MODELLING THE IMPACTS OF DEMAND RESPONSIVE TRANSPORT SYSTEM ON MOBILITY

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ABSTRACT

The recent progress in Information and Communication Technology and the ubiquity of smart devices have revolutionised transportation systems in a potentially disruptive manner. It is culminating in Mobility as a Service platforms and facilitated the advent of demand responsive transport systems. Examples of such systems include ride-sourcing, ride-sharing, and car-sharing, which are emerging flexible transportation options with promising features to be the key to a number of transportation problems, filling the gap between public and active transport. However, their sustainable and successful deployment is notoriously difficult to achieve due to high dynamicity of such systems, which mean high volatility of demand and supply.

This work sheds light on the the feasibility of these systems, with a focus on spatial aspects, using agent-based modelling and the concept of multi-sided markets.

The major outcomes of this work are three fold: first, for the very first time the concept of *spatial critical mass* is developed and analysed in this work, which can have profound impact on the understanding and design of the future schemes of DRT systems for the operators, and identifying and imposing the apt policies for governments and authorities. Spatial critical mass highlights the distinction of spatial systems from their aspatial counterparts in multi-sided markets and emphasizes the significance of spatial components of such systems.

Second, this work presents the first analytical evidence of the advantages of a collaboration among the demand responsive transport operators. With the rapidly growing interest in MaaS concept, it is imperative for the involved parties, including transport network operators and governments, to understand the consequences of such schemes to make informed astute decisions on appropriate planning and policies.

Third, this work demonstrates the feasibility of using simulation to synthesise the required data for developing a mode choice model. This implies the applicability of the approach in travel behaviour studies involving new travel modes, such as demand responsive transport and autonomous ride sharing.

Finally, in addition to the above-mentioned outcomes, this piece of work could be an initial evidence base to nudge governments towards fully integrated transport systems, in which DRT systems play a key role.

PUBLICATIONS

Most ideas and figures have appeared previously in the following publications or papers under review:

- **Navidi, Zahra** and Stephan Winter (under review). "Ride-sourcing platform collaboration".
- **Navidi, Zahra**, Stephan Winter, and Meead Saberi, (revision to be submitted). "A comparison of travel time attribute estimation methods: Potential impacts on policies".
- **Navidi, Zahra**, Kai Nagel and Stephan Winter (2019). "Towards Identifying the Critical Mass in Spatial Two-sided Markets" In: *Environment and Planning B: Urban Analytics and City Science*. DOI: https://doi.org/10.1177/2399808319842181.
- **Navidi, Zahra**, Nicole Ronald, Stephan Winter (2018). "Comparison between ad-hoc demand responsive and conventional transit: a simulation study" In: *Public Transport* 10(1), pp. 147–167. DOI: https://doi.org/10.1007/s12469-017-0173-z
- **Navidi, Zahra**, Stephan Winter and Meead Saberi (2018). "Synthesizing attributes of unchosen alternatives in a mode choice model using an agent-based model and web-based multimodal trip planners". In: *The Transportation Research Board 2018 Annual Meeting*. Washington D.C.
- Ronald, Nicole, **Zahra Navidi**, Yaoli Wang, Michael Rigby, Shubham Jain, Ronny Kutadinata, Russell Thompson and Stephan Winter (2017) "Mobility patterns in shared, autonomous, and connected urban transport". In *Disrupting Mobility*. Eds. by Gereon Meyer and Susan Shaheen Springer. Cham. pp. 275–290.
- **NavidiKashani, Zahra**, Nicole Ronald, Stephan Winter (2016). "Comparing demand responsive and conventional public transport in a low demand context". In: *2016 IEEE International Conference on Pervasive Computing and Communication Workshops (PerCom Workshops)*. Sydney, Australia. pp. 1–6. DOI: 10.1109/PERCOMW.2016.7457089

The best way out is always through.

— Robert Frost

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1 INTRODUCTION

1.1 BACKGROUND AND MOTIVATION

1.1.1 *The critical role of transportation*

Urbanisation has significantly increased in the past few decades raising several challenges for cities around the world. One prominent challenge is transportation, which is the key to accessing employment, education, leisure activities, and maintaining a fulfilling life. Transport systems can be divided into three groups from the user point of view: motorized private, motorized public, and active transport. In many cities around the world, the main challenge is to decrease the share of the first and increase the shares of the last two.

Motorized public transport (referred to as public transport henceforth) in its conventional form with fixed-route and fixed-schedule is an accepted practical solution for high-density areas, e.g., the more compacts European cities or the more central parts of global metropolitans. However, as the demand becomes more dispersed in outer suburbs, temporally or spatially, the conventional form will not be feasible to maintain the passengers' satisfaction. Operators need to sacrifice either spatial or temporal coverage of the services, which in turn results in a lower share of public transport.

The recent developments in information and communication technology (ICT) have facilitated the advent of new solutions to the transportation problems in the cities, especially the dispersedly populated fringes, but also for the mobility-disadvantaged parts of society that have no access to private cars, require door-to-door transport or want more flexibility. They are called demand-responsive transportation (DRT) systems and are expected to be the key to a number of transportation problems, filling the gap between public and active transport.

1.1.2 *New trends in mobility*

The oldest known version of DRT systems is paratransit services that many local communities have been providing for the people with special needs since 1960s (Nelson et al., 2010). To use these services, the passenger must book the service in advance, e.g., one day before, or prior to the vehicle's departure. This kind of operation, although provides an option for those who cannot drive or have no one to help them, has many limitations, such as required planning ahead, and unknown delays due to other bookings.

However, advances in ICT have enabled the harnessing of the flexibility of these systems and their provision for the public. On one hand, routing task is automatised by ever-improving algorithms allowing for real-time changes of a vehicle's route, meaning more flexibility for the passengers and more efficiency for the operators. On the other hand, the ubiquity of personal electronic devices (e.g. mobile phones) and tracking devices allow for more convenience in terms of booking and tracking the vehicles. For instance, the real-time data on vehicles' locations keep passengers informed about their pick-up time, helping them utilise their waiting time efficiently. Chapter 3 presents evidence on how such systems can significantly improve mobility for everyone in dispersedly populated areas.

At the same time, increasing costs of living and environmental necessity fuelled the advent of a new culture of collaborative consumption(Botsman and Rogers, 2010). Studies have shown that younger generations are more open to sharing (Belk, 2014; Elliot and Reyndols, 2014; Godelnik, 2017), whether it is their ride, their vehicle, or their house. They are also more literate and interested in using personal electronic devices, one of the main enabler of such consumption model. On top of that is the shrinking culture of owning a car as a symbol of power, wealth or success.

However, although the tendency of younger generations towards using shared mobility options has been empirically proven, limited studies are measuring this willingness and quantifying its impact on the overall mobility system. This requires developing mode choice models that consider these new modes, preferably based on revealed preference data. In Chapter 4, practical insights have been provided for developing such models.

Consequently, technological developments and cultural changes led not only to the improvements in paratransit-like services, but also to the emergence of other new modes of transport, which are personalised and more tailored to demand, including ride-sharing, ride-hailing (ride-sourcing), and car-sharing. All these terms have been loosely used in the literature with no clear convergence in definition, mostly due to their conceptual overlaps and the rapid evolvement of the subject (Standing, Standing, and Biermann, 2018). To avoid confusion, here a comprehensive definition of all terms used in this thesis is presented.

Ride-sharing is an arrangement between a driver, who has a certain destination, and a passenger who seeks a ride along the way with an acceptable detour. Ride-sharing is not for profit, although passengers usually pay a small price to share the fuel and vehicle's cost of the trip.

Ride-sourcing or *ride-hailing* is when an individual, with no specific destination, decides to offer rides in their private vehicle to others for a price. The implementation model is similar to a taxi operation, with fewer regulatory restrictions.

Car/bike-sharing is the case that a vehicle is owned by a company or a person (peer-to-peer car/bike-sharing) and available for rent. The vehicles are either kept in certain locations or free-floating and people can book and use them at their convenience.

Table 1: Examples of different DRT schemes

Sector	Examples
Ride-sharing	BlaBlaCar, UberPool
Ride-sourcing	Uber, Lyft, DiDi
Car/bike-sharing	CAR2GO, DriveNow, MAVEN, TURO, O'Bike
Microtransit	Split, Kutsuplus, MOIA

Microtransit is a shared vehicle, whose size varies, provided by a private or public operator, offering rides limited to small areas, for example, within the borders of a few neighbouring suburbs. They move people from door to door and are the modern public version of paratransit services.

Numerous transport start-ups and companies emerged around the world, particularly in Europe and North America trying to make one of these modes work. Table 1 presents some well-known companies in each sector. They are ICT-enabled platforms and have one common characteristic: they match those who seek to travel with a transportation option, which could be either a vehicle the traveller can drive or a driver willing to offer a ride.

The above-mentioned platforms can be categorised in multi-sided and one-sided matchmaking platforms. The former owns only the platform and matches two (or more) groups of customers, i.e., drivers and passengers in case of ride-sharing and ride-sourcing, or drivers and private cars in case of peer-to-peer car-sharing. While the latter – one-sided matchmaking platforms – has only one type of customer. For example, a car-sharing company owns all the vehicles that are shared and offer services to people willing to drive.

Multi-sided platforms are platforms that reduce the interaction friction between groups of customers (Rochet and Tirole, 2003a). Reducing interaction friction is beyond just providing an efficient matchmaking algorithm. It requires creating a better user experience, by managing risks and offering added value to all customer groups. For example, passengers find traditional modes of shared transportation by studying schedules and walking to salient pick-up points (e.g., bus stops, train stations). With flexible shared transportation partners, pick-up points and pick-up times have to be individually negotiated. Here matchmaking platforms can serve as intermediary matchmakers resolving the complexity of the negotiation process. The dilemma of matchmaker platforms is the network effect: the more users on all sides, the more valuable is the service. Applied to a flexible multi-sided transportation system, this network effect can be illustrated:

- A car-sharing company puts up a vehicle at a fixed cost. Compared to the fixed cost, the marginal costs of serving each customer are low, meaning that average costs decrease with increasing numbers of customers. In other words, the more customers ask for a shared car, the more attractive is car-sharing for the company.

- Customers look for access to flexible mobility (here: car-sharing). They do not want to check out each company and private operator for current offers each time they look for a car; instead, they look for a single place of information. The platform becomes more attractive with more available cars (car-sharing companies), as the customers will have more versatile options.

Thus, a car-sharing platform provides a service to both market participants: it attracts customers for the companies they would not find on their own, and it provides access to cars a single company would not be able to provide. And this platform could earn money from subscriptions, transaction fees, or advertising.

For flexible shared transportation platforms, the dilemma with this network effect sits at the beginning of their market appearance. A (new) platform has first to reach a certain spatial density of vehicle coverage to be able to offer an attractive service to passengers at certain locations and times. Passengers expect a vehicle nearby when they need one. In practice, this condition requires a heavy upfront investment of a transportation provider or combined upfront investment of a larger number of providers. On the other hand, this certain density highly depends on the number and distribution of customers (both passengers and vehicles) and can vary in space. If there are not sufficient vehicles close to where the passengers are, they will turn away. Higher passenger density may require a higher vehicle density and vice versa. Therefore, to solve the chicken-and-egg problem of providing the critical mass to both sides of the market, the platform has to look at the spatial and temporal components of demand and supply.

In one-sided mobility platforms, the same network effects calling for a critical mass means that the investment in vehicles requires sufficient occupancy rates, and the customers require convenient access. Chapter 5 addresses the challenge of the extra dimension – space – of critical mass in DRT systems.

Platform competition is an inevitable element of all matchmaking markets, where platforms with similar functionalities compete to attract more customers of each group to ultimately achieve a platform monopoly. In each transportation market segment – *ride-sourcing*, *ride-sharing*, *car-sharing*, *bike-sharing*, or even *shared parking* – the various platforms operating in a geographic area compete with each other for customers. These customers, e.g., the drivers and the passengers of ride-sharing services, would have to interact with each platform to compare current offers or to find currently optimal service for their needs. And there is a benefit for customers doing so, such that some customers do *multi-homing* (logging in with multiple platforms). Checking different platforms for their current supply and demand, however, is a daunting task: The passenger customers of ride-sourcing platforms, for example, have to compare waiting times, occupancy rates and fares at the same time. Moreover, in the search process, while looking for a better option it is possible to lose an earlier option that in hindsight turns out to have been the best. Few people attempt this search every time they travel, since the effort is prohibitive, and success is not guaranteed. Convenience leads to just checking one platform, for example, the one that once provided a satisfactory option in the past. Hence, the competition is rather one between platforms than between current service offerings.

Moreover, the market dynamics of platform competition prevents new platform providers entering the market from attracting customers (both driver and passengers), even if they have better services for some customers, more efficient matching algorithms, or a superior user interaction experience. A newcomer does not have the critical mass, while competitors might have. Chapter 6 focuses on the potential collaboration of multiple DRT providers, instead of their competition, with a focus on ride-sourcing.

