fixed locations and multiple time windows, already had much more savings potential: on average 16,7% in distance and 25,1% in travel time. Finally, the combined scenario of multiple locations and multiple time windows reported the biggest savings, with an average of 21,1% in distance and 28,5% in travel time. Moreover, in the last two scenarios, waiting time because of early arrivals to customer locations was (nearly) completely eliminated.

Next, the fifth research question looked at the number of stops per route. The interesting conclusion here was that in general, allowing for multiple potential delivery locations resulted in a decreasing number of unique locations at which deliveries were made. However, at the same time, the number of stops did not decrease with that, most likely because time windows of the different customers at that location did not match. Therefore, these deliveries could not be combined into one stop. On the other hand, when time windows were flexible, the opposite effect was observed, where the number of unique locations did not decrease, but the number of stops did. Therefore, it was concluded that the most important factor in being able to combine deliveries is to not just focus on location, but rather on flexibility in delivery time window.

Finally, the last research question asked whether in-car delivery could be used to extend network capacity by opening additional delivery windows outside the current planning horizon. While the small scale and set-up of the research made it difficult to draw hard conclusions, an estimation was made based on the minimum number of vehicles used to perform all routes in the final solutions. This estimation could then be used in further research. The results showed that extending the daily planning horizon from 12 to 16 or even 20 hours did not negatively impact the number of vehicles needed to perform all routes. This number stayed the same in 40% of the instances, and decreased in the other 60%. In none of the instances this number increased. In the 60% where the number decreased, this saved vehicle would become available to serve additional customers, which could extend network capacity. Therefore, without being able to draw hard conclusions, this indicates that using in-car delivery to extend the daily planning horizon could help LSPs to extend their network capacity without adding additional vehicles to their fleet.

6.2 Conclusions customer research

This section presents the main conclusions from the customer research, by answering the four main research questions for this part.

The first question asked what main factors influence customer adoption of new technologies. The research investigated this by means of the Technology Acceptance Model (TAM). The research confirmed the proposed relationships of this model that indicated a positive relationship between perceived usefulness of the technology and a potential user's intention to adopt it. Moreover, the perceived ease of use of the technology positively related to the perceived usefulness. Ease of use on its own was not tested to significantly relate to behavioral intentions. Finally, these behavioral intentions had a strong positive relationship with predicted actual use. Therefore, the main factors in this research influencing the adoption decision were found to be perceived usefulness and, to lesser extent, perceived ease of use of the innovation. Currently, the research results showed that within this respondent sample, both perceived usefulness and ease of use received high mean scores, meaning that overall, respondents were positive about this. However, both scores came with relatively high variance, indicating quite some division between different respondents. Therefore, it can be concluded that quite some customers still have to be won over in terms of the perceived value of in-car delivery over conventional methods.

However, these were not the only factors identified. The second research question investigated the role of trust in the customer adoption of new technologies such as in-car delivery. For the research, three dimensions of initial trust were investigated, namely perceived integrity, perceived benevolence, and perceived ability. The results showed that initial trust comprised of these dimensions significantly and positively related to adoption intentions. However, the strength of this positive relationship was smaller than the aforementioned factors of perceived usefulness and ease of use. Therefore this implies that trust does seem to play a positive role in customer adoption decisions for innovations, but in our sample it was relatively less important than the aforementioned factors. Overall, in the current sample respondents gave high scores for this initial trust, with relatively low variance. Therefore, it was concluded that based on the current sample, initial trust in the technology was not the biggest issue for potential customers towards adopting in-car delivery.

The third research question examined the other side of the medal, namely which barriers might cause customers to refuse an innovation. Several barriers were considered from literature, namely value, risk, tradition, and image barriers. In the final model, only the value and image barriers could be tested in the current study, of which only the value barrier related significantly (negative) with behavioral intentions. This implies that customers are less likely to consider adoption of in-car delivery when they do not see the added value of it as compared to existing alternatives.

The final research question was about the preferred mode of access to in-car delivery for consumers. This was investigated through the scenario analysis in which respondents rated eight different usage scenarios. The main results from this analysis were that scenarios with low flexibility were scored significantly lower than the other scenarios. Most other scenarios did not differ significantly from each other, just like results showed an indifference in the customer sample between having personal key recorders and central upload stations. Therefore, no hard conclusions could be drawn to favor either of those distribution methods. Finally, results showed that customers scored the personal key recorder scenarios with flexibility and with the in-car delivery function integrated into the retailer app significantly better than having central upload stations with a delivery date day schedule to fill in. This adds to a general conclusion that customers seemed to favor flexibility when it comes to adopting in-car delivery. The fact that having to fill in a delivery date day schedule for using in-car delivery was scored significantly higher than the non-flexible scenario suggests that flexibility is a bigger issue for the respondents in our sample than putting in some extra effort. However, the last finding that scored the delivery date day schedule combined with going to a central upload station lower than other scenarios suggests that there also is a limit on the amount of extra effort customers are willing to make to use in-car delivery.

6.3 Conclusions employee research

Finally, this section discusses the main conclusions from the employee research by addressing the three research questions from Chapter 2 on this part.

The first research question addressed the changes in-car delivery had on employee's job characteristics and work environment. In doing this, JD-R theory and psychological safety climate theory was consulted. In general, based on the problem description, it was concluded that in-car delivery most likely changes employees' job characteristics and demands in several ways. When they get to work with in-car delivery, this entails learning to work with a new technology, and also adapting to a new work routine. This could be difficult for delivery employees. Moreover, if LSPs decide to utilize in-car delivery to enable overnight deliveries, working hours could change, which might negatively influence employee health. Additionally, when working at night, unsafe situations might occur when deliverers open a customer's car and are for instance mistaken for a burglar by an unknowing neighbor. Therefore, the job and its environment could change a lot after implementing in-car delivery.

The second research question focused on solutions to mitigate potential negative effects of these changed job demands. To this end, a set of design propositions was developed in a context-intervention-mechanism-outcome (CIMO) structure, on the basis of scientific literature. First, it was proposed that employees should receive extensive training on the technology to get acquainted to it faster, and in this way feel more comfortable using in-car delivery on the job. Next, to mitigate the potential negative effects of overnight deliveries on employee health, it was proposed that fast, forward rotating shift schedules are used when implementing these overnight deliveries. Moreover, to increase employee autonomy in the job, self-scheduling of shifts was proposed. Finally, it was proposed to provide employees with sufficient resources to be able to learn to master the new technology by providing extensive performance feedback. Together with this, making sure that employees experience a sufficient degree of supervisor support can help to make them feel more comfortable, and happier in their work.

Finally, the main measures that were proposed regarding safety related to the implementation of a psychological safety climate. This can be established by implementing a clear, comprehensive, and coherent set of policies and practices regarding employee psychological safety. These policies should make clear what an employee should do in case of an unsafe work situation, who can be contacted, and what can be done to resolve such a situation. Moreover, it is essential that these policies are implemented with full commitment from management, such that employees feel the support of the employer. This way, an employee can feel safer when performing his or her job, knowing that in case of a bad work situation, he or she can count on the company.

Chapter 7: Discussion, implications, and practical recommendations to stakeholders

This chapter brings the three research fields together and discusses them generally. Moreover, the chapter discusses the theoretical and practical implications of the study, as well as its limitations and potential avenues for future research. Finally, a set of practical recommendations to stakeholders is presented for guiding a large-scale implementation of in-car delivery. The rest of the chapter is structured as follows. Section 7.1 presents a general discussion that combines the different research fields. Then, section 7.2 discusses the theoretical implications for all research fields, before section 7.3 presents the practical implications. Next, section 7.4 briefly discusses the research limitations, as well as opportunities for future research. Finally, section 7.5 presents recommendations to stakeholders.

7.1 General discussion: integrating the three research fields

A large-scale implementation of a rather radical innovation such as in-car delivery is a challenge, with multiple stakeholders. Therefore, this research tried to identify the critical success factors to such an implementation by presenting a multi-angle review, that investigated the opportunities and challenges for the three most important stakeholders: LSPs, customers, and delivery employees. By integrating the interests of these three stakeholder groups, a holistic overview of potential chances and pitfalls was developed such that the interests of each group were taken into account.

Clearly, the main advantages of this technology are for the LSPs and the customers. For the first, it enables more (cost-)efficient routing and the potential to sustainably increase network capacity. For the customers, in-car delivery can provide increased comfort by having parcels delivered wherever and whenever they want, as long as the car is available for delivery.

However, with these advantages also come challenges that cannot be overlooked, in which all these stakeholders interconnect. When the LSP wants to implement in-car delivery for its customers to obtain its savings potential, the actual savings potential depends heavily on customer willingness to adopt in-car delivery. Moreover, LSP planning departments could create very efficient routes and increase network capacity, but they will need the manpower to execute this new network design. If the effects of in-car delivery on employees is not taken into account here, the logistics savings potential could be largely undone by loss in employee productivity and happiness.

The same applies to potential customer advantages. Whether a customer actually fully experiences the potential advantages of in-car delivery depends on its implementation form, but also whether the customer actually sees its value. Furthermore, customers should feel secure about the service and trust that the delivery employees know how to work with the technology, such that no harm to private property is caused. All these interconnected interests make a successful large-scale implementation complex, and the goal of this research was to dive into this complexity.