1.2 RESEARCH QUESTIONS

The overall objective of this thesis is to investigate the different aspects of the feasibility of DRT systems. This thesis is specially focused on lower demand areas, as they have a stronger struggle with transportation compared to densely populated areas. This thesis addresses four sets of hypothesis and questions in four chapters as follows:

NICHE ESTABLISHMENT Microtransit systems have been originally designed for helping people with special needs in the 1960s (Nelson et al., 2010). However, the flexibility in the design and operation of microtransit drew transit operators' attention to make it available to everyone. As a result, microtransit services were designed to consist of smaller sized vehicles (such as taxis, minivans, minibuses) that are shared and run according to the passengers' demand, which results in lower costs compared to taxis. This puts microtransit services in between taxi services and conventional fixed-route fixed-schedule public transport in terms of cost and flexibility. While older systems have relied on fixed-line telephones for passengers to book ahead, for example, the day before travel, emerging information and communication technologies facilitate the operation of more advanced microtransit systems by allowing passengers to obtain real-time information about the service and book for immediate travel, and allowing operators to update schedules and communicate with drivers.

Despite the promising concept of microtransit services, many schemes had been implemented and failed around the world (Enoch et al., 2006). Therefore, there is high scepticism about their potential contributions to the improvement of transit compared to the existing systems, i.e., fixed-route fixed-schedule transit. Hence, it is crucial to first establish the superiority of DRT systems to conventional services in a context prior to any further investigation. Therefore, the first hypothesis in this work is that a microtransit in a small area is capable of providing a better option compared to the conventional fixed-route fixed-schedule public transport (CPT), with a focus on low demand areas. It is important to establish that the proposed option is not only a better option for the passengers but also the operators. The research questions are:

1. Can a microtransit service provide shorter travel time than the CPT system for passengers in low demand areas?

2. Will a microtransit system that provides shorter travel time than the CPT cost more than it?

Considering the high cost of real-world testing on one hand, and the recent advances in transport simulation methods and computational technology on the other hand, an in-silico approach is suggested for investigating the hypothesis. It uses an ad-hoc dynamic routing algorithm embedded in the MATSim (Multi Agent Transport Simulation) software package that normally can manage only static routing. In Chapter 3, an extensive comparison between DRT and CPT is performed to test the hypothesis and demonstrate the potential of the used model, not only in theoretical scenarios but also in the real world. The performance of both CPT and DRT systems are simulated and evaluated firstly in two conceptual networks with several scenarios including variations in demand and supply level, and then in a real-world scenario. Each mode is simulated separately assuming that the passengers have no other options but the offered mode.

PEOPLE'S CHOICE: The objective superiority of a transportation system, e.g., a system that offers shorter perceived travel time, is no guarantee for its success. The passengers may have different criteria or different perceptions of various parts of the trip. For example, an elderly person may not care much about the waiting time, while they desire a short walking time, while a younger person may choose an option with shorter waiting time and longer walking time. Therefore, investigating people's behaviour and choices has profound importance in studying new transportation systems.

Choices are mostly studied using the Random Utility Maximization (RUM) methods, and revealed preference (RP) or stated preference (SP) survey data. RUM methods assume that each individual gains a certain level of utility from their choice, among the existing alternatives, and they always choose the one with the highest associated utility. SP data provides information on people's choices in hypothetical scenarios, while RP data consists of the actual choices made by travellers reflecting their constraints and considerations. However, the main shortcoming in using RP data is the absence of attributes of non-chosen alternatives. One option to tackle this issue is to synthesize the data using simulation, which has not been explored and is yet to be thoroughly investigated. Consequently, the hypothesis here is that it is possible to develop a mode choice model based on existing RP survey and synthetic data. The research questions are:

1. What is the best application or software package to synthesize the attributes of non-chosen alternatives in a travel mode choice model?

2. Is RP data always diverse enough to develop a detailed travel mode choice model?

Chapter 4, first, investigates a number of approaches for estimating the attributes of non-chosen alternatives to identify the implications and consequences of their application in the context of mode choice modelling. It focuses on traffic simulation tools such as agent-based models (ABM) and multi-modal trip planners, both offline (e.g., OpenTripPlanner) or online (e.g., Google API Directions), which can be used to estimate travel time and cost attributes of non-chosen alternatives. Then, it provides the results of the investigation of the mixture of RP and synthetic data and the possibility of developing a detailed mode choice model.

CRITICAL MASS: All matchmaker platforms are subject to securing the critical mass in time for their success. However, DRT systems, as spatial matchmaker systems, face a new dimension of complexity in identifying critical mass: *space*. The role of spatial elements in critical mass frontier has not been studied before. Critical mass frontier consists of all the possible situations, in which there are sufficient members of each group's participants for a system to be self-sustained (Evans and Schmalensee, 2016a). The hypothesis here is that in spatial multi-sided markets, other than in non-spatial markets, there is not a single critical mass frontier that needs to be reached to make the system self-sustained, and that this frontier is varying from one location to the next, depending on the density and distribution of the demand and supply over space and time. Here, there is only one question:

1. How do the spatial components of a ride-sourcing system impact its critical mass frontier?

This additional challenge will be studied in Chapter 5, where the hypothesis is argued, and illustrated by simulations using a two-sided ride-sourcing market. A conceptual simulation is designed and implemented consisting of the essential components of a two-sided market and a spatial system. Identification of the critical mass frontier in the context of flexible transport systems will allow for better evaluation of implementation policies and regulations.

OPERATORS COLLABORATION: Securing a critical mass is even more difficult with the current state of the market, where there are already big companies on the verge of dominating the market. There are identified problems with the current state of DRT operators' competition that bring disadvantages to the customers(Zha, Yin, and Du, 2017), which raised calls on authorities to intervene via regulations. Concurrently, there are movements towards convening all transportation service operators and providers to offer their services on the same platform under the term Mobility as a Service (MaaS). However, the consequences of such collaboration have not been investigated much. Therefore, the hypothesis here is that operators feeding into a single meta-platform will bring benefit to all customers (passengers and drivers) and thus also the operators. The following questions are investigated:

1. How does the spatial separation of the fleets of participating operators impact an individual operator's success, particularly for small operators?

2. How does the spatial separation of the fleets impact the minimum market share for an operator to survive?

3. Will customers, i.e., passengers and drivers, benefit from a meta-platform?

Chapter 6 focuses on ride-sourcing platform operators and their potential collaboration using a simulation approach. In particular, this research investigates the identified sub-optimality of platform competition for all market participants (in the case of ride-sourcing, these are the drivers and passengers). It is imaginable that service competition rather than platform competition benefits every market participant, thus, leads to market growth benefiting also the platform providers.

1.3 CONTRIBUTIONS

This thesis aims at providing in-depth insights into the feasibility of DRT systems using simulations. It has focused on operational issues and established fundamental concepts. The contributions of this work are on two levels:

CONCEPTUAL: For the very first time the concept of *spatial critical mass* is developed and analysed in this work, which can have a profound impact on the understanding and design of the future schemes of DRT systems. Spatial critical mass highlights the distinction of spatial systems from their aspatial counterparts in multi-sided markets and emphasizes the significance of spatial components of the system. The exploration of the impact of system size and spatial distribution of the components had the highest interest and priority in the study.

PRACTICAL: The practical insights into the implementation of DRT services are three folds: first, prior to the implementation of a new system, realistic studies are necessary to assure the involved parties about its benefits. An extensive comparison of conventional public transport and microtransit services using an agent-based model is presented in this work to establish the expected advantages of DRT over the conventional system. Second, conducting sensible studies requires integration of realistic people's preferences into transport models. This work demonstrates the feasibility of using simulation to synthesize the required data for developing a mode choice model including the new modes and reflecting real-world constraints and considerations of people. Third, with the rapidly growing interest in

MaaS concept, it is imperative for the involved parties (e.g., transport network companies (TNC) and governments) to understand the consequences of such system. This work presents the first simulation analysing the advantageous of a collaboration among the DRT operators.

1.4 THESIS STRUCTURE

The remainder of this thesis is structured as follows. Chapter 2 sets the scene and provide the background knowledge necessary for understanding the content of this work. First, it reviews the existing literature on microtransit systems, the necessity of simulation in their study, and the significance of choice modelling and handling missing data in choice modelling. Then, the fundamental concepts in economics related to two-sided market dynamics and critical mass are presented, followed by the current state of studies on competition and collaboration in multi-sided markets. The next four chapters are dedicated to methods and results for research questions listed in Section 1.2:

- Chapter 3 presents the comparison of a microtransit service and existing conventional transit services.
- Chapter 4 investigates the possibility of developing a mode choice model for DRT systems using synthesized data.
- Chapter 5 introduces the concept of spatial critical mass.
- Chapter 6 presents the outcomes of platform collaboration analysis.

Chapter 7 provides a thorough discussion of the results and presents the overarching outcome of the presented research. The final chapter, Chapter 8, concludes the outcomes and their significance and indicates the future directions of the research.

2 LITERATURE REVIEW

In this chapter, the first section reviews the simulation methods of microtransit systems and emphasises the importance of people's choice in the model. The second section is dedicated to reviewing the opportunities and challenges in using revealed preference data for choice modelling and the existing methods to tackle the problem of missing data. The third section, first, explains the concepts of *multi-sided market* and *critical mass*, then presents a summary of studies on critical mass. The last section is dedicated to highlighting the literature on competition in multi-sided markets and the niche for collaboration studies.

2.1 MICROTRANSIT SIMULATION APPROACHES AND THEIR SHORTCOMINGS

Similar to any new system, implementing microtransit can be highly risky due to its unknown financial and operational aspects. Enoch et al. (2006) have described 11 cases of failed microtransit systems around the world and referred to costing and marketing as their main problem. Also, more recent systems, regardless of their initial success, did not sustain for more than a few years, for example, Kutsuplus in Helsinki, Finland (Sulopuisto, 2016) or Split in Washington D.C., United States of America[1]. Therefore, it was necessary to provide better understanding of the DRT, and guidelines for its implementation. Numerous studies were conducted to survey the current status of microtransit services and to find the determinant elements in their viability (Brake and Nelson, 2007; Brake, Nelson, and Wright, 2004; Currie, 2007; Palmer, Dessouky, and Abdelmaguid, 2004; Palmer, Dessouky, and Zhou, 2008) or develop a qualitative framework or guideline for designing services (Brake and Nelson, 2007; De Jong et al., 2011; Ferreira, Charles, and Tether, 2007). Although these studies provided valuable facts about the consequences of running microtransit, they are still limited in providing effective suggestions for designing microtransit systems in new areas that have completely different circumstances. Some studies strongly advise against duplicating a successful microtransit system in another area without considering its new conditions (De Jong et al., 2011; Enoch et al., 2006).

Additionally, there are numerous studies on optimising the routing algorithms of the system, also known as Dial-a-Ride-Problem or Pick-up and Delivery problem (Berbeglia, Cordeau, and Laporte, 2010; Cordeau and Laporte, 2003, 2007; Dessouky, Rahimi, and Weidner, 2003; Fu, 2002; Ho et al., 2018; Marković et al., 2015; Pillac et al.,

1 http://www.splittechnology.com/

2013). However, despite the importance of routing algorithm, it cannot help decision makers to foretell the consequences of running a microtransit system in full.

Simulations have been developed in the recent decades to help scientists conduct controlled experiments for investigating the phenomena that are not easily operable or controllable in the real world (O'Sullivan and Perry, 2013). The high cost and long time of testing a microtransit system in the real world make it an appropriate case for a simulation study. To go beyond the routing algorithm and provide a more informative insight into implementing such new modes of transport, more detailed simulations than the traditional strategic models are necessary to identify and demonstrate the extent of viability of a system (Ronald, Thompson, and Winter, 2017). Agent-based models are capable of providing results on an individual basis, which has been identified as the necessary approach for modelling any new flexible transportation mode (Ronald, Thompson, and Winter, 2015c, 2017), e.g., car-sharing, ride-sourcing, microtransit (Ciari, Balmer, and Axhausen, 2009; Dubernet, Rieser-Schüssler, and Axhausen, 2013; Ronald, Thompson, and Winter, 2015a). In these models, each traveller is defined as an agent, who has a personal objective function, moves around according to his/her plan, and may be able to improve that plan according to his/her constraints. Agent-based models can be considered a subset of microsimulation models.

Microsimulation approaches have been proposed and explored in a number of early microtransit studies. Probably the best-known model was introduced in the work of Horn (2002). His model was capable of modelling and evaluating the performance of several modes of public transport (e.g., smart shuttles, microtransit, taxi) and showed the effectiveness of microtransit. Deflorio, Chiara, and Murro (2002) proposed a three-module simulation (a travel requests generator, a trip planner, and a service simulator) to assess the performance of microtransit systems. Häll, Högberg, and Lundgren (2012) introduced a similar modelling system and studied planning structures. Quadrifoglio, Dessouky, and Ordóñez, 2008 have applied simulation to assess the impact of service zoning and decentralization of demand management.