The research results provided more clarity in what critical success factors can contribute to successfully implement in-car delivery and unlock its full potential, despite the complexity. The results indeed showed a significant logistics savings potential when in-car delivery was utilized to give customers multiple potential delivery options. These savings occurred at all levels, such as in costs, distance, and travel and waiting time, but also in the average number of stops per route. This directly influences the work experience of delivery employees, where a potential increase in job demands from using new technology could be partially reduced by lower physical job demands. The latter would be the result of having less stops on a route, which reduces the necessity to hop on and off the vehicle.

The customer research showed potential enthusiasm about in-car delivery and its advantages, but also made clear that much work is still to be done. The results showed that customers see potential value, given the high survey scores on for instance perceived usefulness. Moreover, the mean score on behavioral intentions to use in-car delivery was relatively high. However, when asked for actual predicted use (how much respondents actually thought to use it when available), the scores dropped, signaling doubts to be taken away on this matter. Moreover, the scores on perceived usefulness, behavioral intentions, and predicted use came with high variance, which indicated quite some division among different respondents. This will definitely be something to still take into account.

While research showed perceived usefulness to be a predictor of customer adoption intentions, it is not the only one. The initial trust customers have in the service, as well as in the LSPs and delivery employees using it was shown to relate with adoption intentions. Building this trust, however, is not easy, as the strategic director of a German in-car delivery pilot experienced over the last years. According to him "the main learning of their in-car delivery project was that most response to in-car delivery came from people who were already familiar with keyless entry techniques, because their car manufacturer already used it for mobile repairs and the like. This way, they were already educated by the car manufacturer to use these techniques, and without this education it was very challenging for third-party service providers to reach customers and make them enthusiastic about in-car delivery" (R. Wegener, personal communication, 6-11-2020). This was also reflected in the customer survey, where a few respondents left an additional comment about their doubts in trusting such a service. Together with the division among respondents on in-car delivery usefulness, adoption, and usage intentions, this implies that a lot of work still has to be done to convince customers to switch to in-car delivery.

As mentioned earlier, one necessary factor to unlock the full potential of in-car delivery for customers is to choose the correct implementation form. The way customers have access to in-car delivery should match the way potential customers see its value as compared to conventional delivery. In the scenario analysis, it appeared that the main important factor was flexibility. Moreover, the extra effort needed to make use of in-car delivery should be limited. However, this directly conflicts with the LSP interest of efficient planning, as more customer flexibility can lead to more complex route planning. This implies a balance should be found between both interests. This could for instance be done by allowing customers to enter multiple potential delivery locations and time slots, such that the LSP can pick the most convenient one, like in our logistics research. This way, the burden and the advantages of allowing extra flexibility is divided between both parties.

While efficient routing might be a good solution for the LSP, it cannot ignore the employees that have to execute these routes. Therefore, when implementing in-car delivery LSPs should also take their interests into account, to actually realize the savings potential of in-car delivery. As mentioned earlier, trust was an important issue for several respondents in the customer survey. Their main concerns related to the trustworthiness of the employee, as he or she could potentially have access to customer possessions when opening the car. Here the three areas connect again. For LSPs to obtain the benefits of in-car delivery, customers should adopt it, and for them to adopt it, employees should behave trustworthy and responsible. Therefore, it is absolutely essential for employers to make their delivery employees familiar with the technology, and do everything to make them behave responsibly. Without this specific attention, implementing in-car delivery successfully is less likely.

Finally, the research showed that taking a decision that benefits one stakeholder can influence what needs to be done for other stakeholders. One example of this is the potential decision of LSPs to use in-car delivery to extend network capacity by extending the planning horizon to include late night and/or early morning deliveries. If this decision is taken this would benefit the LSP as more parcels could be delivered with the same amount of vehicles. However, then a night shift has to be worked by delivery employees, and the employee research showed that these should be implemented very carefully to mitigate any negative effects on employee health and productivity. Another example would be increasing the level of flexibility in adjusting delivery options for consumers. When flexibility is increased for customers this means more comfort and value for them, but it would make efficient route planning for LSPs more complex.

All in all, this discussion shows that the three research areas cannot be seen separately. To successfully implement in-car delivery in a mass market, all three perspectives should be taken into account. After all, the research and its implications show that the benefits for one party cannot be achieved without full focus on the perspective of the other stakeholders as well.

7.2 Theoretical implications

This study has several theoretical implications. In general, it adds to scientific literature as a unique combination of three research fields, combining logistical routing with customer adoption and job design theories. However, contributions are also made to these individual fields.

When it comes to logistics research, this thesis adds to the scarce literature on the young subfield of the VRPRDL. Its approach comes closest to the study by Reyes et al. (2017), although the current study was more limited in terms of for instance the size of customer instances. However, the current study still adds to this young variant of the VRP by confirming the savings potential of multiple delivery options as compared to the traditional VRPTW, where customers only have one delivery option. The choice of modeling the routing problem with delivery options also connects to the generalized VRPDO (Tilk, Olkis, & Inrich, 2020), on which literature is even more scarce than on the VRPRDL. Finally, this research contributes in analyzing several degrees of flexibility, by analyzing and comparing all combinations of fixed and flexible locations and time windows.

For the customer research, its main contribution is that it unites three different theories into one conceptual framework. These include the TAM (Davis, 1985), consumer trust theory (e.g. Gefen & Straub, 2004), and innovation resistance theory (e.g. Ram & Sheth, 1989). By combining these three theories into one framework, this study offers a comprehensive overview of reasons customers would accept or reject innovations, and how these together determine the behavioral intentions of the customer. While several studies have integrated trust into models of customer adoption (e.g. Gefen et al., 2003; Pavlou, 2003; Gao & Waechter, 2017), as well as integrated innovation resistance into TAM (e.g. Lee, 2013; Oh, Park, & Min, 2019), to the best of our knowledge no literature exists that integrated all three into one framework.

Finally, the employee research adds to the field by analyzing job design theories in a context of parcel delivery, which has not been done so far to the best of our knowledge. While the JD-R theory has not been tested quantitatively in this study, its insights from existing literature have been applied to form design propositions in this new context. Even though practical validation of the design propositions by delivery employees was not possible due to the Covid-19 pandemic, this is still a first step towards applying JD-R theory in a different context.

7.3 Practical implications

The research also has some practical implications for managers wanting to innovate their parcel delivery execution by implementing in-car delivery. The main practical implication is that they need to be careful and take a multiple-stakeholder perspective, to maximize the chances of successful implementation, as this research showed that the interests of these stakeholders can interact. For logistics managers, this research showed how having multiple potential delivery options per customer can yield substantial savings in costs, distance, and execution time of the delivery network. This especially is the case when customers are allowed to have multiple potential delivery time windows, both at one fixed location and across multiple locations. Moreover, it showed that in-car delivery can potentially be used to sustainably expand network capacity. This extension of network capacity could happen both by the shorter occupancy time of existing vehicles due to more efficient routing, or when in-car delivery is utilized to open additional delivery windows outside regular delivery hours. However, the latter is an indication, as the research did not allow for firm conclusions so far.

For the technology developers, the research has several implications if they want to maximize the chances of a successful product adoption. First, they should focus on promoting the value of in-car delivery as compared to other delivery methods to customers, such that the value barrier is eliminated and the customer perceives the service as useful. The research showed that perceived ease of use of the service was a strong predictor of perceived usefulness. This could either be achieved by focusing on the usability of the service itself, such as having an easy-to-use user interface, but a stronger antecedent to this perceived ease of use might be users' technology self-efficacy, as Venkatesh and Davis (1996) found this self-efficacy to be a significant predictor of ease of use. Therefore, effort could be spent on a combination of making the service itself easy to use, as well as on stimulating the beliefs of potential customers that they are able to use technological innovations like in-car delivery. Another important implication for the technology developers is that significant effort should be spent into generating a sufficient level of initial trust with customers, in both the service and those using it. Its security should be clear, potential customers should be made aware that under normal circumstances no harm is done to their private property when using in-car delivery. One method of using that would be to use a third-party person or institution that is considered trustworthy to recommend the service as being trustworthy as well. Using such a third-party guarantee can enhance trust in a service like in-car delivery (Beldad, De Jong, & Steehouder, 2010).

Finally, the research yielded several practical implications for managers of delivery employees. The design propositions mainly focused on mitigating potential negative effects of changed job demands on employee outcomes by providing several resources to allow employees to cope with the changes in their work situation because of in-car delivery. The research found training as a main resource, as it allows employees to get acquainted with the technology to be able to work with it securely and safely. It would make them more comfortable in using the app and opening customer cars in a safe and responsible manner. Additionally, when employees start using the technology, managers should provide extensive performance feedback, such that employees know how they are performing. Finally, managers should pay attention to the psychological safety of employees, as delivering in customer cars could potentially lead to tense situations with for instance concerned neighbors, mistaking it for burglary.

7.4 Limitations and future research

This section discusses several limitations to be taken into account when interpreting the results. One general limitation on this project was the impact of the COVID-19 pandemic, which made research execution challenging. However, this impact was minimized by timely adjusting some research set-ups. Next, some research-specific limitations, as well as avenues for future research, are discussed.