The number of studies using explicit agent-based modelling was limited. Cubillos, Guidi-Polanco, and Demartini (2005) have developed MADARP, which uses the Java Agent Development Framework (JADE)[2] for designing and performing experiments on decentralized and centralized systems. This model was improved by Cubillos, Crawford, and Rodríguez (2007) and Cubillos, Gaete, and Crawford (2007) for a better architecture and scheduling algorithm. Finally the model was further developed and called SIM-MADARP with improved agents (Donoso, Sandoval, and Cubillos, 2009; Donoso et al., 2010). However, overall, the lack of experimental results highlighted that the model is only applicable in theory. Ronald, Thompson, and Winter (2017) have compared three simulation software packages: a custom made,

2 http://jade.tilab.com

a microsimulation and one agent-based. They have concluded that although the results are 'relationally replicant', they are statistically different.

Furthermore, one topic that is yet to be investigated thoroughly is the explicit comparison of a microtransit system to the existing infrastructure (especially the public transport infrastructure), which may have the greatest impact on the decision makers to switch from conventional public transport (CPT) to microtransit. It should be demonstrated that not only microtransit is a high-quality service but also is better than already existing services in terms of costs and performance. Edwards and Watkins (2013) developed analytical techniques to compare the efficiency of microtransit and CPT regarding the users' and operators' costs. Diana et al. compared the two modes in terms of their emission (Diana, Quadrifoglio, and Pronello, 2007), and their travelled distance and thus operating cost (Diana, Quadrifoglio, and Pronello, 2009) using mostly aggregated approaches. Besides, there are studies on hybrid and semi-flexible systems that investigate the impact of partially replacing CPT by microtransit using survey (Errico et al., 2013), analytical model (Li and Quadrifoglio, 2010) or simulation (Atasoy et al., 2015). Also, Chang and Yu (1996) and Quadrifoglio and Li (2009) have employed analytical models to determine the demand switch point, which is the exact demand density below which DRT outperform CPT in terms of user performance and operator's cost, between these two modes.

Main issues with these simulations include integration of traffic (Atasoy et al., 2015; Deflorio, Chiara, and Murro, 2002; Ronald, Thompson, and Winter, 2017), realistic demand or environment modelling (Häll, Högberg, and Lundgren, 2012), and integration of people's realistic preferences (Horn, 2002; Ronald, Thompson, and Winter, 2015b).

Microtransit simulation is a fast-emerging topic, many of the above-mentioned issues have been addressed. Also, the usage of agent-based models has become prevalent due to the level of details that the agent-based models can provide, their flexibility in simulation design, and their capability in simulating the interaction of demand and supply (Ronald, Thompson, and Winter, 2015c). For example, acknowledging the importance of the passengers' behaviour and their preferences, many models have focused on improving the integration of choice modelling and conducting surveys (for example Frei, Hyland, and Mahmassani, 2017; Liu et al., 2018). Djavadian and Chow (2017b) have gone a step further and incorporated the preferences of drivers.

In Chapter 3, an agent-based model is used to compare microtransit and CPT. Although more advanced simulations have been developed in the past couple of years, at the time of the submission of this chapter as a paper, it was one of the first works using an agent-based model to compare the two modes of CPT and microtransit and highlight the importance of choice modelling and has been subsequently cited in relevant literature (Archetti, Speranza, and Weyland, 2018; Czioska et al., 2017).

2.2 TRAVEL BEHAVIOUR

There is an overall consensus among the researchers in the field of microtransit simulation on the crucial role of people's preferences and their travel behaviour (Ronald, Thompson, and Winter, 2015c), and the necessity of their integration in the modelling. Travel behaviour is often analysed and modelled as short- and long-term. Short-term travel behaviour includes day-to-day behaviour such as route choice, mode choice, and response to operational changes in the transportation system (e.g., traffic conditions, work zone, special events, or adverse weather). Long-term travel behaviour includes decisions such as residential choice, work location choice, and car ownership. Travel time and cost are decisive factors in adjustment of short-term travel behaviour that may cause a shift in travel mode or route. Travel choice models are often estimated using revealed preference (RP) or stated preference (SP) data collected from a sample of travellers. RP data consists of the actual choices made by travellers reflecting their constraints and considerations.

One of the fundamental criticisms on SP data is that it carries hypothetical bias due to the lack of obligation for the participants to back up their choices (Fifer, Rose, and Greaves, 2014; Hensher, 2010). In other words, there is a high possibility that SP overestimates or underestimates the participants' preferences as they do not have to make real commitments to their choices. To mitigate the hypothetical bias, many methods have been introduced in the literature, which can be categorized in two groups: ex ante (e.g., cheap talk, and cognitive dissonance) and ex post (e.g., pooling data, certainty scales, in-sample calibration, and referencing to a real) (Fifer, Rose, and Greaves, 2014). However, there is still no prevailing evidence of the success of these methods in completely mitigating the bias under any circumstances.

Presumably, using RP data, when possible, is an apt solution for this problem. Since RP data constitutes of the choices made in the real world, it represents personal constraints and considerations of individuals in addition to the existing circumstances in the market. In other words, RP data conveys to the analyst "reliability" and "face validity" as defined by Hensher, Rose, and Greene (2005). One major shortcoming of RP data is the lack of observed information from non-chosen alternatives. To overcome this, three main approaches are introduced in the literature: missing data imputation, stated data collection, and data synthesizing (Balakrishna, Sundaram, and Salvin, 2010; Washington et al., 2014). Table 2 provides a summary of the existing approaches, and their practical methods, many of them adopted from Hensher, Rose, and Greene (2005).

The first two methods follow the same principle and estimate the attributes of the non-chosen alternatives based on the users' chosen alternatives for the same origin-destination (OD) pairs. In the first method, the average value for each specific alternative's attribute is calculated using the data from users who have chosen that alternative. Limitation on sample size and thus, possible shortage of variation in the attribute levels are the main shortcomings of this method (Brown-

Table 2: Approaches and methods for dealing with absence of non-chosen alternatives' attributes.

Approach	Methods
Missing data imputation	Estimating the non-chosen alternatives' attributes based on the users' chosen alternatives averages
	Estimating the non-chosen alternatives' attributes based on the users' chosen alternatives distributions
	Bayesian Imputation Multinomial Logit (Washington et al., 2014)
Stated data collection	Collecting data from survey respondents (Hensher, Rose, and Greene, 2005)
Data synthesizing	Network Skim Matrix (Jou et al., 2006)
	Simulation
	Web-based routing application

stone, 1998). The second method uses a more advanced approach and estimates a distribution based on the observed attributes of the chosen alternatives. While this method still suffers from sample size issues in the chosen alternatives, it does address the variation of attribute levels. Both methods are, however, highly dependent on the existing data from chosen alternatives. The Bayesian Imputation Multinomial Logit (BI-MNL) method employs the Bayes' theorem, the multinomial logit choice model, and sampling-based estimation to synthesize the unobserved data (Washington et al., 2014). The method also heavily relies on observed data for training and calibration, which makes it prone to insufficient sample sizes for some OD pairs.

The fourth method is to collect stated data on non-chosen alternatives from survey participants, assuming that collecting perceptual data brings the estimated behavioural data closer to reality. The shortcomings of this approach are the extra workload for the respondents, increasing the chances of their random response and the required data cleaning (Hensher, Rose, and Greene, 2005).

The fifth and probably the most common method is using network skim matrices. Skim matrices represent the traveling impedance between pairs of traffic analysis zones (TAZ) in a transportation planning model. The problem with this approach is the lack of data for within-zone trips, the lack of variability of attributes of trips between certain TAZ pairs, and the lack of sufficient data for some OD pairs (Jou et al., 2006). Collectively, all the methods discussed above suffer from two major limitations: (a) they heavily rely on existing observed or reported attribute values to estimate either a distribution, or a mean value, or train a method (the first four methods), and (b) they do not represent the variation or dynamics of the travel attributes because the calculation is simply either static using network skim values or on a coarse level based on the mean values from the chosen alternatives (the first and the fifth methods).

Alternative approaches for synthesizing missing data, which belong to the last category (synthesizing) of Table 2, are agent-based and/or dynamic simulation tools and web-based (offline or online) routing applications. Both are able to route single trips on a fine spatial and temporal granularity. Therefore, it is possible to collect travel time and distance for every single trip with minimal previous information, i.e., origin, destination, and start time of a trip. This guarantees the variability of the trips attributes and the provision of data for any trip length including the within zone trips. The main advantages of these methods are that (a) they do not require any observed or reported alternative attributes; (b) they do not require calibration data; (c) they capture the variations of attributes; and (d) they do not increase the work load of participants.

Estimating the attributes of unobserved alternatives has several implications, one of the most important ones is estimating the choice models and, in turn, value of travel time, which is the most important criterion in evaluating transportation projects. Despite the theoretical and practical advances in modelling travel choices, the limitations in estimating attributes of the non-chosen alternatives undercuts the improved capacity of the choice models (Balakrishna, Sundaram, and Salvin, 2010). Furthermore, if simulation proves to be a reliable tool for data synthesis in this context, it can be used in travel behaviour studies involving new travel modes, such as microtransit and autonomous ride sharing. Chapter 4 presents the comparison of different tools in travel data synthesis and the results of choice models based on them. Further, it provides suggestions on using synthesized data for developing mode choice model for new modes of transport.

2.3 THEORY OF MULTI-SIDED MARKETS AND CRITICAL MASS

Standard economics assumes that average costs increase with increasing supply. In such a market, companies can start with small amounts, and increase production at increasingly higher cost until marginal revenue is equal to marginal costs. More precisely:

- If there is high demand but low supply, prices are high, reducing demand and increasing supply (top left in Figure 1).
- If there is low demand but high supply, prices are low, increasing demand and decreasing supply (bottom right in Figure 1).
- If both demand and supply are low, prices should be medium, thus somewhat increasing the low demand to medium levels, and somewhat increasing the low supply to medium levels (bottom left in Figure 1).
- If both demand and supply are high, prices should also be medium, thus somewhat decreasing the high demand to medium levels, and somewhat decreasing the high supply to medium levels (top right in Figure 1).

Overall, the dynamics has only one attractive fixed point, which lies in the centre of Figure 1, and is more conventionally given by the intersection of the demand and the supply curves.

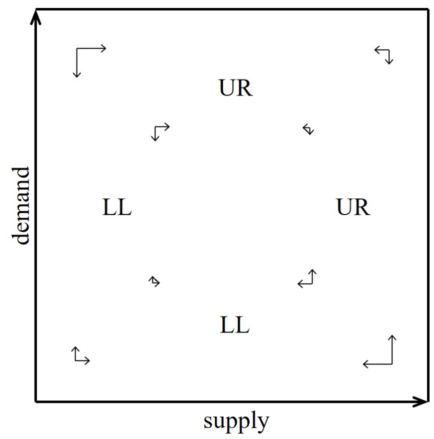


Figure 1: Regular market.

With economies of scale on the supply side and network effects on the demand side, these cases behave as follows:

- If there is high demand but low supply, prices are high, reducing demand and increasing supply (top left in Figure 2).
- If there is low demand but high supply, prices are low, increasing demand and reducing supply (bottom right in Figure 2).
- If both demand and supply are low, prices are medium. For economies of scale on the supply side, this will mean that the price is below the supply curve, further decreasing supply. Conversely, for network effects on the demand side, the price is above the demand/willingness-to-pay (w.t.p.) curve, also further reducing demand (bottom left in Figure 2).
- If both demand and supply are high, prices are again medium. For economies of scale on the supply side, costs will be lower than prices, thus further increasing supply. Similarly, for network effects on the demand side, the willingness to pay will be above prices, thus further increasing demand (top right in Figure 2).

That is, the dynamics has two attractive fixed points, one in the bottom left, one in the top right. A supplying company (roughly) needs to estimate the size of the market (the size of the demand in the upper right corner of Figure 2), divide the cost of the supply by the size of the market, and then assess if the market will bear the resulting price. If the product appears to be profitable, and all underlying assessments are correct, then a company can in principle (e.g., barring competition) enforce the outcome by subsidizing the product long enough until demand has followed the large supply. That is, the dynamics has in principle two attractive fixed points, but the supplier by its own actions can render one of them irrelevant.

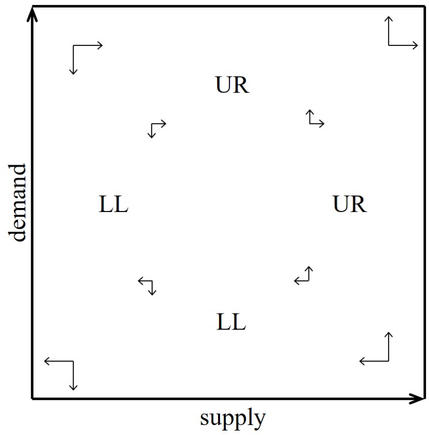


Figure 2: Economies of scale.

The two-sided market with economies of scale on both sides has a flow diagram similar to a market with economies of scale on both sides (Figure 3). However, the platform provider, even when being a monopolist, is not the supplier, and thus can no longer force the outcome of the dynamics. Clearly, high subsidies and marketing campaigns can reduce the basin of attraction of the bottom left fixed point. Yet, it cannot be rendered irrelevant by the platform provider alone. Evans and Schmalensee, 2016b use the term "critical mass frontier", which can be seen as the line separating the basins of attraction of the two fixed points, when plotting numbers of customers and number of suppliers (Figure 3).