First of all, in the logistics research, the test instances were rather small. As the main focus of this research was not on building a state-of-the-art routing algorithm, combined with the limited time availability, the current instance sizes were the maximum number of customers for which all different analyses could be done within a reasonable amount of time. This means that the conclusions drawn from this research should be interpreted with care when it comes to larger customer sets. This mainly applies to the second part of the analysis, where the effect of in-car delivery on network capacity was analyzed. Because of the research set-up, hard conclusions on the effect of extended planning horizons on network capacity cannot be made. In future research, it could be interesting to further examine these potential effects by performing analysis based on a shift schedule. In such a research, a set of vehicles could be assigned to certain shifts with their time limits, with a different driver assigned to drive the vehicle each shift. Moreover, following Reyes et al. (2017), robust planning of in-car delivery routes, as well as using real-time data to dynamically adjust routing are two interesting avenues for future research.

In the customer research, the main limitation was the sample size. While the sample size of 191 was appropriate for the final regression analyses, it was not sufficient for building a reliable structural equation model as intended. Therefore, not all relationships could be tested at once, but rather in groups, thereby maybe omitting some additional interaction effects a structural equation model would take into account. Therefore, future research could be done with more respondents in the form of a structural equation model. Despite this, the sample was relatively diverse, with people from multiple ages and provinces represented. However, a slight level of bias might be included as the survey was distributed via online channels. This implies that some people that were not reachable in this way might be excluded in the sample. However, it should be noted that these people are then also less likely to shop online, and therefore be part of the target group. An interesting opportunity for future research is to further explore the interactions between technology acceptance and trust on the one hand, and resistance barriers on the other. To the best of our knowledge, this three-way interaction has not been investigated as such so far, while reasons for innovation resistance are important to take into account when talking about customer innovation adoption. Moreover, as an additional route for future research, the identification of several types of customer groups based on their likelihood to adopt in-car delivery could be investigated, following the idea of innovation diffusion theory. This theory distinguishes between innovators, early adopters, early majority, late majority, and laggards when it comes to the speed with which different customer groups adopt an innovation (Rogers, 2002). For each of these groups it could then be investigated how they can be reached, to increase the knowledge from a marketing perspective in an in-car delivery context.

Finally, the main limitation of the employee research was that JD-R theory could not be tested on delivery employees empirically. Due to the coronavirus pandemic, the pressure on parcel delivery networks, and especially the delivery employees, was very high. Therefore, unfortunately it was not possible to find an appropriate number of deliverers willing to take part in a survey or interviews. While the theoretical research and the resulting design propositions are based on a sound body of literature, this makes that the model has not been tested as such on a sample of employees to verify its validity in this context. This presents an interesting opportunity for future research, as JD-R has not been empirically verified in a parcel delivery context so far to the best of our knowledge.

7.5 Practical recommendations to stakeholders

Finally, to conclude this chapter, the main results of this research are converted into a set of practical recommendations to stakeholders, presented below.

- LSPs should offer customers the possibility to indicate several locations and time slots at which their car would be available for delivery. The minimum length of such a time slot might vary depending on the planning capabilities of the company. For planning complexity reasons, it is suggested to limit the possible number of options per customer to 5 based on this research, as the research results already showed computational efforts to increase substantially for larger instances with 5 options. Moreover, the results indicated that after the fourth option, in many cases adding a fifth option did not make a large difference as compared to 4 options.

- In offering in-car delivery to their customers, LSPs should make sure enough flexibility is available for customers to create sufficient value for in-car delivery as compared to other delivery modes, as the scenario analysis showed that non-flexible scenarios were rated significantly worse than other scenarios. However, a sweet balance should be found here between customer flexibility and planning capability, as increased flexibility in customer delivery options means increased dynamism in vehicle routing planning for the LSP. While research has been done on a dynamic variant of the VRPRDL (Ozbaygin & Savelsbergh, 2019), so far only a computationally relatively expensive exact method has been found to solve this, increasing planning complexity as compared to the basic scenario with static information.
- When LSPs offer multiple delivery options per customer and pick the most convenient one for delivery, it is recommended that this chosen time slot is communicated to the customer as soon as possible, if possible already the night before delivery. This way, customers can adjust their time planning optimally to the delivery moment and make sure the car is at the right place at the right time. This would also contribute to LSPs First Time Right score as it is logical that when customers have more time to adjust their plans to the delivery window, the probability of them (or at least their car) being present during the delivery window is higher.
- In selling the technology to customers, the technology developers should do everything to stress the additional customer value created by in-car delivery. This can be done by focusing on the comfort and additional flexibility it offers, to have your parcel delivered any place, any time. Moreover, as part of this, the focus should be on showing the usability of the application, such that customers perceive relatively lower adoption barriers, as the research results showed that perceived usefulness and ease of use positively related to adoption intentions, and that adoption (value) barriers negatively relate to these adoption intentions. Following Venkatesh & Davis (1996), promoting ease of use should not just be done by spending effort on the user interface and usability of the service, but also by enhancing potential customers' beliefs that they are able to use such a technological innovation, for instance by training.
- LSPs and the technology developers should work together with car manufacturers to seek educating potential customers in using keyless entry techniques. When the car manufacturer for instance uses these techniques to perform mobile repairs to the car, the customer gets acquainted more easily with the idea of someone else utilizing these techniques to enter their car. This might educate potential customers and lower the barrier to switch to in-car delivery (R. Wegener, personal communication, 6-11-2020).
- Substantial effort should be put into building initial customer trust with the technology. An important aspect of this is familiarizing customers with the safety and security of the technology, as literature showed this to be an important antecedent to building consumer trust (e.g. Koufaris & Hampton-Sosa, 2004). One potential method of doing this is by using a third party. When using a third-party guarantee, trust in the service can be enhanced by using a well-known person or institution considered trustworthy to recommend the service as being trustworthy as well (Beldad et al., 2010). An example of such a third-party guarantee would be to make a well-known and trusted technology institution, expert, or influencer familiar with all the ins and outs of the technology, such that he or she considers it to be trustworthy. Then this third party can, in turn, provide this 'trustworthiness stamp' for the service towards a large-scale audience to increase their initial trust in the service.
- Employers of delivery employees should provide extensive training to them before starting to use in-car delivery, following the design proposition formulated based on literature. These

trainings should focus on the functioning of the technology, and how to quickly, safely, securely, and responsibly use it in actual parcel delivery. Employees should be made aware of their responsibility when using in-car delivery and offered explanation on how to deal with this additional responsibility without feeling additional pressure.

- Employers of delivery employees should provide in extensive feedback and support from supervisors when starting to use in-car delivery. With this feedback, a delivery employee can actively track how he or she is performing using the new technology and what can still be improved. Especially at the beginning it is recommended that this feedback is more frequent, as employees are still getting used to working with in-car delivery, and this feedback invokes the psychological state of knowledge of results, facilitating the learning and adaptation to working with the new technology, which is related to improved performance and satisfaction (Hackman & Oldham, 1976). This also applies to the supervisor support, such that employees can report back to someone within the company as soon as they need any help and feel that they have a good relationship with this supervisor, as the design propositions derived.
- Employers of delivery employees should put in place clear protocols, procedures, and guidelines for psychological safety, as the employee research found. Concretely this means that these procedures should make clear to employees what support is available in case of a difficult work situation as a result of in-car delivery, and who they can contact. This way, employees can feel more secure during performing the delivery work. This is especially important when in-car delivery is used to facilitate overnight deliveries, as at night the chances of unsafe work situations are higher.
- When in-car delivery is used to facilitate late night or early morning deliveries, employers of delivery employees should implement fast, forward rotating shift schedules to mitigate as much negative health effects of shift and night work as possible. This way, additional delivery hours can be staffed adequately while the negative health effects of working these hours are mitigated, as the research found. Moreover, employers should give their delivery employees some extent of autonomy in self-scheduling their shifts. This way employees are more likely to be happy with their new work routine, likely relating with better performance as well.

Chapter 8: Final conclusions

This final chapter briefly presents the final conclusions of the research by answering the general, main research questions.

The research investigated the critical success factors for implementing in-car delivery from three perspectives: logistics, customer, and delivery employee. As the previous chapter showed, these areas are interconnected in determining a successful implementation for in-car delivery.

The first main research question was what the savings potential of in-car delivery was as compared to conventional parcel delivery. This research looked at in-car delivery as an enabler of having multiple potential delivery locations per customer. When in-car delivery is implemented that way, its savings potential is substantial. The current research showed an average cost saving of 30%, with similar figures on distance and travel time savings. Moreover, waiting times were essentially eliminated from the routes when multiple delivery options were available. When the dataset is more realistic in terms of working hours and locations, a more accurate modeling of commuting behavior might even show further savings potential as more deliveries could be combined. Therefore, the main conclusion of this part was that implementing in-car delivery has substantial savings potential for LSPs.

The second main research question was how the technology developers could stimulate adoption among customers. The research integrated three theories to form an integrated framework of customer adoption of and resistance to innovation. The main stimulants to adoption resulting from this research were perceived usefulness and to some extent perceived ease of use. Moreover, initial trust towards the innovation and its users was found to be a stimulant of adoption. Additionally, the research concluded that customers are more likely to resist an innovation when they do not see the additional value of an innovation compared to current alternatives. Finally, the research indicated that adoption can be stimulated by offering flexibility to customers, while also making sure that not too much additional effort is needed to successfully start using in-car delivery.

The third and final main research question was what impact in-car delivery would have on employees both on a work and personal level. The main conclusion here was that in-car delivery is likely to influence employees because of changed job demands, which might make the job more difficult for them as the way of delivering parcels changes. The magnitude of this effect also depends on the form of implementation, as implementing in-car delivery to enable overnight deliveries has a bigger impact than only using it during current delivery hours. Possible negative effects include increased work pressure because of the new technology, an increased feeling of responsibility, and possible adverse physical and mental health effects when overnight deliveries are implemented. The research identified several job resources that could help employers to mitigate these negative effects on their employees. These resources include training, providing feedback, implementing a psychological safety climate, and optimizing work hour scheduling. These were formulated into several design propositions, serving as guidelines for managers that want to implement in-car delivery taking their employees into account.

List of references

ACM (2019, August 23). *Post- en pakkettenmonitor 2018.* Retrieved from ACM website: https://www.acm.nl/sites/default/files/documents/2019-08/post-en-pakkettenmonitor-2018.pdf, 25 February 2020.

Adams, D. A., Nelson, R. R., & Todd, P. A. (1992). Perceived usefulness, ease of use, and usage of information technology: A replication. *MIS Quarterly, 16*(2), 227-247.

Aken, J. E. V. (2004). Management research based on the paradigm of the design sciences: the quest for field-tested and grounded technological rules. *Journal of management studies*, *41*(2), 219-246.

Allen, J., Piecyk, M., Piotrowska, M., McLeod, F., Cherrett, T., Ghali, K., ... Wise, S. (2018). Understanding the impact of e-commerce on last-mile light goods vehicle activity in urban areas: The case of London. *Transportation Research Part D: Transport and Environment*, *61*, 325-338.

Amazon (n.d.). *Key, open anywhere: Conveniently turn your vehicle into a personal mobile locker.* Retrieved from: https://www.amazon.com/b?ie=UTF8&node=17051031011, 06 March 2020.

Anderson, J. C., & Gerbing, D. W. (1988). Structural equation modeling in practice: A review and recommended two-step approach. *Psychological bulletin*, *103*(3), 411-423.

Babin, B. J., & Boles, J. S. (1996). The effects of perceived co-worker involvement and supervisor support on service provider role stress, performance and job satisfaction. *Journal of retailing*, *72*(1), 57-75.

Bakker, A. B. (2015). A job demands–resources approach to public service motivation. *Public Administration Review*, *75*(5), 723-732.

Bakker, A.B., Demerouti, E., Taris, T.W., Schaufeli, W.B., & Schreurs, P.J.G. (2003). A multigroup analysis of the job demands-resources model in four home care organizations. *International Journal of Stress Management, 10*(1), 16-38.

Bakker, A. B., Van Veldhoven, M., & Xanthopoulou, D. (2010). Beyond the demand-control model. *Journal of Personnel Psychology, 9*(1), 3-16.

Bakker, A. B., & Demerouti, E. (2014). Job demands–resources theory. *Wellbeing: A complete reference guide*, 1-28.

Bakker, A.B., Demerouti, E., Hakanen, J.J., & Xanthopoulou, D. (2007). Job resources boost work engagement, particularly when job demands are high. *Journal of Educational Psychology, 99*(2), 274-284.

Bakker, A.B., Demerouti, E., & Euwema, M.C. (2005). Job resources buffer the impact of job demands on burnout. *Journal of Occupational Health Psychology, 10*(2), 170-180.

Bakker, A.B., & Demerouti, E. (2007). The job demands-resources model: state of the art. *Journal of Managerial Psychology, 22*(3), 309-328.

Bakker, A. B., & Sanz-Vergel, A. I. (2013). Weekly work engagement and flourishing: The role of hindrance and challenge job demands. *Journal of Vocational Behavior*, *83*(3), 397-409.

Balducci, C., Schaufeli, W. B., & Fraccaroli, F. (2011). The job demands–resources model and counterproductive work behaviour: The role of job-related affect. *European Journal of Work and Organizational Psychology*, *20*(4), 467-496.

Bambra, C. L., Whitehead, M. M., Sowden, A. J., Akers, J., & Petticrew, M. P. (2008). Shifting schedules: the health effects of reorganizing shift work. *American journal of preventive medicine*, *34*(5), 427-434.

Bandura, A. (1982). Self-efficacy mechanism in human agency. *American Psychologist, 37*, 122-147.

Beldad, A., De Jong, M., & Steehouder, M. (2010). How shall I trust the faceless and the intangible? A literature review on the antecedents of online trust. *Computers in human behavior*, *26*(5), 857-869.

Bertsimas, D. J. (1992). A vehicle routing problem with stochastic demand. *Operations Research*, *40*(3), 574-585.

Bräysy, O., & Gendreau, M. (2005). Vehicle routing problem with time windows, Part II: Metaheuristics. *Transportation science*, *39*(1), 119-139.

Burke, M. J., Borucki, C. C., & Hurley, A. E. (1992). Reconceptualizing psychological climate in a retail service environment: A multiple-stakeholder perspective. *Journal of applied Psychology*, *77*(5), 717-729.

CBS (2016, June 23). *Transport en Mobiliteit 2016.* Retrieved from CBS website: https://www.cbs.nl/nl-nl/publicatie/2016/25/transport-en-mobiliteit-2016, 20 February 2020.

CBS (2020, January 24). *Europese webwinkels zetten bijna 20 procent meer om in Nederland.* Retrieved from: https://www.cbs.nl/nl-nl/nieuws/2020/04/europese-webwinkels-zetten-bijna-20-procent-meer-om-in-nederland, 25 February 2020.

Chen, J., & Dibb, S. (2010). Consumer trust in the online retail context: Exploring the antecedents and consequences. *Psychology & Marketing*, *27*(4), 323-346.

Christian, M. S., Bradley, J. C., Wallace, J. C., & Burke, M. J. (2009). Workplace safety: a meta-analysis of the roles of person and situation factors. *Journal of Applied Psychology*, *94*(5), 1103-1127.

Clark, K., & Kalin, S. (1996). Technostressed Out? How to Cope in the Digital Age. *Library Journal*, *121*(13), 30-32.

Cordeau, J. F., Laporte, G., & Mercier, A. (2001). A unified tabu search heuristic for vehicle routing problems with time windows. *Journal of the Operational research society*, *52*(8), 928-936.

Costa, G., Sartori, S., & Åkerstedt, T. (2006). Influence of flexibility and variability of working hours on health and well-being. *Chronobiology international*, *23*(6), 1125-1137.

Crawford, E.R., LePine, J.A., & Rich, B.L. (2010). Linking job demands and resources to employee engagement and burnout: a theoretical extension and meta-analytic test. *Journal of Applied Psychology, 95*(5), 834-848.

Davis, F. D. (1985). *A technology acceptance model for empirically testing new end-user information systems: Theory and results* (Doctoral dissertation, Massachusetts Institute of Technology).

Dantzig, G., Fulkerson, R., & Johnson, S. (1954). Solution of a large-scale traveling-salesman problem. *Journal of the operations research society of America*, *2*(4), 393-410.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319-340.

De Jonge, J. (2017). Structural Equation Modeling Part 1: Introduction & CFA [PDF document].

Demerouti, E., Bakker, A.B., Nachreiner, F., & Schaufeli, W.B. (2001). The job demands-resources model of burnout. *Journal of Applied Psychology, 86*(3), 499-512.

Denyer, D., Tranfield, D., & Van Aken, J. E. (2008). Developing design propositions through research synthesis. *Organization studies*, *29*(3), 393-413.

Dishaw, M.T., & Strong, D.M. (1999). Extending the technology acceptance model with task-technology fit constructs. *Information & Management, 36,* 9-21.

Dollard, M. F., & Bakker, A. B. (2010). Psychosocial safety climate as a precursor to conducive work environments, psychological health problems, and employee engagement. *Journal of Occupational and Organizational Psychology*, *83*(3), 579-599.

Dollard, M. F., & McTernan, W. (2011). Psychosocial safety climate: a multilevel theory of work stress in the health and community service sector. *Epidemiology and psychiatric sciences*, *20*(4), 287-293.

Dumez, D., Lehuédé, F., & Péton, O. (2021). A large neighborhood search approach to the vehicle routing problem with delivery options. *Transportation Research Part B: Methodological*, *144*, 103-132.

Dumez, D., Tilk, C., Irnich, S., Lehuédé, F., & Péton, O. (2020). Hybridizing Large Neighborhood Search and Exacts Methods for Generalized Vehicles Routing Problems with Time Windows.

El-Sherbeny, N. A. (2010). Vehicle routing with time windows: An overview of exact, heuristic and metaheuristic methods. *Journal of King Saud University-Science*, *22*(3), 123-131.