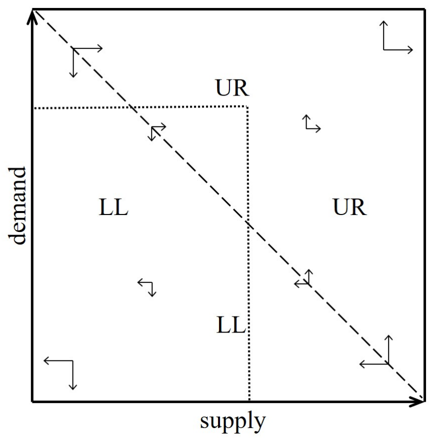


Figure 3: Two-sided market with economies of scale and network effects. The dashed line divides UR (upper right) from LL (lower left). The dotted line denotes a possible market where the densities of demand and supply are smaller (e.g., in rural areas) than they maximally could be (e.g., in urban centres).

Evans and Schmalensee (2016b) discuss the challenges of some multi-sided platforms to reach critical mass. The commonality of these platforms is that their market participants – the 'sides' – are stuck with their location. Multi-sided platforms that have to consider location are a crisply defined subset of multi-sided platforms. News, media, or advice can be provided or sought independent of location, but for example booking a table in a restaurant (the prime example of Evans and Schmalensee (2016b)) requires to consider the location of the customers as well as the location of the restaurants. A person wanting to book a table for the evening is interested only in restaurants within an acceptable travel distance. In this category are other services as well, such as platforms matching repair services, or matching travellers for shared or flexible forms of transportation.

Evans and Schmalensee (2016b) discuss how a particular restaurant booking platform, seemingly unaware of the spatial aspects of the network effect, struggled to achieve critical mass originally, and only by trial and error found strategies to create critical mass at least in the city centres. The fundamental empirical principles of geographic information science (Chrisman, 2012; Goodchild, 2009, 2011) are highlighting that geographical phenomena are heterogeneous, and that near things are more related than distant things (Tobler, 1970). These principles should guide the notion of *critical mass* for spatially dependant matchmaking platforms, i.e., the determination of *critical mass* must become location-dependent.

A remarkable consequence of spatial autocorrelation is the hierarchical organization of space (Batty, 2006). Central place theory (Batty, 2009; Christaller, 1933) postulates that (economic) centres serve surrounding areas depending on the range people would travel for particular goods. These hierarchic centres are forming a lattice, and the regularity has later been linked to fractal nature (Batty and Longley, 1994; Jiang and Brandt, 2016). Spatial hierarchy emerging from economic considerations impacts on settlement structures, transportation networks (Jiang, 2009), and induced mobility demand (Bento et al., 2005). For example, a common challenge in shared transportation is the reallocation of resources that have left the centres: Algorithms still assume (falsely) a homogeneous demand (Fricker and Gast, 2016).

The hierarchy and inhomogeneity of the road network has led to characterizations by network centrality measures (Claramunt and Winter, 2007). However, network centrality is induced by the inhomogeneous distribution of settlements. Thus network centrality alone cannot explain transportation demand; the population distribution adds to the complexity of urban morphology and derived transport demand (Kazerani and Winter, 2009). On the other hand, the emergence of flexible transportation systems, namely ride-sharing, carpooling, car-sharing, and demand responsive transport systems, provides a potential unique opportunity to address this complexity. However, their failure in the real world, mostly due to economic reasons (Enoch et al., 2006; Sulopuisto, 2016), proves that their market is yet to be fully understood. The concept of critical mass and critical mass frontier may be the key to their success, as it guarantees the success in other platforms or phenomena.

Since the development of the two-sided market concept by Rochet and Tirole (2003b), numerous studies have explored platform competition in this context (e.g., Armstrong, 2006; Caillaud and Jullien, 2003;

Kodera, 2015), and many have investigated the critical mass in mostly technology related platforms (e.g., Dubé, Hitsch, and Chintagunta, 2010; Grajek and Kretschmer, 2012). However, a flexible transportation market as an inherently spatial market with many unique characteristics cannot easily adopt or benefit from those studies and requires more specific and to-the-point investigations, which are scarce. For instance, Wang et al. (2016) have looked at pricing in taxi hailing applications by investigating the existence and stability of equilibria in a two sided-market with the taxi hailing application being the matchmaker. Djavadian and Chow (2017b) has framed the flexible transportation systems in a two-sided market, and demonstrated the expected direct interdependence of demand and supply. Their work includes a simulation platform showing that there is benefit in investigating flexible transport systems in a two-sided market.

However, none discusses critical mass or provide understanding of the critical mass frontier in the context of spatial systems. Identifying critical mass in spatial systems, such as transportation, requires deep understanding of the impact and its significance of urban structure, and demand and supply spatial characteristics. Chapter 5 aims at bridging this gap by providing an initial study on the effect of basic spatial characteristics of an area in critical mass of a spatial two-sided market.

2.4 COMPETITION OR COLLABORATION?

Ride-sourcing companies have been the topic of many studies since their advent in 2006 and they have caused numerous controversies about pricing. The cost of a ride using ride-sourcing can be significantly lower than a taxi ride in the same situation (same distance and time) (Gabel, 2016), mainly due to the fewer imposed regulations, which has caused strikes and law-suits from taxi companies globally objecting unfair competition (Zha, Yin, and Yang, 2016).

On the other hand, it is also possible that a sourced ride is priced higher than a taxi ride for a passenger. The reason for that is the company that provides the platform controls the price using a dynamic pricing strategy, affected by the number of available drivers (supply) and passengers (demand) (Cachon, Daniels, and Lobel, 2017). A shortage of drivers in an area is compensated by increasing the price, which in turn leads to either motivating more drivers to show up (become available), or discouraging a subset of passengers with lower willingness-to-pay from travelling (Chen and Sheldon, 2016; Hall, Kendrick, and Nosko, 2015), or both. Examples of this are Uber's surge pricing or Lyft's prime time pricing, where the prices are increased by a multiplier. Literature has shown that this type of market mechanism is disadvantageous to the passengers (Zha, Yin, and Du, 2017), and caused their dissatisfaction (Gurley, 2014). Moreover, the presence of other ride-sourcing companies affects the pricing as well and causes competition.

Competition between ride-sourcing platforms have been studied often using the principles introduced by Rochet and Tirole (2003a). Their ground-breaking work laid the theoretical foundation of platform competition studies of two-sided markets. They have mentioned that almost any market with network externalities can be considered a two-sided market. One important point of their work was that in two-sided markets the pricing structure is more important to the platform benefits than the level of prices that customers pay. Since each market's individual conditions call for different strategies, researchers have focused on distinct markets. While the models of Rochet and Tirole (2003a) and Chakravorti and Roson (2006) are more apt for markets such as credit card and online shopping platforms, Armstrong (2006) has worked on a model suited for shopping malls and nightclubs. Others have focused on advertising markets (Reisinger, 2012) or the video game industry (Cennamo and Santalo, 2013).

Particularly in the context of ride-sourcing there are numerous work on platform competition and pricing strategies. This is mostly due to the controversies around the necessity of the regulatory intervention of the government on ride-sourcing platforms pricing. Zha, Yin, and Yang (2016) have used an exogenous matching function to match drivers and passengers in an aggregate model and investigated the trade-offs of pricing strategies under Nash equilibrium in a duopoly market. Heilker and Sieg (2018) studied the pricing structure using Hotelling's model (Hotelling, 1929) based on the average cost and companies' fleet size. Lee (2017) have used a Salop circle (Salop, 1979) to model a ride-sourcing system to investigate the various pricing strategies and components, such as price distribution and dynamic pricing, i.e., fixed versus surge pricing. He has emphasized the role of spatial components in significant pricing fluctuation of a dynamic platform competition and mentioned that "space and stochastic luck can mitigate winner-take-all effects in price competition" (Lee, 2017, P.1). All of these studies consistently arrived at the conclusion that competition does not necessarily lead to lower prices, and that a platform monopoly contributes to the general welfare of the passengers, and thus they called for regulatory intervention from the authorities.

Although platform monopoly has been identified better than competing ride-sourcing platforms, there are limited studies on the collaboration of ride-sourcing companies and how it impacts the collaborating operators and their registered drivers. One example is the work of Cohen and Zhang (2017), who looked at a partnership between a ride-sharing platform, *Via*, and a taxi-hailing platform, *Curb*, in New York City, which allows the passengers to share their taxi ride. They have concluded that with the right arrangement all parties would benefit from such partnership.

Chapter 6 bridges this gap and provide a systematic investigation of spatial characteristics in the collaboration of ride-sourcing platforms for the first time. The intention of this work is not to make contribution to the simulation of ride-sourcing systems, but to use a pertinent simulation to shed light on the collaboration of platforms and its initial consequences (for more advanced simulation of ride-sourcing please see Bischoff and Maciejewski, 2016; Djavadian and Chow, 2017a).

3 COMPARISON BETWEEN MICROTRANSIT AND CONVENTIONAL TRANSIT: A SIMULATION STUDY

This chapter is adapted from the manuscript titled "Comparison between ad-hoc demand responsive and conventional transit: A simulation study" published in the journal *Public Transport*. I conducted the majority of the work, including research implementation, result analysis, discussions, and paper-writing. My supervisor Prof. Stephan Winter was supervising the progress, contributing to research ideas, and actively discussing the results. My co-supervisor, Dr. Nicole Ronald helped in research design and implementation and suggested literature for reviewing.

3.1 CONTRIBUTION

The expectation from the microtransit services is that the adaptive nature of this system will bring benefits to operators and customers alike. On one hand, the operators may replace underutilised and uneconomical forms of conventional public transport (CPT) with an appropriate microtransit system, which operates as needed and with smaller vehicles, hence, more economically. On the other hand, customers can benefit from the door-to-door convenience of this transport mode without suffering the high cost of a taxi or their private vehicles, and without the hassle of conventional public transport that in areas of low demand operates infrequently and thus is inconvenient. This chapter challenges this expectation.

The main hypothesis of this chapter is that microtransit systems perform considerably better than CPT. Demonstrating this superiority is necessary in order to justify the introduction of microtransit into the current public transport system. The investigation will be based on user performance and operators' cost to be able to investigate whether a service providing higher quality mobility to users does not cost extra for operators.

An extensive comparison between microtransit and CPT is performed using an agent-based simulation, MATSim, to test the hypothesis and demonstrate the potential of the used model, not only in theoretical scenarios but also in the real world. The performance of both CPT and microtransit systems are simulated and evaluated firstly in two conceptual networks with several scenarios including variations in demand and in supply level, and then in a real-world scenario. Each mode is simulated separately assuming that the passengers have no other options but the offered mode.

The rest of this chapter is organised as follows. The modelling and evaluation methods are explained in Section 3.2, followed by the implementation scenarios' descriptions in Section 3.3. The results and their analysis are presented in Section 3.4. Section 3.5 includes an overall discussion on the results and the methods. Finally, the last section is dedicated to conclusions and future work.

3.2 METHODS

This work utilises MATSim to model and compare microtransit and CPT. The following describes the structure of MATSim, the embedded ad-hoc dynamic routing algorithm, and the evaluation procedure.

3.2.1 *Simulation Software*

The simulation approach follows mainly the design philosophy of MATSim (Charypar and Nagel, 2005). In MATSim, each agent (traveller) has a daily plan including the spatial and temporal characteristics of the agent's activities and the desired transport mode. All the plans are simultaneously executed according to an event-driven queue-based traffic flow simulation (Charypar, Axhausen, and Nagel, 2007), also known as Mobility Simulation. Then, all the plans are scored according to (Charypar, Axhausen, and Nagel, 2007):

$$F = \sum_{i=1}^{n} U_{act,i} + \sum_{i=2}^{n} U_{trav,i} \tag{1}$$

where F is the fitness of the plan (score), $U_{act,i}$ is the utility of performing activity i and $U_{trav,i}$ is the (dis)utility of travelling between activities i and $i-1$. This process is repeated in several iterations until the system reaches an equilibrium state, meaning that no agent can significantly improve its plan. The utility of performing an act ($U_{act,i}$) depends mainly on its type and starting time, and the amount of time allocated to it, which is calculated according to:

$$U_{act} = U_{dur} + U_{wait} + U_{late,ar} + U_{early,dep} + U_{short,dur} \tag{2}$$

where $U_{act,i}$ is the utility of performing an act, U_{wait} is the (dis)utility of waiting to start an act (for example, if an agent arrives at store for shopping before the store's opening time), $U_{late,ar}$ is the (dis)utility of arriving late, $U_{early,dep}$ is (dis)utility of departing early, and $U_{short,dur}$ is (dis)utility of short duration of performing an act. U_{trav} is aligned with Vickrey's model of departure choice (Arnott, De Palma, and Lindsey, 1993) and is computed according to:

$$U_{trav(t_{trav})} = \beta_{trav} \times t_{trav} \tag{3}$$

where β_{trav} is marginal utility of travel, and t_{trav} is duration of travelling between two activities.