Ellwood, P., Grimshaw, P., & Pandza, K. (2017). Accelerating the innovation process: A systematic review and realist synthesis of the research literature. *International Journal of Management Reviews*, *19*(4), 510-530.

Gao, L., & Waechter, K. A. (2017). Examining the role of initial trust in user adoption of mobile payment services: an empirical investigation. *Information Systems Frontiers*, *19*(3), 525-548.

Garcia, B. L., Potvin, J. Y., & Rousseau, J. M. (1994). A parallel implementation of the tabu search heuristic for vehicle routing problems with time window constraints. *Computers & Operations Research*, *21*(9), 1025-1033.

Garrick, A., Mak, A. S., Cathcart, S., Winwood, P. C., Bakker, A. B., & Lushington, K. (2014). Psychosocial safety climate moderating the effects of daily job demands and recovery on fatigue and work engagement. *Journal of Occupational and Organizational Psychology*, *87*(4), 694-714.

Gauderer, P. C., & Knauth, P. (2004). Pilot study with individualized duty rotas in public local transport. *Le travail humain*, *67*(1), 87-100.

Gefen, D., & Straub, D. (1997). Gender differences in the perception and use of e-mail: an extension to the technology acceptance model. *MIS Quarterly, 21*(4), 389-400.

Gefen, D., & Straub, D. (2003). Managing user trust in B2C e-services. *e-Service*, *2*(2), 7-24.

Gefen, D., Karahanna, E., & Straub, D. (2003). Inexperience and experience with online stores: the importance of TAM and trust. *IEEE transactions on engineering management, 50*(3), 307-321.

Gefen, D., & Straub, D. W. (2004). Consumer trust in B2C e-Commerce and the importance of social presence: experiments in e-Products and e-Services. *Omega*, *32*(6), 407-424.

Gendreau, M., Laporte, G., & Séguin, R. (1996a). A tabu search heuristic for the vehicle routing problem with stochastic demands and customers. *Operations research*, *44*(3), 469-477.

Gendreau, M., Laporte, G., & Séguin, R. (1996b). Stochastic vehicle routing. *European Journal of Operational Research*, *88*(1), 3-12.

Glover, F. (1986). Future paths for integer programming and links to artificial intelligence. *Computers & operations research*, *13*(5), 533-549.

Hackman, J.R., & Lawler, E.E. (1971). Employee reactions to job characteristics. *Journal of Applied Psychology, 55*(3), 259-286.

Hackman, J.R., & Oldham, G.R. (1976). Motivation through the design of work - test of a theory. *Organizational Behavior and Human Performance, 16*(2), 250-279.

Hair Jr., J.F., Black, W.C., Babin, B.J., Anderson, R.E. (2010). Multiple Regression Analysis. In Chapter 4 of *Multivariate Data Analysis, 7th edition* (pp. 151-230). London, Person Education Limited.

Hakanen, J. J., Bakker, A. B., & Schaufeli, W. B. (2006). Burnout and work engagement among teachers. *Journal of School Psychology*, *43*(6), 495-513.

Hakanen, J. J., Bakker, A. B., & Demerouti, E. (2005). How dentists cope with their job demands and stay engaged: The moderating role of job resources. *European journal of oral sciences*, *113*(6), 479-487.

Hall, G. B., Dollard, M. F., & Coward, J. (2010). Psychosocial safety climate: Development of the PSC-12. *International Journal of Stress Management*, *17*(4), 353-383.

Hall, G. B., Dollard, M. F., Winefield, A. H., Dormann, C., & Bakker, A. B. (2013). Psychosocial safety climate buffers effects of job demands on depression and positive organizational behaviors. *Anxiety, Stress & Coping*, *26*(4), 355-377.

Harrington, J. M. (2001). Health effects of shift work and extended hours of work. *Occupational and Environmental medicine*, *58*(1), 68-72.

Harris, E. G. (2020). Another look at frontline employee productivity propensity: a job demands–resources approach. *Journal of Marketing Theory and Practice*, *28*(3), 318-329.

Hawkins, A.J. (April 30, 2019). *Amazon expands in-car delivery service to Ford and Lincoln vehicles.* Retrieved from: https://www.theverge.com/2019/4/30/18523216/amazon-key-ford-in-car-package-delivery, 06 March 2020.

He, Y., Qi, M., Zhou, F., & Su, J. (2020a). An effective metaheuristic for the last mile delivery with roaming delivery locations and stochastic travel times. *Computers & Industrial Engineering*, *145*, 106513.

He, Y., Qi, M., Zhou, F., & Li, H. (2020b). Performance Analysis of Greedy-based Construction Heuristics on Classical Vehicle Routing Problem. In *2020 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)* (pp. 591-594). IEEE.

Heidenreich, S., & Spieth, P. (2013). Why innovations fail—The case of passive and active innovation resistance. *International Journal of Innovation Management*, *17*(05), 1350021.

Idris, M. A., & Dollard, M. F. (2011). Psychosocial safety climate, work conditions, and emotions in the workplace: A Malaysian population-based work stress study. *International Journal of Stress Management*, *18*(4), 324.

Jozefowiez, N., Semet, F., & Talbi, E. (2008). Invited review: Multi-objective vehicle routing problems. *European Journal of Operational Research, 189*(2), 293-309.

Kahn, W. A. (1990). Psychological conditions of personal engagement and disengagement at work. *Academy of management journal*, *33*(4), 692-724.

Karatepe, O. M., Yavas, U., & Babakus, E. (2007). The effects of customer orientation and job resources on frontline employees' job outcomes. *Services Marketing Quarterly*, *29*(1), 61-79.

Kaushik, A. K., Mohan, G., & Kumar, V. (2020). Examining the Antecedents and Consequences of Customers' Trust Toward Mobile Retail Apps in India. *Journal of Internet Commerce*, *19*(1), 1-31.

Kleijnen, M., Lee, N., & Wetzels, M. (2009). An exploration of consumer resistance to innovation and its antecedents. *Journal of economic psychology, 30,* 344-357.

Klomp, R. (2019). *In-car pilot results.* Electronic source presentation 2DEAL/Zalando/PostNL.

Klomp, R. (2020, February 14). Telephone interview with Richard Klomp on the current package delivery process at a big Dutch logistic service provider.

Kochan, C. G., & Nowicki, D. R. (2018). Supply chain resilience: a systematic literature review and typological framework. *International Journal of Physical Distribution & Logistics Management, 48*(8), 842-865.

Kontoravdis, G., & Bard, J.F. (1995). A GRASP for the vehicle routing problem with time windows. *ORSA Journal of Computing, 7*(1), 10-23.

Korunka, C., Kubicek, B., Schaufeli, W. B., & Hoonakker, P. (2009). Work engagement and burnout: Testing the robustness of the Job Demands-Resources model. *The Journal of Positive Psychology*, *4*(3), 243-255.

Koufaris, M., & Hampton-Sosa, W. (2004). The development of initial trust in an online company by new customers. *Information & management*, *41*(3), 377-397.

Kroeze, T. (2020, February 13). Telephone interview with Thijs Kroeze on the functioning of the 2DEAL technology.

Laporte, G. (1992). The vehicle routing problem: An overview of exact and approximate algorithms. *European journal of operational research*, *59*(3), 345-358.

Laukkanen, T. (2016). Consumer adoption versus rejection decisions in seemingly similar service innovations: The case of the Internet and mobile banking. *Journal of Business Research*, *69*(7), 2432-2439.

Laukkanen, P., Sinkkonen, S., & Laukkanen, T. (2008). Consumer resistance to internet banking: postponers, opponents and rejectors. *International journal of bank marketing*, *26*(6), 440-455.

Laukkanen, T., Sinkkonen, S., Kivijärvi M., & Laukkanen, P. (2007). Innovation resistance among mature consumers. *Journal of Consumer Marketing*, *24*(7), 419–427.

Lin, C., Choy, K. L., Ho, G. T., Chung, S. H., & Lam, H. Y. (2014). Survey of green vehicle routing problem: past and future trends. *Expert systems with applications*, *41*(4), 1118-1138.

Little, J. D., Murty, K. G., Sweeney, D. W., & Karel, C. (1963). An algorithm for the traveling salesman problem. *Operations research*, *11*(6), 972-989.

Llorens, S., Bakker, A.B., Schaufeli, W.B., & Salanova, M. (2006). Testing the robustness of the job-demands-resources model. *International Journal of Stress Management, 13*(3), 378-391.

Lombard, A., Tamayo-Giraldo, S., & Fontane, F. (2018). Vehicle Routing Problem with Roaming Delivery Locations and Stochastic Travel Times (VRPRDL-S). *Transportation research procedia*, *30*, 167-177.

Malhotra, Y., & Galletta, D.F. (1999) "Extending the Technology Acceptance Model to Account for Social Influence Theoretical Bases and Empirical Validation" Proceedings of the 32nd Hawaii International Conference on System Sciences.

May, D. R., Gilson, R. L., & Harter, L. M. (2004). The psychological conditions of meaningfulness, safety and availability and the engagement of the human spirit at work. *Journal of occupational and organizational psychology*, *77*(1), 11-37.