At the start of each iteration, a percentage of the agents are allowed to change their plans. This change includes choosing from previous plans (each agent has a limited memory for the previous plans with the highest scores), rerouting, or changing the activity time. Due to the modular approach of MATSim, it is also possible to define other variations such as changing mode or activity location. Since the agents' memories are limited and just the plans with the highest scores are stored, over iterations it is possible for the agents to improve their plans. At the end of each iteration, the output is a file in XML format including the spatial and temporal details of all the events of the simulation. The high granularity of the output and input (the capability of defining utility functions for each agent), which facilitates the analysis of every scenario on an individual level, is of the main features of MATSim.

3.2.2 *Microtransit Modelling in MATSim*

The routing algorithm is one of the most important components of a microtransit system. Due to the modular structure of MATSim, it is possible to plug in any desired algorithm for microtransit simulation. In this work, the dynamic routing algorithm developed by Ronald et al. (2013) is implemented that extends the standard Dynamic Vehicle Routing Problem (DVRP) module in MATSim, which has the capability of simulating a wide range of vehicle routing algorithms (Maciejewski, 2016). It currently has the limitation of performing no iterations, i.e., the agents can only run their initial given plan and are not able to improve their plans over several iterations. This limitation is accepted in this work as well as previous studies (Ronald, Thompson, and Winter, 2015a,b), since it causes only underestimation (not overestimation) of the microtransit performance. At each time interval, the passenger demand file is checked for new requests received during the previous time interval. If any request is found, the passenger will be allocated to a vehicle using an exhaustive search algorithm that finds the vehicle with the least additional travel time and penalty cost after considering the new request. The penalty cost is calculated according to:

$$PC_i = TTR_i = \frac{PTT_i}{DDT_i} \tag{4}$$

where PC_i is the penalty cost for Passenger i, TTR_i is the travel time ratio for Passenger i, PTT_i is planned travel time for Passenger i (minutes), DTT_i is direct travel time for Passenger i (minutes). This involves a travel time ratio for each passenger, i.e., the ratio of the planned travel time over the direct travel time.

3.2.3 *Evaluation Methods*

Dowling, Skabardonis, and Alexiadis (2004, pp. 75) define Measures of Effectiveness (MOE) as "the system performance statistics that best characterise the degree to which a particular alternative meets the project objectives". Accordingly, the MOEs in this work should demonstrate how well a transport system caters for the demand from both passengers' and operators' perspective. Virtual In-Vehicle Time (VIVT) is a widely used indicator to assess the performance of a transit service (Diana, Quadrifoglio, and Pronello, 2009; Edwards and Watkins, 2013; Quadrifoglio and Li, 2009) and operation cost is one

Table 3: The MOEs, their indicators, and the necessary variables for their calculation.

MOE	**Indicators**	**Variables Derived from Simulation**
User Performance	Virtual In-Vehicle Time	Riding Time
		Waiting Time
		Walking Time
		No. of Transfers
Operation Cost	Cost	Kilometers Driven
		Hours Driven
		Number of Vehicles

of the key factors affecting the decision makers' choice to operate a new system. However, qualitative criteria, such as on-board comfort that may influence passengers' choice of mode, have not been considered here. Table 3 summarises the MOEs, their indicators, and the variables needed to calculate each indicator.

VIVT reflects the perceived travel time by travellers and is calculated according to:

$$VIVT = RT + \alpha_1 \times WWT + \alpha_2 \times WLKT + \alpha_3 \times TRF \tag{5}$$

where VIVT is virtual in-vehicle time, RT is ride time on-board, WTT is waiting time, $WLKT$ is walking time, TRF is number of transfers, and weighting coefficients α_1, α_2, and α_3. The perceived travel time is an important factor in travellers' decision about their mode of transportation (Beirão and Cabral, 2007; Hensher, Stopher, and Bullock, 2003). Since passengers' perceptions of the duration of different parts of travelling (e.g., riding on-board, waiting, walking) are different, coefficients are needed to normalise these times and make them comparable. The variables α_1, α_2, and α_3 are set to 1.7, 1.8 and 10 respectively according to literature (Wardman, 2004). It should be noted that the lower the VIVT for a mode, the more desirable that mode is for passengers.

The operation cost of a transit service mainly depends on three factors: the size of the fleet, the operating hours, and the kilometres driven by each vehicle (Australian Transport Council, 2006), and is calculated according to:

$$OC = \sum_{i=1}^{n} [(OH_i \times COH) + (VKT_i \times CVKT)] \tag{6}$$

where OC is the operator's cost, OH_i is the operating hours of vehicle i, COH is the vehicle's cost per one operating hour, VKT_i is the total kilometres driven of vehicle i, CVKT is the cost per one kilometre driven by a vehicle, and n is the number of vehicles. The cost per hour

Table 4: Costs for vehicles in AUD.

$/km for taxi	1.18
$/hour for taxis	18.71
$/km for bus	0.313
$/hour for bus	49.58

and per kilometre are very different for CPT vehicles (buses) and microtransit ones (cars or mini-vans). Table 4 summarises these costs for bus and taxi (as a proxy for microtransit), which is taken from the National Guidelines for Transport System Management in Australia: Part 4 Urban Transport (Australian Transport Council, 2006) and the Review of Victorian Taxi Costs (Lennon, 2008). In this study, it is intended to compare the cost of microtransit to various CPT services to ascertain that a better mobility, and higher performance does not cost significantly more. Since the uptake is equal for both services (CPT and microtransit), by assuming the same ticket price for both services, the operator's income from the tickets will be the same and could be ignored.

3.3 IMPLEMENTATION

The main contribution of this work is to present an extensive comparison of CPT and microtransit to investigate if replacing the former with the latter improves people's mobility. To this end, several hypothetical scenarios including variation in demand level, network shape, and supply system are designed. Additionally, a realistic scenario has also been investigated. The details of all scenarios are described in the following sections.

3.3.1 *Network*

Two hypothetical network shapes, grid and star-shaped, and one real-world network have been modelled. While the first two have been designed and produced entirely by the researchers, the last one has been extracted from Open Street Map (OSM) data. The properties of each shape are presented as follows.

GRID NETWORK (G): Since a grid network is considered to be the perfect network type for public transport (Nielsen, 2005), it provides the opportunity to compare microtransit to the ideal situation of CPT. The simulated area is a square (16 km^2) divided into 25 smaller squares with a mesh of public transport. This network contains six bus lines riding on horizontal roads and six bus lines riding on vertical roads. The stops on each line are on the intersections in a convenient distance of 800 meters (the black dots represent stops in Figure 4(left)), which is the ideal distance for public transport sta-

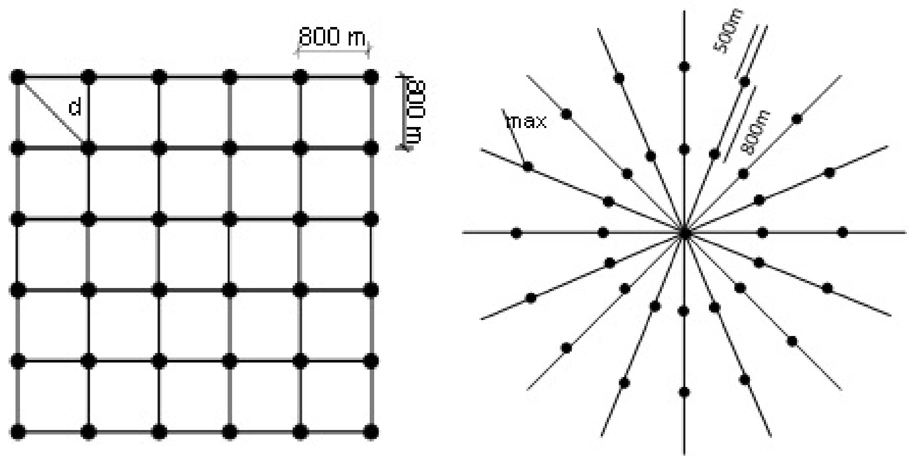


Figure 4: Grid network (left), Star-shaped network (right)

tion (Nielsen, 2005). Theoretically, the farthest one should travel on foot to reach a transit stop is 566 meters, half the diagonal length of the small squares (d/2).

STAR-SHAPED NETWORK (S): Many cities have star-shaped public transport networks. It is also the underlying form of the realistic scenario discussed, which makes it possible to compare the results of a pure conceptual model with a real-world scenario. The simulated area is a circle ($r = 2.1$ km) of approximately 16 km^2 served by a star-shaped transit network (Figure 4(right)). Similar to the previous case, the distance between stops on each line is 800 meters. However, in this case the maximum walking distance to reach a stop is slightly longer (max = 625 m). This transit network consists of eight bus lines riding on the eight diametrical roads.

REAL-WORLD NETWORK (B): Belgrave (Victoria, Australia) was the chosen suburb for the real world scenario in this project. This area heavily relies on feeder public transport at commuter times, and is geographically heterogeneous. It has been earmarked by the local transit operating agency, Public Transport Victoria, as a candidate for experimenting with microtransit. An area of approximately 16km^2 centred by Belgrave railway station has been selected that includes six bus lines. The bus network in this area is conceptually similar to the star-shaped network (Figure 5).

3.3.2 *Demand Levels and Modelling*

The designed demand for the hypothetical networks starts from one request per minute up to five with an increment of one (this allows to investigate the lower demands more closely), and from five to 15 with an increment of five. Here, x number of requests per minute means the number of trips that are requested in the whole network in each minute. The time and location of the demands were generated ran-

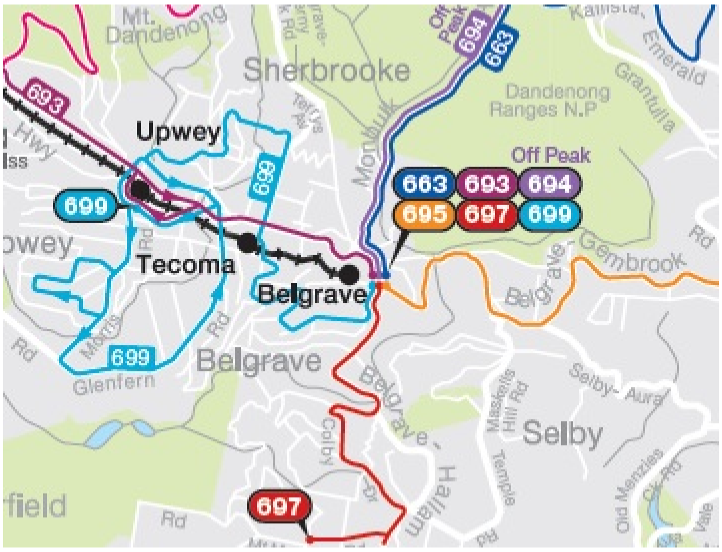


Figure 5: Belgrave CPT network.

domly by a Python script using different random seeds. The requests were temporally spread over one hour.

The demand for the Belgrave scenario was generated mainly according to real-world data, which had been collected through surveys on bus routes. The available data includes the number of passengers boarding and alighting buses at each bus station and the estimated weekday patronage by hour for each line in percentage.

In order to generate the demand for the Belgrave scenario, the six bus lines operating in the area were chosen. For all the lines' stops that were inside the case study area, the number of boarding and alighting passengers were retrieved from the data source. Since the passengers' trajectories or directions are not known, the origins and the destinations of the trips were assigned randomly, in a way that total numbers of demand are equal to the number of passengers boarding on the buses in different bus stops in the chosen area during one weekday (935 trips per day). However, although at each stop the number of boarding passengers was the same as in the data set, there are more alighting passengers (compared to the data set) in some stops. This adjustment was necessary due to the inconsistent numbers for boarding versus alighting passengers in the data. This inconsistency is expected because the survey has been done in a larger area than the investigated area by this study. Also, the adaptation is so small that no significant effect on the results is expected.

Demand in the Belgrave scenario was temporally spread across 17 hours from five in the morning to nine in the evening. The demand in each hour during this time was in accordance with the average estimated weekday patronage by hour for each line in percentage (the average of six lines is presented in Table 5). For instance, there are 186 trips in the AM peak, which is equal to 20% of 935 trips.

Table 5: Estimated weekday patronage by hour, average of all lines.

Pre AM Peak	5:00-6:00	4%
AM Peak	7:00 – 8:00	20%
Interpeak	9:00 -14:00	38%
PM Peak	15:00 - 18:00	35%
PM Late	19:00 – 21:00	3%

Table 6: The details of bus lines in Belgrave.