McKnight, D. H., Choudhury, V., & Kacmar, C. (2002). Developing and validating trust measures for e-commerce: An integrative typology. *Information systems research*, *13*(3), 334-359.

McKnight, D.H., Cummings, L.L., & Chervany, N.L. (1998). Initial trust formation in new organizational relationships. *The Academy of Management Review, 23*(3), 473-490.

Moccia, L., Cordeau, J. F., & Laporte, G. (2012). An incremental tabu search heuristic for the generalized vehicle routing problem with time windows. *Journal of the Operational Research Society*, *63*(2), 232-244.

Monk, T. H., Folkarc, S., & Wedderburn, A. I. (1996). Maintaining safety and high performance on shiftwork. *Applied Ergonomics*, *27*(1), 17-23.

Montemanni, R., Gambardella, L. M., Rizzoli, A. E., & Donati, A. V. (2005). Ant colony system for a dynamic vehicle routing problem. *Journal of Combinatorial Optimization*, *10*(4), 327-343.

Moorthy, K., Ling, C. S., Fatt, Y. W., Yee, C. M., Yin, E. C. K., Yee, K. S., & Wei, L. K. (2017). Barriers of mobile commerce adoption intention: perceptions of generation X in Malaysia. *Journal of theoretical and applied electronic commerce research*, *12*(2), 37-53.

Morgan, R. M., & Hunt, S. D. (1994). The commitment-trust theory of relationship marketing. *Journal of marketing*, *58*(3), 20-38.

Nguyen, D. T., Teo, S. T., Grover, S. L., & Nguyen, N. P. (2017). Psychological safety climate and workplace bullying in Vietnam's public sector. *Public Management Review*, *19*(10), 1415-1436.

Nielsen, M. B., Mearns, K., Matthiesen, S. B., & Eid, J. (2011). Using the Job Demands–Resources model to investigate risk perception, safety climate and job satisfaction in safety critical organizations. *Scandinavian Journal of Psychology*, *52*(5), 465-475.

Oh, Y. J., Park, H. S., & Min, Y. (2019). Understanding location-based service application connectedness: Model development and cross-validation. *Computers in human behavior*, *94*, 82-91.

Osman, I.H. (1993). Metastrategy simulated annealing and tabu search algorithms for the vehicle routing problem. *Annals of Operations Research, 41*(4), 421-451.

Ozbaygin, G., Karasan, O. E., Savelsbergh, M., & Yaman, H. (2017). A branch-and-price algorithm for the vehicle routing problem with roaming delivery locations. *Transportation Research Part B: Methodological*, *100*, 115-137.

Ozbaygin, G., & Savelsbergh, M. (2019). An iterative re-optimization framework for the dynamic vehicle routing problem with roaming delivery locations. *Transportation Research Part B: Methodological*, *128*, 207-235.

Pallesen, S., Bjorvatn, B., Magerøy, N., Saksvik, I. B., Waage, S., & Moen, B. E. (2010). Measures to counteract the negative effects of night work. *Scandinavian journal of work, environment & health*, 109-120.

Pavlou, P.A. (2003) Consumer Acceptance of Electronic Commerce: Integrating Trust and Risk with the Technology Acceptance Model, *International Journal of Electronic Commerce, 7*(3), 101-134.

Pikkarainen, T., Pikkarainen, K., Karjaluoto, H., & Pahnila, S. (2004). Consumer acceptance of online banking: an extension of the technology acceptance model. *Internet research, 14*(3), 224-235.

Pilbeam, C., Alvarez, G., & Wilson, H. (2012). The governance of supply networks: a systematic literature review. *Supply Chain Management: An International Journal, 17*(4), 358-376.

Pillac, V., Gendreau, M., Guéret, C., & Medaglia, A. L. (2013). A review of dynamic vehicle routing problems. *European Journal of Operational Research*, *225*(1), 1-11.

Prieto, L.L., Soria, M.S., Martínez, I.M., & Schaufeli, W. (2008). Extension of the job demands-resources model in the prediction of burnout and engagement among teachers over time. *Psicothema, 20*(3), 354-360.

Ragu-Nathan, T. S., Tarafdar, M., Ragu-Nathan, B. S., & Tu, Q. (2008). The consequences of technostress for end users in organizations: Conceptual development and empirical validation. *Information systems research*, *19*(4), 417-433.

Ram, S. and Sheth, J.N. (1989). Consumer resistance to innovations: the marketing problem and its solutions. *Journal of Consumer Research, 6(2),* 5-14.

Reyes, D., Savelsbergh, M., & Toriello, A. (2017). Vehicle routing with roaming delivery locations. *Transportation Research Part C: Emerging Technologies*, *80*, 71-91.

Rogers, E. M. (2002). Diffusion of preventive innovations. *Addictive behaviors*, *27*(6), 989-993.

Sampaio Oliveira, A., Kinable, J., Veelenturf, L., & van Woensel, T. (2019). A scenario-based approach for the vehicle routing problem with roaming delivery locations under stochastic travel times.

Savelsbergh, M., & Van Woensel, T. (2016). 50th anniversary invited article—city logistics: Challenges and opportunities. *Transportation Science*, *50*(2), 579-590.

Savelsbergh, M. W. (1992). The vehicle routing problem with time windows: Minimizing route duration. *ORSA journal on computing*, *4*(2), 146-154.

Schaufeli, W.B., & Salanova, M. (2008), Enhancing work engagement through the management of human resources. In Näswall, Kl, Hellgren, J., & Sverke, M. (Eds), The Individual in the Changing Working Life, Cambridge University Press, New York, NY, pp. 380-402.

Schierz, P.G., Schilke, O., Wirtz, B.W. (2010). Understanding consumer acceptance of mobile payment services: an empirical analysis. *Electronic commerce research and applications, 9,* 209-216.

Schinkels, C. (2019, December 18). *Trends in e-commerce 2020: bezorgschaamte & tegengeluiden marketplaces*. Retrieved from: https://www.frankwatching.com/archive/2019/12/18/trends-ecommerce-2020/, 25 February 2020.

Schreurs, B. H., Van Emmerik, H. I. J., Guenter, H., & Germeys, F. (2012). A weekly diary study on the buffering role of social support in the relationship between job insecurity and employee performance. *Human Resource Management*, *51*(2), 259-279.

Shanock, L. R., & Eisenberger, R. (2006). When supervisors feel supported: Relationships with subordinates' perceived supervisor support, perceived organizational support, and performance. *Journal of Applied psychology*, *91*(3), 689-695.

Sheth, J.N. (1981). Psychology of innovation resistance: the less developed concept (LDC) in diffusion research. *Research in marketing, 4,* 273-282.

Shivakumar, F. (2019, June 10). *Giant cargo drones will deliver packages farther and faster.* Retrieved from: https://www.theverge.com/2019/6/10/18657150/autonomous-cargo-drones-delivery-boeing-aircraft-faa-regulation, 09 March 2020.

Solomon, M. M. (1987). Algorithms for the vehicle routing and scheduling problems with time window constraints. *Operations research*, *35*(2), 254-265.

Straub, D., Keil, M., & Brenner, W. (1997). Testing the technology acceptance model across cultures: A three country study. *Information & management, 33,* 1-11.

Szajna, B. (1994). Software evaluation and choice: predictive validation of the technology acceptance instrument. *MIS Quarterly*, *18*(3), 319–324.

Szmigin, I., & Foxall, G. (1998). Three forms of innovation resistance: the case of retail payment methods. *Technovation, 18*(6-7), 459-468.

Tadić, M., Bakker, A. B., & Oerlemans, W. G. (2015). Challenge versus hindrance job demands and well-being: A diary study on the moderating role of job resources. *Journal of Occupational and Organizational Psychology*, *88*(4), 702-725.

Taillard, É., Badeau, P., Gendreau, M., Guertin, F., & Potvin, J. Y. (1997). A tabu search heuristic for the vehicle routing problem with soft time windows. *Transportation science*, *31*(2), 170-186.

Talke, K., & Heidenreich, S. (2014). How to overcome pro-change bias: incorporating passive and active innovation resistance in innovation decision models. *Journal of Product Innovation Management*, *31*(5), 894-907.

Tas, D., Dellaert, N. P., Woensel, van, T., & Kok, de, A. G. (2013). Vehicle routing problem with stochastic travel times including soft time windows and service costs. *Computers & Operations Research*, *40*(1), 214-224.

Thuiswinkel. (2019, September 19). *Online b2c-bestedingen groeien in HY1 van 2019 met 9% naar €12,5 miljard* [Press release]. Retrieved from: https://www.thuiswinkel.org/nieuws/4192/online-b2c-bestedingen-groeien-in-hy1-van-2019-met-9-naar-12-5-miljard, 25 February 2020.

Tilk, C., Olkis, K., & Irnich, S. (2020). *The last-mile vehicle routing problem with delivery options* (No. 2017).

Ullman, J. B., & Bentler, P. M. (2003). Structural equation modeling. *Handbook of psychology*, 607-634.

Van den Broeck, A., De Cuyper, N., De Witte, H., & Vansteenkiste, M. (2010). Not all job demands are equal: Differentiating job hindrances and job challenges in the Job Demands–Resources model. *European journal of work and organizational psychology*, *19*(6), 735-759.

Venkatesh, V., & Davis, F. D. (1996). A model of the antecedents of perceived ease of use: Development and test. *Decision sciences*, *27*(3), 451-481.

Venkatesh, V., & Davis, F.D. (2000). A theoretical extension of the technology acceptance model: four longitudinal field studies. *Management Science, 46*(2), 186-204.

Volvo (2018, April 24). *Volvo voegt 'in-car delivery' van Amazon toe aan connected services* [Press release]. Retrieved from: https://www.media.volvocars.com/nl/nl-nl/media/pressreleases/227845/volvo-voegt-in-car-delivery-van-amazon-toe-aan-connected-services, 06 March 2020.

Watson, R., Wilson, H. N., & Macdonald, E. K. (2020). Business-nonprofit engagement in sustainability-oriented innovation: What works for whom and why?. *Journal of Business Research, 119,* 87-98.

Wegener, R. (2020, 6 November). Skype interview with Ralf Wegener, strategic director of a German in-car delivery pilot project about his experiences with and learnings from the technology.

Wolter, C., Santa Maria, A., Wörfel, F., Gusy, B., Lesener, T., Kleiber, D., & Renneberg, B. (2019). Job demands, job resources, and well-being in police officers—a resource-oriented approach. *Journal of Police and Criminal Psychology*, *34*(1), 45-54.

Xanthopoulou, D., Bakker, A. B., Demerouti, E., & Schaufeli, W. B. (2007). The role of personal resources in the job demands-resources model. *International journal of stress management*, *14*(2), 121-141.

Yang, H. C. (2013). Bon Appétit for apps: young American consumers' acceptance of mobile applications. *Journal of Computer Information Systems*, *53*(3), 85-96.

Zurel, O. (2020, February 17). *Is Europe ready for in-car delivery?* Retrieved from: https://www.parcelandpostaltechnologyinternational.com/opinion/is-europe-ready-for-in-car-delivery.html, 06 March 2020.

Appendix 1: Full overview of all customer survey statements

Table 27 presents the complete list of all statements used in the customer survey from section 4.2. This table includes the deleted items as well (risk barrier item 3 and the two tradition barrier items), that were deleted before the analysis but that were part of the survey as sent to the respondents.

Variable	**Question**
Perceived usefulness 1	*Using in-car delivery would improve my online shopping experience.*
Perceived usefulness 2	*Using in-car delivery would increase my productivity in online shopping.*
Perceived usefulness 3	*Using in-car delivery would make my online shopping experience more effective.*
Perceived usefulness 4	*Using in-car delivery would make it easier for me to shop online and have my package delivered to me.*
Perceived usefulness 5	*I think using in-car delivery would be very useful for me when shopping online.*
Perceived ease of use 1	*I think learning to use in-car delivery is easy.*
Perceived ease of use 2	*I think it would be easy to become skillful at using in-car delivery.*
Perceived ease of use 3	*I think it would be easy to use in-car delivery as a delivery method.*
Behavioral intentions 1	*Assuming I had access to in-car delivery, I would have the intention to use it.*
Behavioral intentions 2	*I predict that I would intend to use in-car delivery as soon as I had access to it.*
Predicted actual use	*How often do you expect to use in-car delivery as a delivery option when shopping online?*
Perceived integrity 1	*I think promises made by the involved companies are likely to be reliable.*
Perceived integrity 2	*I do not doubt the honesty of the involved companies.*
Perceived integrity 3	*I expect that the involved companies would keep the promises they make to consumers*
Perceived benevolence 1	*I expect that I could count on the involved companies to consider how their actions would affect me as a consumer.*
Perceived benevolence 2	*I expect that the intentions of the involved companies are benevolent (with goodwill).*
Perceived benevolence 3	*I expect that the involved companies put the customers' interests before their own.*
Perceived benevolence 4	*I expect that the involved companies are well meaning.*
Perceived ability 1	*I believe that the involved companies are competent to develop a good in-car delivery service.*
Perceived ability 2	*I believe that the involved companies have good knowledge on what it takes to implement in-car delivery*
Perceived ability 3	*I believe that the involved companies would know how to provide excellent customer service.*
Value barrier 1 (reversed)	*I think using in-car delivery would be economical.*
Value barrier 2	*In my opinion, in-car delivery would NOT offer any advantage compared to other package delivery methods.*
Value barrier 3 (reversed)	*I feel that in-car delivery would increase my ability to control the delivery of my packages.*
Risk barrier 1	*I fear that while using in-car delivery, I might make mistakes in uploading the car key codes and location information.*

Risk barrier 2	*I fear that my information (entered through the app) might get lost and end up in the wrong hands.*
Risk barrier 3 (reversed)	*I trust that third parties are not able to see or use any of the information I upload into the application when I am using in-car delivery*
Tradition barrier 1	*Opening the door for the deliverer and having a quick chat with him or her is a nice occasion for me.*
Tradition barrier 2 (reversed)	*I find less personal delivery methods such as in-car delivery more pleasant than personal package delivery at the door.*
Image barrier 1	*In my opinion, new technology is often too complicated to directly be useful to me.*
Image barrier 2	*I have the idea that mobile services such as in-car delivery are difficult to use.*

Table 27: Overview of all survey statements for the customer research

Appendix 2: Complete customer research factor analysis

This appendix presents the more elaborate factor analysis of the customer research. Its goal was to check the distinctiveness of several constructs, and to verify the dimensionality of both trust and resistance barriers. The tables in each section present the analysis results. In these tables, only factor loading greater than 0.40 in absolute value are reported. These loadings are significant with this sample size (Hair Jr. et al., 2010). Moreover all factor loadings were obtained after a varimax rotation.

A2.1 Perceived usefulness and ease of use

First, the distinctiveness of perceived usefulness and perceived ease of use was tested. Table 28 shows that in general, this yielded positive results with distinct constructs. The only exception is the third perceived ease of use item, which behaves unexpectedly. However, as mentioned in Chapter 4 as well, it was chosen to keep these scales as they were, as they were existing scales from scientific literature.

Variable	***Question***	***Factor 1***	***Factor 2***
PU1	*Using in-car delivery would improve my online shopping experience.*	0.879	
PU2	*Using in-car delivery would increase my productivity in online shopping.*	0.838	
PU3	*Using in-car delivery would make my online shopping experience more effective.*	0.887	
PU4	*Using in-car delivery would make it easier for me to shop online and have my package delivered to me.*	0.867	
PU5	*I think using in-car delivery would be very useful for me when shopping online.*	0.891	
PEOU1	*I think learning to use in-car delivery is easy.*		0.930
PEOU2	*I think it would be easy to become skillful at using in-car delivery.*		0.795
PEOU3	*I think it would be easy to use in-car delivery as a delivery method.*	0.718	
	Cronbach alpha of the factor	0.952	0.876
	Proportion of variance explained	0.552	0.231

Table 28: Factor analysis results for perceived usefulness and ease of use

A2.2 Trust

For the concept of trust, it was important to see whether the factor analysis would indicate a strict division between different dimensions, or whether they all loaded on one factor. The scree plot of all ten items from the questionnaire indicated that one factor had an eigenvalue higher than 1, so all ten items loaded onto the same factor. The same thing happened when a similar analysis was made on a dimensional level, checking whether the proposed dimensions of perceived integrity, benevolence, and ability would load on one or separate factors. Table 29 presents the factor analysis results. These clearly show that trust can be seen as one, reliable construct. Moreover, it shows that each proposed dimension contributes similarly to trust, as the dimensional level loadings (right column) are similar.

Variable	***Question***	***Factor 1***	***Loading on trust***
Perceived integrity	Items INT1, INT2, INT3		**0.846**
INT1	*I think promises made by the involved companies are likely to be reliable.*	0.718	

INT2	*I do not doubt the honesty of the involved companies.*	0.703	
INT3	*I expect that the involved companies would keep the promises they make to consumers*	0.802	
Perceived benevolence	Items BENE1, BENE2, BENE3, BENE4		**0.843**
BENE1	*I expect that I could count on the involved companies to consider how their actions would affect me as a consumer.*	0.741	
BENE2	*I expect that the intentions of the involved companies are benevolent (with goodwill).*	0.774	
BENE3	*I expect that the involved companies put the customers' interests before their own.*	0.727	
BENE4	*I expect that the involved companies are well meaning.*	0.769	
Perceived ability	Items AB1, AB2, AB3		**0.830**
AB1	*I believe that the involved companies are competent to develop a good in-car delivery service.*	0.800	
AB2	*I believe that the involved companies have good knowledge on what it takes to implement in-car delivery*	0.726	
AB3	*I believe that the involved companies would know how to provide excellent customer service.*	0.764	
	Cronbach alpha of the factor	0.927	0.878
	Proportion of variance explained	0.567	0.705

Table 29: Factor analysis results of trust on an item and dimensional level

A2.3 Barriers

The resistance barriers were examined similarly. The analysis mainly showed that the different barriers did not load onto one single factor, but rather on two. The three items of the proposed value barrier loaded together on the first factor, while the (remaining) items of the proposed risk and image barriers also loaded together. The third item of the risk barrier as well as the two tradition barrier items were not taken into account in this factor analysis after the Cronbach Alpha tests indicated them as weakly reliable. Table 30 presents full results of this factor analysis.