Line Number	Start time	End time	Headway
663	6:15:00	22:00:00	30 mins. or more
693	6:20:00	21:20:00	30 mins. or more
694	6:20:00	15:00:00	1 hour or more
695	6:00:00	10:30:00	30 mins. or more
697	6:10:00	19:35:00	30 mins. or more
699	8:30:00	17:00:00	1 hour or more

3.3.3 *Transit Supply Systems*

The alternative services to be investigated in the hypothetical networks are three different headways of CPT, 7.5 minutes (CPT7.5), 15 minutes (CPT15), and 30 minutes (CPT30), and the microtransit service with zero rejection rate, meaning that for each demand level the number of microtransit vehicles was determined in a way that all the agents could reach their destination and no one was rejected due to the lack of vehicle availability. The reason for this restriction on the rejection rate is to make the comparison between microtransit and CPT fair: As all agents that use CPT are able to reach their destination, so should the microtransit-using agents.

However, the alternatives in Belgrave were just the current public transport headways and microtransit. The public transport in Belgrave consists of one train line ending in Belgrave station, and the six regular bus lines. In this study, only the regular bus lines and their demand have been modelled, since microtransit cannot and is not designed to compete with mass transit (the train). The lines' numbers, start and end times, and their headways are presented in Table 6. The bus lines were modelled using the published General Transit Feed Specification (GTFS) data and existing Java codes.

The CPT vehicles are buses with a capacity of 75 (sitting and standing) passengers, and microtransit vehicles are cars with four people capacity.

3.3.4 *Simulation*

The scenarios are run according to the description in Section Section 3.2.1. However, the scoring function in the simulation is defined with fewer parameters. Here only the utility of performing an act U_{act} is considered for scoring the plans, which is calculated according to Equation 8.

$$U_{act} = U_{dur} \tag{7}$$

$$U_{dur}\,(t_{trav}) = \beta_{dur} \times t^{*} \times \ln\left(\frac{t_{dur}}{t_0}\right) \tag{8}$$

Here, t_{dur} is the actual duration of the activity, t^{*} is the duration at which the marginal utility is β_{dur}, β_{dur} is the marginal utility, and t_0 is a parameter that determines the minimum duration of and activity and its priority. β_{dur} is set to 6 in line with the default settings of MATSim.

In CPT scenarios' setting, agents can store up to five plans. To generate new plans at the start of each iteration, 80% of the agents were allowed to change between their previous plans, while 10% were allowed to change their travel starting time and 10% were allowed to change their route, i.e. using different bus routes.

The required number of runs is calculated through an iterative procedure and depends mainly on three criteria, 1) confidence level ($1 - \alpha$, α: the probability of the true mean of the investigated result not lying within the confidence interval), 2) confidence interval (CI: the numerical span within which the true mean may sit), and 3) standard deviation (S) of the model results. In this work, the confidence level and the desired range (CI/S) is set to 95% and 2.0 respectively according to published microsimulation guidelines (Dowling, Skabardonis, and Alexiadis, 2004).

3.4 RESULTS

Figure 6 presents the results of simulations in terms of user performance in grid (left) and star-shaped (right) networks. The VIVT for CPT users is almost the same in both networks, while it slightly differs for microtransit, especially in lower demand scenarios. As expected the VIVT does not depend on the demand in CPT, while it changes for different demand in microtransit. Moreover, the passengers travelling by microtransit have the lowest VIVT in both networks and statistical tests on the results of VIVT revealed that this difference is significant between the different CPT services and microtransit. In other words, microtransit provides a significantly better service than any CPT in terms of user performance. For example, in grid network VIVT for microtransit varies between 15 and 19, while it is 29 for CPT7.5, meaning that microtransit provides a performance approximately twice as good as CPT7.5. Although 7.5 minutes is considered

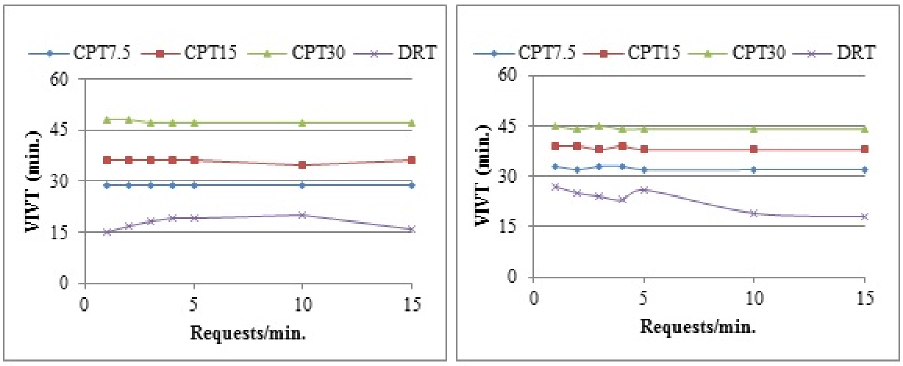


Figure 6: Average passengers' VIVT (Left: G network, Right: S network).

a very high quality bus service and grid network is the ideal form of conventional public transport (Nielsen, 2005), microtransit is still outperforming a service with these characteristics.

In order to provide a better understanding of the performance of the microtransit, the percentage of passengers waiting more than 10 minutes has also been calculated and presented in Table 7. This number for CPT passengers is less than 2%, while for microtransit passengers it goes up to 25%. As seen in the table, the figures for microtransit are not monotonically proportional to the demand, as one might expect. The reason is that there are a few parameters impacting the microtransit figures in each network, including the number of vehicles, and the spatial and temporal distributions of passengers' origins and destinations. Therefore, although the number of vehicles is increasing as the number of calls increasing, the percentage of passengers with short waiting times (i.e. less than 10 minutes) should not necessarily change monotonically proportional to the demand. For instance, with more demand there might be more or less opportunities for matching passengers, or some passengers may like to walk further. The slightly higher percentage of microtransit passengers with short waiting times in the grid network (75% - 87%) compared to the star-shaped network (63% - 79%) suggests that grid-shaped networks might provide better conditions for running microtransit.

One might suggest that the fact that almost no one (less than 2% of passengers) is waiting more than 10 minutes when traveling by CPT is a sign of its higher performance; however, it should be taken into account that the passengers waiting more than 10 minutes for microtransit are in the minority (average 25%) and they wait comfortably at home instead of rather uncomfortably at bus stops, where the CPT passengers have to wait during their transfers. Even with schedule-based transit, there may always be a waiting time for CPT users due to the uncertainty of the traffic condition or driver behaviour. Moreover, as mentioned earlier, the agents in CPT simulations have the chance of improving their plans and changing the time of their arrival to the bus stop to have the shortest waiting time, while in microtransit simulation this is not possible and the agents just have one chance for trial. Another point to notice is that in CPT simulation, the agents can walk a part of their trip if its required time is lower

Table 7: Percentage of passengers waiting less than 10 minutes.

Requests	CPT7.5	CPT15	CPT30	microtransit
per min.	Star-shaped network			
1	98%	98%	98%	63%
2	99%	99%	99%	65%
3	99%	99%	99%	70%
4	99%	99%	99%	70%
5	99%	99%	99%	66%
10	99%	99%	99%	78%
15	99%	99%	99%	79%
	Grid network			
1	98%	98%	98%	87%
2	99%	99%	99%	80%
3	99%	99%	99%	77%
4	99%	99%	99%	79%
5	99%	99%	99%	78%
10	99%	99%	99%	75%
15	99%	99%	99%	84%

than the waiting time and riding time with a bus. Thus, a number of agents might walk instead of waiting long times, which is expected in scenarios with 30 minutes headway.

There are two main reasons for lower VIVT for microtransit passengers, regardless of their higher wait time and ride time. First, microtransit customers need no transfer, which is a highly undesirable action (every transfer is perceived as 10 minutes ride time, see Section 3.2.3). Second, since the microtransit service is door-to-door the passengers do not need to walk, instead they wait longer, which is a slightly more desirable activity in travelling (see Section 3.2.3).

Additionally, the VIVT for every single passenger has been compared in different scenarios to find out the percentage of people who are not better off using microtransit. The results are presented in Figure 7. This percentage, predictably, decreases in both networks as the CPT headway drops, showing that replacing CPT with microtransit has higher advantages in transit networks with long headway compared to the ones with shorter headway. Moreover, the minor percentage of passengers (lower than 10% and 30% in G and S network respectively) have a higher perceived travel time (VIVT) when travelling by microtransit compared to CPT. In other words, the majority of the people (more than 90% and 70% in G and S network respectively)

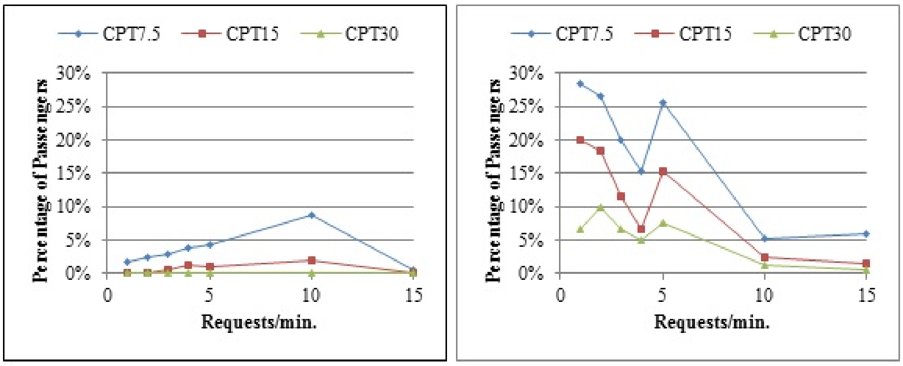


Figure 7: Percentage of passengers with higher VIVT when using microtransit instead of CPT (left: G network, right: S network).

will have a better mobility option if the CPT services are replaced by microtransit.

The percentage of passengers, who are worse off with microtransit, is higher in S network scenarios in lower demands. The reason is that although the number of microtransit vehicles are enough to deliver everyone to their destinations (Section Section 3.3.3), it is not enough to keep the waiting time for everyone at a low level. Further simulations showed that by adding just one vehicle in these situations the percentage of disadvantaged passengers drops dramatically without a significant increase in the cost. For instance, if in S network with one request per minute four vehicles runs instead of three, the percentage of disadvantaged customers decrease from 28% to 2%. However, in this work it was decided to stay with the initial assumption and keep the number of vehicles at its possible minimum.

Similar results are observable for the Belgrave scenario. The average VIVT is 18 minutes for microtransit travellers, almost half the VIVT of the CPT travellers (35 minutes), which is considered a significant improvement in the passengers' mobility. However, this excludes a small minority (5%) of the passengers who suffer from a longer VIVT if CPT is replaced by microtransit. Similar to the test scenarios, lengthy walking time is an important factor in prolonging the VIVT for CPT passengers. This problem worsens in the Belgrave scenario due to the irregular timetable of the bus lines.

Analysis of agents' individual waiting times has revealed that the number of people with waiting times less than 10 minutes is almost equal for CPT and microtransit passengers in the Belgrave scenario, with 91% and 90% respectively. This figure has improved for microtransit users in the real world, while worsened for CPT passengers. In this scenario, unlike CPT buses, which are bound to run in certain streets, microtransit vehicles are flexible and have no limitation to use all the streets in the network. This results in lower waiting time for microtransit users in the real world compared to the hypothetical scenarios, in which both modes' vehicles run on the same network. It is the same in almost any real-world environment.

For the results of the Belgrave scenario, the passengers are sorted according to the starting time of their travel to test if travelling in peak hour would affect their VIVT in both modes. However, no specific decrease or increase in the VIVT at any time was observed, meaning that the microtransit performance is constant throughout a day.

The results reflect that regardless of the demand density, microtransit is outperforming CPT in terms of user performance. Thus, in making decision about replacing them the cost of operation will be the determinant factor. Table 8 and Table 10 provide details on the cost of each service, and the difference between microtransit and each CPT services in grid and star-shaped network respectively. This difference is expressed as the percentage of each corresponding CPT service's cost. For example, in the grid network, given a demand of one request per minute, 88% of CPT7.5 cost is saved if microtransit runs instead. As another example, given a demand of five requests per minute in the same network, an extra 17% of CPT30 cost is required to replace the CPT30 by microtransit. The point of this comparison is to find the critical demand: The demand at which microtransit outperforms CPT with the same cost.

According to the Table 8 and Table 10, although the operating cost of CPT in grid network is considerably higher than in star-shaped network, the operating cost of microtransit appears to be independent from the network shape. It should be noted that the small difference between the microtransit costs in different networks is caused by the difference in required vehicles for grid network (Table 9). Also, the steady increase in the number of vehicles is an evidence to the low level of sharing in the two networks, which makes the system comparable to ride-sourcing.

According to Table 8, in the grid network, 4, 10 and 15 requests per minute are the critical demand comparing microtransit with CPT30, CPT15, and CPT7.5 respectively. Meaning that, for example, it is possible to provide microtransit for demand density up to 15 requests per minutes (900 requests per hour) with just three percent cost difference with CPT7.5. Fifteen requests per minute could be considered even a high demand situation, where providing a public transport with 7.5 minutes headway is justifiable.

However, the situation is very different in the star-shaped network. At three requests per minute, microtransit cost marginally higher than CPT15 and CPT30 with two and ten percent difference. Just adding one request per minute increases this difference to 30 and 40 percent respectively. However, the critical demand for CPT7.5 is yet to be determined. Further simulations revealed that at seven requests per minute microtransit service cost almost the same as CPT7.5 (just 3% difference).

Accordingly, it is expected that a microtransit service costs less than current CPT in Belgrave due to its similarity to one of the previous scenarios (star-shaped network with one request per minute). This expectation is met by calculating both services' cost, which confirms that the cost of providing microtransit in this scenario is equal to just 43% of the current CPT service.

Table 8: Operator's cost for each service, and microtransit and CPT cost comparison in the grid network.

Requests per min.	Cost to the Operator			
	CPT7.5	CPT15	CPT30	microtransit
1	$4,051	$2,710	$1,310	$479
2	$4,051	$2,710	$1,310	$748
3	$4,051	$2,710	$1,310	$1,007
4	$4,051	$2,710	$1,310	$1,284
5	$4,051	$2,710	$1,310	$1,532
10	$4,051	$2,710	$1,310	$2,792
15	$4,051	$2,710	$1,310	$3,910
	Difference between microtransit and			
	CPT7.5	CPT15	CPT30	
1	-88%	-82%	-63%	
2	-82%	-72%	-43%	
3	-75%	-63%	-23%	
4	-68%	-53%	-2%	
5	-62%	-43%	17%	
10	-31%	3%	113%	
15	-3%	44%	198%	

Table 9: Number of required microtransit vehicle in each network according to demand level.

Requests per min.	Grid Network	Star-Shaped Network
1	4	3
2	6	5
3	8	7
4	10	9
5	12	10
10	21	20
15	31	28

Table 10: Operator's cost for each service. and microtransit and CPT cost comparison in the star-shaped network.

Requests per min.	Cost to the Operator			
	CPT7.5	CPT15	CPT30	microtransit
1	$1,893	$956	$883	$418
2	$1,893	$956	$883	$703
3	$1,893	$956	$883	$973
4	$1,893	$956	$883	$1,243
5	$1,893	$956	$883	$1,448
10	$1,893	$956	$883	$2,655
15	$1,893	$956	$883	$3,729
	Difference between microtransit and			
	CPT7.5	CPT15	CPT30	
1	-78%	-56%	-53%	
2	-63%	-26%	-20%	
3	-49%	2%	10%	
4	-34%	30%	41%	
5	-24%	51%	64%	
10	40%	178%	201%	
15	97%	290%	322%	

3.5 DISCUSSION

In this work, two modes of transport (microtransit and CPT) were simulated separately and compared in terms of user performance and operator cost in different scenarios. The main objectives are to determine if replacing CPT with microtransit results in an improvement in people's mobility and to identify the demand switch point.

The results show that regardless of the network, by replacing CPT with microtransit, a significant increase in people's mobility occurs particularly in low demand areas. However, the higher switch point in the grid network might lead to a conclusion that there is a better chance to save the cost by replacing CPT with microtransit. The reason is that providing a comprehensive public transport in a grid network requires buses to run in close proximity of each other, which is expensive. This makes microtransit comparable even with a short headway (7.5 minutes) CPT in a grid network in terms of not only user performance, but also operator's cost.

The only observed microtransit service's drawback for the users was the longer waiting time, which is usually experienced at the comfort of their homes. It is possible to increase this convenience by providing the right communication tools to inform the users about their waiting time, so they can do other activities at home.

There were also two pieces of evidence for capability of microtransit in competing with CPT even in areas with medium to high demand. First, given 15 requests per minute, microtransit outperformed a CPT with short headway of 7.5 minutes in a grid network. Secondly, the percentage of passengers with a higher perceived travel time (VIVT) when travelling by microtransit compared to CPT dropped after a certain point (see Figure 7) in both networks. However, congested roads, which are a usual condition in high demand areas (e.g., central business districts), might contradict this conclusion, while providing a high-quality microtransit might encourage people to avoid driving a car themselves and relaxes the mentioned condition. Thus, more complex simulations are required to study microtransit in this condition and provide even stronger evidence.

In terms of demand switch points, the analysis reveals differences when comparing the microtransit with different CPT services. Unlike CPT, microtransit operation highly depends on the demand and the situation. Thus, although it is possible to determine the demand switch point using simulation, it is hardly possible to make any general statement about it.

In this study the vehicles are assumed to have capacity of 4 and their number equals the minimum number of vehicle required to serve all requests (rejection rate of 0). While this is a reasonable assumption for the purpose of this study, it has certain implications on the results. For example, a bigger fleet may decrease the waiting time or VIVT in general as more vehicles are available and passengers will have lower waiting time or ride time. However, this may have significant impact on the cost to the operators. On the other hand, while a smaller fleet may be of economical interest to the operators, it may increase passengers VIVT to the point that they stop using the microtransit system. Therefore, vehicle fleet design and optimisation (in terms of size and capacity per vehicle) is a critical and complex problem that should be addressed before implementation of any microtransit systems. The solution can include a certain set of vehicles (e.g., 10 4-seaters vehicles) or a time-based combination of various capacities (e.g., five 4-seaters and two 10-seaters in the peak time and five 4-seaters in off-peak times).

Finally, investigating the same hypothesis in the Belgrave scenario, including a complex network and realistic bus routes, revealed that microtransit can contribute to solving the problem of underutilised buses in the real world. The density in this scenario is almost equal to one request per minute, and when comparing the results to the star-shaped conceptual network similar outcomes are observable. The VIVT of passengers is cut to half in both scenarios when replacing CPT with microtransit as well as the cost of providing the service. This means that not only the customers are better off by reaching their destination in half the time, but also the transit supplier can save half the cost, which is a win-win situation for both parties. The consistent outcomes of the hypothetical scenarios and the Belgrave scenario indicate the validity of the method and its potential to be expanded further.

3.6 CONCLUSION

The extensive comparison of different scenarios in this work confirmed the hypothesis and demonstrated that replacing CPT with microtransit results in a significant decrease in passengers' perceived travel time, and in turn, in an increase in the quality of their mobility with no extra cost in certain situations. Also, since perceived travel time is a determinant factor in changing people's mode choice behaviour, replacing CPT with microtransit might encourage more people to use public (demand-responsive) transport, which has certain advantages (e.g., fewer vehicles on the road, less congestion, and less pollution than with using private cars).

Moreover, it was shown that the performance and costs of CPT services are independent from the demand, while microtransit costs depend on the demand. This shows the potential flexibility of microtransit for adapting to demand and avoiding unnecessary cost and is the reason why identifying a general demand switch point is impossible.

Although this work utilises a capable simulation tool, MATSim, there are still limitations. Although all passengers were modelled and analysed individually, they were homogeneous. They did not have different preferences (e.g., different perceptions of walking time), and although they have preferences, they could not make an individual choice between different modes. For example, the small percentage of people who are not better off when CPT is replaced by microtransit might continue to use their own private vehicle in the real world or in a more comprehensive simulation. Moreover, the microtransit users did not have the opportunity of refining their plans in iterations, which results in simulation outcomes for microtransit users that are rather a lower threshold and could be even stronger in real scenarios. Nonetheless, the individual and aggregated results showed a significant superiority of microtransit, and the capacity of the employed tool to provide a realistic simulation of microtransit.

Overall, this work demonstrated the benefits of microtransit. Microtransit's unique features are promising in affecting the use of other transport modes, if implemented correctly. Thus, further studies are required to prove microtransit's efficiency and advantages in a broader context, and to find the right implementation circumstances. Therefore, in the future work it is intended to expand the existing model to incorporate all transportation modes (e.g., microtransit, CPT, private vehicle) with heterogeneous agents, who have the option to choose the best transportation mode according to their preferences over several iterations. Such powerful comprehensive tool will enlighten further the understanding of the role of microtransit in future transportation.

4 MODE CHOICE MODELLING

This chapter is adapted from the manuscript titled "A comparison of travel time attribute estimation methods: Potential impacts on policies" submitted for peer review to an international journal and the revision is to be submitted. I conducted the majority of the work, including research implementation, result analysis, discussions, and paper-writing. My supervisor Prof Stephan Winter was supervising the progress, providing feedback and helping in editing. Our collaborator, Dr. Meead Saberi helped in content planning and research design. He also assisted in result analysis.

4.1 CONTRIBUTION

The potential of microtransit in improving the mobility has been demonstrated. However, the success of these modes depends highly on people's preferences and their acceptance. Mode choice modelling is one method to address this shortcoming. To avoid the biases associated with SP data, it was decided to use RP data in this work. While RP data allows to observe the attributes of the chosen alternative, the attributes of the non-chosen alternatives often remain unknown since the alternatives remain unobserved. To overcome this limitation, several methods are usually employed in practice, which suffer from two major limitations. First, they heavily rely on existing observed attributes. Secondly, they do not represent the variation or dynamics of the travel attributes.

This chapter investigates a number of approaches for estimating the attributes of unobserved alternatives to identify the implications and consequences of their application in the context of mode choice modelling. It focuses on traffic simulation tools such as agent-based models (ABM) and dynamic traffic assignment (DTA) models, which can be used to estimate travel time and cost attributes of non-chosen alternatives. Although simulation has been suggested in the literature as one of the methods to synthesize missing data (Balakrishna, Sundaram, and Salvin, 2010), there is not much work on its application for synthesizing the attributes of the non-chosen alternatives. Other approaches include the use of multi-modal trip planners, both offline (e.g., OpenTripPlanner) or online (e.g., Google API Directions). Calibrated traffic simulations should provide realistic traffic patterns for different times of the day and thus, realistic estimated time and cost attributes, while trip planners in many instances do not consider traffic at all (e.g., OpenTripPlanner), and in other instances (e.g., Google Directions) consider typical traffic, learned over time.

The contribution of this chapter is twofold: One, it compares the results of two recent methods of estimating attributes of non-chosen travel alternatives and highlights the sensitivity of mode choice models and implied value of travel time to using different tools, which is discussed in Section 4.6. Two, if it is confirmed that simulation provides the best fit to estimate the attributes of existing non-chosen alternatives, it can be implied that it is possible to use synthesized data in certain hypothetical situations to provide realistic travel choice behaviour even for any future mode of transportation, for which no RP data can be collected, and for which SP data is questionable.

The rest of this chapter is organised as follows. First, Section 4.2 outlines the dataset containing the attributes of chosen alternatives, and explains the tools used to synthesise the attributes of non-chosen alternatives. Next, Section 4.3 presents a comprehensive comparison of the datasets synthesised by the different tools. In Section 4.4, the choice modelling method and the evaluation criteria are described. Results of the modelling are presented in Section 4.5, followed by discussion on their meaning and implications in Section 4.6. Finally, Section 4.7 summarises the conclusion and the lessons learned from this chapter.

4.2 DATA AND TOOLS

4.2.1 *VISTA*

This work uses data from Melbourne, Australia. The demand data is obtained from the local household travel survey results of Melbourne, VISTA (The Victorian Department of Transport, 2011). The data contains details of travel (e.g., duration, distance, start time, origin, and destination) and activities (e.g., duration and purpose) of one percent of the Greater Melbourne population during 24 hour of a typical weekday, as well as their socio-economic demographics. The origins and the destinations of individual trips are reported on a granularity of Statistical Area Level 1 (SA1), a fine geographical unit defined by the Australian Bureau of Statistics (ABS) for statistical data reporting and analysis. The survey has been done from 6 July 2009 to 4 July 2010.

The demand data for the following experiment is derived from VISTA, according to the origin SA1, destination SA1, and start time of trips extracted from VISTA. The demand was disaggregated by assigning random locations within an SA1 to each traveler travelling to or from that zone. The trip start times were obtained from VISTA and assigned to each trip respectively. In total 68,828 trips were generated, 8% of which are done by public transport and 92% by private vehicle (either driver or passenger). Trips done by walking or cycling were not considered in this study as the main reason for this study was not to actually estimate a mode choice model but to compare the datasets and draw conclusion for further use. Figure 8 shows the reported temporal demand profile in Melbourne by VISTA, separated by the two considered modes. Table 11 provides a summary of socio-economic characteristics of the sample and the Greater Melbourne. According

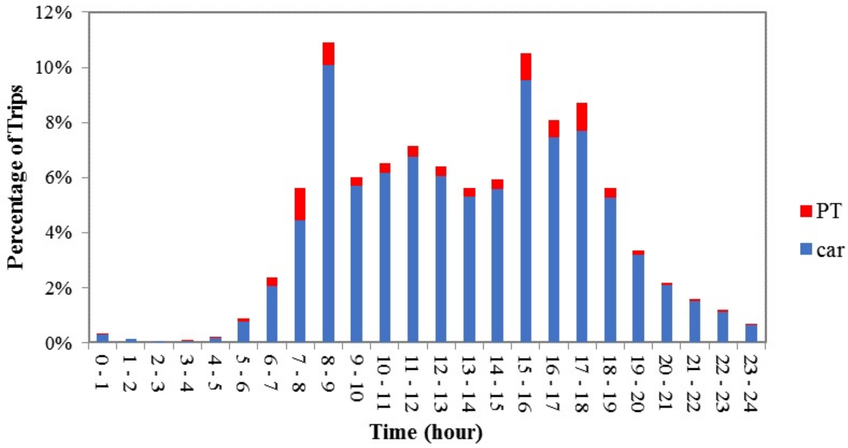


Figure 8 Temporal profile of demand in Melbourne on a working day (24 hours)

to Table 11, the sample is representative of the overall population of Greater Melbourne in terms of age and sex, and income.