Variable	***Question***	***Factor 1***	***Factor 2***
VAL1_REV	*I think using in-car delivery would be economical.*	0.785	
VAL2	*In my opinion, in-car delivery would NOT offer any advantage compared to other package delivery methods.*	0.689	
VAL3_REV	*I feel that in-car delivery would increase my ability to control the delivery of my packages.*	0.824	
RISK1	*I fear that while using in-car delivery, I might make mistakes in uploading the car key codes and location information.*		0.700

RISK2	*I fear that my information (entered through the app) might get lost and end up in the wrong hands.*		0.445
IMG1	*In my opinion, new technology is often too complicated to directly be useful to me.*		0.712
IMG2	*I have the idea that mobile services such as in-car delivery are difficult to use.*		0.762
	Cronbach alpha of the factor	0.801	0.742
	Proportion of variance explained	0.267	0.266

Table 30: Factor analysis for the remaining resistance barrier items

A2.4 Trust and barriers combined

Finally, to conclude the factor analysis regarding trust and barriers, an analysis was performed to check whether trust and barriers could indeed be regarded as separate constructs. This was done by taking all items measuring trust and resistance barriers used for the separate analyses, and then performing a factor analysis on them. In total this resulted in four factors, where the results slightly differed from the separate analyses (trust loaded on two factors instead of one). However, the main conclusion is that items from trust and from barriers did not load onto the same factor, so it was assumed they could be treated as separate constructs. Table 31 presents the full results of this factor analysis.

Variable	***Factor 1***	***Factor 2***	***Factor 3***	***Factor 4***
INT1	0.508			0.520
INT2	0.553			0.403
INT3	0.761			
BENE1	0.740			
BENE2	0.813			
BENE3	0.728			
BENE4	0.786			
AB1	0.591			0.595
AB2	0.469			0.693
AB3	0.658			0.426
VAL1_REV		0.702		
VAL2		0.734		
VAL3_REV		0.763		
RISK1			0.728	
RISK2			0.453	
IMG1			0.709	
IMG2			0.752	
Cronbach alpha of the factor	0.927	0.801	0.742	0.882
Proportion of variance explained	0.275	0.114	0.112	0.104

Table 31: Factor analysis results for trust and the resistance barriers

A2.5 Perceived usefulness and trust

Next, several other analyses were carried out to check whether the perceived usefulness and ease of use constructs are different from the trust and barrier constructs. This analysis started by examining perceived usefulness and trust. Table 32 shows that factor analysis confirmed their distinctiveness.

Variable	***Question***	***Factor 1***	***Factor 2***
PU1	*Using in-car delivery would improve my online shopping experience.*		0.885

PU2	*Using in-car delivery would increase my productivity in online shopping.*		0.839
PU3	*Using in-car delivery would make my online shopping experience more effective.*		0.876
PU4	*Using in-car delivery would make it easier for me to shop online and have my package delivered to me.*		0.877
PU5	*I think using in-car delivery would be very useful for me when shopping online.*		0.866
INT1	*I think promises made by the involved companies are likely to be reliable.*	0.643	
INT2	*I do not doubt the honesty of the involved companies.*	0.664	
INT3	*I expect that the involved companies would keep the promises they make to consumers*	0.785	
BENE1	*I expect that I could count on the involved companies to consider how their actions would affect me as a consumer.*	0.714	
BENE2	*I expect that the intentions of the involved companies are benevolent (with goodwill).*	0.753	
BENE3	*I expect that the involved companies put the customers' interests before their own.*	0.715	
BENE4	*I expect that the involved companies are well meaning.*	0.769	
AB1	*I believe that the involved companies are competent to develop a good in-car delivery service.*	0.774	
AB2	*I believe that the involved companies have good knowledge on what it takes to implement in-car delivery*	0.681	
AB3	*I believe that the involved companies would know how to provide excellent customer service.*	0.760	
	Cronbach alpha of the factor	0.927	0.952
	Proportion of variance explained	0.368	0.282

Table 32: Factor analysis results for perceived usefulness and trust

A2.6 Perceived ease of use and trust

Next, a similar factor analysis was performed on perceived ease of use and trust. As Table 33 shows, the factor analysis revealed a clear distinction between these proposed two factors. Also note that here, the three perceived ease of use items indeed load together on one factor.

Variable	***Question***	***Factor 1***	***Factor 2***
PEOU1	*I think learning to use in-car delivery is easy.*		0.848
PEOU2	*I think it would be easy to become skillful at using in-car delivery.*		0.844
PEOU3	*I think it would be easy to use in-car delivery as a delivery method.*		0.542
INT1	*I think promises made by the involved companies are likely to be reliable.*	0.634	
INT2	*I do not doubt the honesty of the involved companies.*	0.637	

INT3	*I expect that the involved companies would keep the promises they make to consumers*	0.761	
BENE1	*I expect that I could count on the involved companies to consider how their actions would affect me as a consumer.*	0.732	
BENE2	*I expect that the intentions of the involved companies are benevolent (with goodwill).*	0.760	
BENE3	*I expect that the involved companies put the customers' interests before their own.*	0.743	
BENE4	*I expect that the involved companies are well meaning.*	0.770	
AB1	*I believe that the involved companies are competent to develop a good in-car delivery service.*	0.744	
AB2	*I believe that the involved companies have good knowledge on what it takes to implement in-car delivery*	0.665	
AB3	*I believe that the involved companies would know how to provide excellent customer service.*	0.745	
	Cronbach alpha of the factor	0.927	0.792
	Proportion of variance explained	0.408	0.177

Table 33: Factor analysis results for perceived ease of use and trust

A2.7 Perceived usefulness and barriers

This factor analysis tested the distinctiveness of the perceived usefulness and barrier constructs. Table 34 presents the 2-factor solution the analysis proposed, which shows the proposed distinction when it comes to the risk and difficulty barrier. However, the value barrier is loaded on the same factor as perceived usefulness, albeit with negative factor loadings. This indicates a contradiction between the two, which can be explained by the fact that these two constructs essentially measure each other's opposite.

Variable	***Question***	***Factor 1***	***Factor 2***
PU1	*Using in-car delivery would improve my online shopping experience.*	0.905	
PU2	*Using in-car delivery would increase my productivity in online shopping.*	0.858	
PU3	*Using in-car delivery would make my online shopping experience more effective.*	0.886	
PU4	*Using in-car delivery would make it easier for me to shop online and have my package delivered to me.*	0.882	
PU5	*I think using in-car delivery would be very useful for me when shopping online.*	0.914	
VAL1_REV	*I think using in-car delivery would be economical.*	-0.769	
VAL2	*In my opinion, in-car delivery would NOT offer any advantage compared to other package delivery methods.*	-0.616	
VAL3_REV	*I feel that in-car delivery would increase my ability to control the delivery of my packages.*	-0.819	

RISK1	*I fear that while using in-car delivery, I might make mistakes in uploading the car key codes and location information.*		0.702
RISK2	*I fear that my information (entered through the app) might get lost and end up in the wrong hands.*		0.458
IMG1	*In my opinion, new technology is often too complicated to directly be useful to me.*		0.703
IMG2	*I have the idea that mobile services such as in-car delivery are difficult to use.*		0.762
	Cronbach alpha of the factor	0.801	0.742
	Proportion of variance explained	0.474	0.156

Table 34: Factor analysis results for perceived usefulness and resistance barriers

A2.8 Perceived ease of use and barriers

Finally, the perceived ease of use construct was tested against the two barrier constructs. Table 35 shows that in general the factor analysis confirms the proposed division of constructs. However, the third item of perceived ease of use loads onto the value barrier, albeit with opposite signs, indicating a contradiction. While this is not as expected, it can be explained from the fact that this item already seemed to switch between perceived ease of use and perceived usefulness in an earlier factor analysis. Therefore, this behavior was possible when considering the behavior of perceived usefulness with the value barrier before.

Variable	**Question**	***Factor 1***	***Factor 2***	***Factor 3***
PEOU1	*I think learning to use in-car delivery is easy.*			0.892
PEOU2	*I think it would be easy to become skillful at using in-car delivery.*			0.803
PEOU3	*I think it would be easy to use in-car delivery as a delivery method.*	-0.742		
VAL1_REV	*I think using in-car delivery would be economical.*	0.792		
VAL2	*In my opinion, in-car delivery would NOT offer any advantage compared to other package delivery methods.*	0.709		
VAL3_REV	*I feel that in-car delivery would increase my ability to control the delivery of my packages.*	0.792		
RISK1	*I fear that while using in-car delivery, I might make mistakes in uploading the car key codes and location information.*		0.698	
RISK2	*I fear that my information (entered through the app) might get lost and end up in the wrong hands.*		0.440	
IMG1	*In my opinion, new technology is often too complicated to directly be useful to me.*		0.709	
IMG2	*I have the idea that mobile services such as in-car delivery are difficult to use.*		0.758	
	Cronbach alpha of the factor	0.801	0.742	0.876
	Proportion of variance explained	0.248	0.189	0.170

Table 35: Factor analysis results for perceived ease of use and barriers