4.2.2 *MATSim*

MATSim[1] is an open source agent-based simulation software package capable of multimodal transportation simulation and modeling. In MATSim, agents maximize the utility of their daily schedule over several iterations based on a co-evolutionary algorithm. A MATSim based model takes initial demand as input, which contains the agents' plans including a chain of activities, their location and start time and the initial travel mode. Then, the iterations start with *mobsim* phase, during which agents execute their plan, i.e. travel from one activity to another according to their plan in a network. Agents evaluate and score their executed plans in *scoring* phase based on the predefined scoring function and update their memory, which contains a certain number of selected (the criteria for selection is defined by the user) plans. In the *replanning* phase, which is the end of each iteration, agents either alter components of their plan using a genetic algorithm or draw from their memory and the system is ready for the next iteration. After a certain number of iterations, the system reaches a stable Stochastic User Equilibrium (SUE), where no individual can significantly improve their plan. The modular structure of MATSim allows for flexible implementation of various modes and choice behaviours (Horni, Nagel, and Axhausen, 2016). MATSim's capacity to model and route different modes of travel for individuals with a high level of spatial and temporal granularity makes it a suitable tool for this study.

In MATSim it is possible to model public transport using General Transit Feed Specification (GTFS) data, and street networks, extracted, for example, from OpenStreetMap. The simulations are run

1 https://www.matsim.org/

Table 11 Socioeconomic characteristics of the sample.

Age	VISTA sample	Greater Melbourne
< 15	18%	19%
15 - 25	11%	13%
25 - 60	55%	47%
> 60	16%	21%
Gender	VISTA sample	Greater Melbourne
Female	51%	51%
Male	49%	49%
Income	VISTA sample	Greater Melbourne
Quintile 1 (18,000)	9%	8%
Quintile 2 (30,000)	14%	12%
Quintile 3 (40,000)	19%	17%
Quintile 4 (55,000)	23%	23%
Quintile 5 (94,000)	35%	40%

separately for cars and buses without allowing the agents to change their mode. This restriction was to ascertain that each agent optimizes its plan for the given mode.

4.2.3 *Routing by Google Maps API*

The Google Maps Directions API is a web-based application programming interface that computes the directions between two points, through an HTTP request by various modes (e.g., car, public transport, and cycling). Its request structure and routing algorithms are flexible and allow for setting different optimization criteria, such as minimizing the travel time (default option) and distance or number of turns, and adding other routing options, such as stop points and toll avoidance. The required parameters of a request are origin, destination and the user's API key. The output is returned in either JavaScript Object Notation (JSON) or XML format. Other optional components are also available for modification of the trip characteristics (e.g., departure time, arrival time, mode, and traffic model) or output features (such as, language, format, and units). This API provides an opportunity to calculate the travel attributes closer to what people may experience given variability and dynamicity of alternative modes (Frei, Hyland, and Mahmassani, 2017).

In this study, using the available libraries of the Python client for Google Maps, a Python script was created for direction enquiries. First, it reads and saves the origin, destination and start of each trip from a csv file, then automatically creates and sends requests to the Google Maps server, and finally saves the returned output as a JSON file. This process was conducted for two modes: car and public trans-

Table 12 Data sets and their sources.

Name	Source for the chosen alternative	Source for the non-chosen alternative(s)
G	Google Maps API Directions	Google Maps API Directions
GV	VISTA	Google Maps API Directions
M	MATSim	MATSim
MV	VISTA	MATSim
MO	MATSim for car and OTP for public transport	MATSim for car and OTP for public transport
MOV	VISTA	MATSim for car and OTP for public transport

port. The saved files were analyzed using a different Python script to extract the various attributes of the trips.

4.2.4 *Routing by OpenTripPlanner*

OpenTripPlanner (OTP) is an open-source web-based multimodal trip planner that works using OpenStreetMap (OSM) and GTFS data. Similar to the Google Maps Directions API, it is a web service used for routing from a specific origin to a specific destination by different modes, returning the calculated itinerary in XML or JSON format. OTP can be considered the open-source version of the Google Maps Directions API and is used in some cities (e.g., Helsinki[2], Adelaide[3], and Portland[4] as the official trip planner of the transit network. In this work, OTP was tested for routing public transport trips; no significant differences to the other methods above could be observed. Python scripts were used for calling OTP Analyst to route trips via web-service API of a previously set-up OTP server. Then, the output JSON files were post-processed to obtain the trips' time and distance.

4.3 COMPARISON OF DATA SETS

In this study, six different data sets were generated, all of which contain travel time and distance for a 24-hour demand obtained from the above-mentioned tools and VISTA data. These data sets are first compared together and then used for estimating mode choice model. Table 12 presents the name of the datasets and summarizes the sources of their content.

Figure 9 to Figure 11 present the comparison of travel time and distance from VISTA to the other methods only for the chosen alternatives, both car and PT. According to Figure 9, the estimated distance from Google (Google_DIST) and MATSim (MATSim_DIST) for the chosen alternatives seem to be analogous to VISTA, in terms of dis-

2 https://digitransit.fi/en/
3 http://www.adelaidemetro.com.au/planner/
4 http://ride.trimet.org/

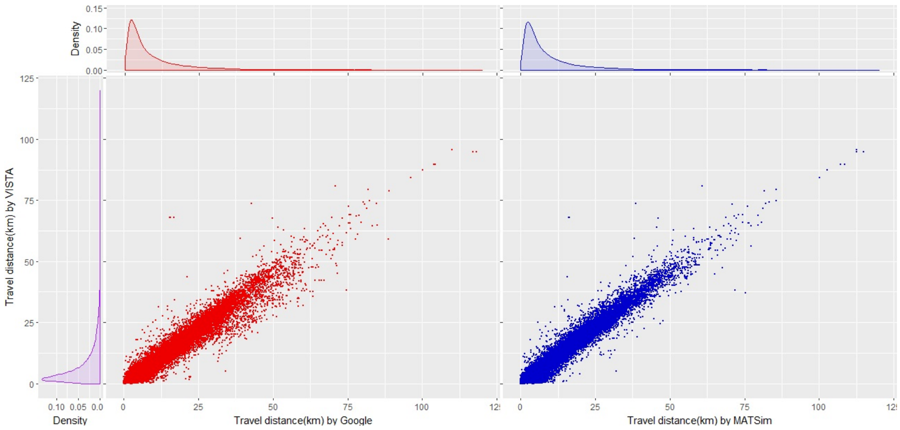


Figure 9 Estimated distance comparison for chosen alternatives

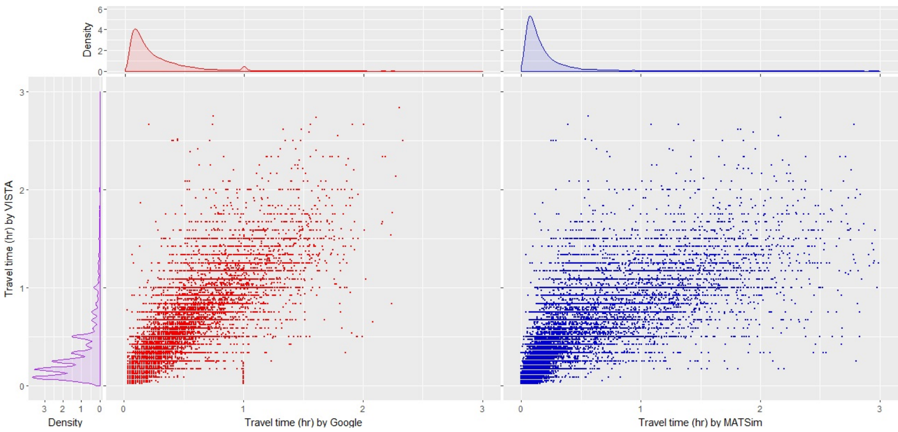


Figure 10 Estimated time comparison for chosen alternatives

tribution and values, since the scatter plots for both methods demonstrate a strong correlation.

However, the estimated travel times by various methods show more discrepancy compared to VISTA. As seen in Figure 10, the distributions of the estimated travel times by Google and MATSim are different from the VISTA travel time distribution, and none was able to capture the smaller peaks visible in VISTA dataset density. Furthermore, the estimated travel times are generally more scattered compared to the travel distances, with MATSim dataset having much weaker correlation with VISTA. Since OTP was only used to estimate the travel time for PT users, Figure 11 presents the comparison of OTP generated data set with only those from VISTA that used PT for their trip. Similarly, while estimated travel distance from OTP seems to be very similar to VISTA, the travel time is different.

Table 13 shows the Pearson correlation coefficients estimated for each pair of data sets for attributes of different trips, i.e. travel time (TT) and travel distance (DIST) by both car and public transport (PT), for both chosen and non-chosen alternatives. The estimated travel distances for both modes have a high correlation among all data sets implying that there is not much difference in the underlying methods and algorithms of the employed tools when it comes to routing and calculating distance.

Figure 11 Estimated time and distance comparison for PT users

Table 13 Estimated coefficients of Pearson correlation between data sets with different sources.

		G	GV	M	MV	MO	MOV
CAR_DIST	G	1					
	GV	0.98	1				
	M	0.98	0.98	1			
	MV	0.98	1	0.99	1		
	MO	0.98	0.98	1	0.99	1	
	MOV	0.98	1	0.99	1	0.99	1
CAR_TT	G	1					
	GV	0.66 *	1				
	M	0.72§	0.80$	1			
	MV	0.62 *	0.98	0.78$	1		
	MO	0.72§	0.80	1	0.78	1	
	MOV	0.62 *	0.98	0.78$	1	0.78	1
PT_DIST	G	1					
	GV	1	1				
	M	0.96	0.96	1			
	MV	0.96	0.96	1	1		
	MO	0.89	0.89	0.90	0.89	1	
	MOV	0.90	0.90	0.90	0.90	0.99	1
PT_TT	G	1					
	GV	0.96	1				
	M	0.75œ	0.75	1			
	MV	0.76œ	0.77	0.96	1		
	MO	0.54+	0.53	0.50	0.49	1	
	MOV	0.53+	0.54	0.48#	0.51	0.97	1

In contrast, estimated travel times demonstrate more diverse correlation values between data sets. The high correlation among the car travel time related data sets including VISTA data (GV, MV, MOV) is due to the fact that the majority of users are traveling by car, so a significant amount of data is actually coming from the same source. In estimating car travel time (CAR_TT in Table 13), the correlations between the Google Maps generated data and the data sets including VISTA (3 values denoted by $*$) are lower than the correlations between the Google Maps generated data and the MATSim generated data (2 values denoted by §). The mentioned correlations (3 values denoted by $*$) are also lower than the correlations between MATSim and VISTA ($). Thus, MATSim generated data has a higher correlation with data obtained from VISTA. This means an agent-based simulation with minimal calibration provides travel time estimation closer to reality compared to a web-based routing application.

The differences appear to be higher when calculating the travel time for PT trips. The lowest correlation can be seen in calculating the travel time for public transport users (PT_TT in Table 13) by MATSim and OTP (#). There is a high correlation among the datasets generated by Google Maps and MATSim (œ) compared to Google Maps and OTP (+). This means that Google Maps and MATSim provide similar results to VISTA; this is confirmed by their high correlation together as well (0.75).

It appears that all three tools use relatively similar algorithms to route between two points, as they all provide almost identical results for CAR_DIST and similar outcome PT_DIST. The reason behind the difference between CAR_TT from MATSim and Google Maps API is that while the latter returns a minimum and a maximum travel time as the result of the query, in MATSim the traffic situation is actually simulated and the calculated travel time reflects a more realistic estimation. This is also confirmed by the higher correlation of MATSim-based with VISTA-based results.

While calculating travel time by car is mostly dependant on the routing algorithm and traffic situation, estimating travel time by public transport, and its comparison, presents a bigger challenge as it depends on normalizing multiple parameters (e.g., walking time, waiting time, and transfers) to have one single number as the total perceived travel time. On top of that is the question of services' punctuality, which presumably accounts for a major share of difference between estimated and reported travel times.

4.4 METHODOLOGICAL FRAMEWORK OF CHOICE MODELING

The modelling of the mode choice behaviour of people follows the Random Utility Model (RUM) framework developed by Domencich and McFadden (1975), formulated as:

$$P_n(i) = f(X_n) + \varepsilon \tag{9}$$

where $P_n(i)$ is the probability of individual n chooses alternative i, X_n represents the vector of all observed explanatory variables, such

Table 14 Parking cost according to the destination location and trip purpose

	Work - $/day	Non-work - $/hour
CBD	25	4
City of Melbourne	18	2
Inner suburbs	10	1

as travel time, travel distance, travel cost, and socio-economic characteristics of the individuals, and ε is a random term capturing all the unobserved factors that affect the utility. ε is assumed to be independently and identically distributed (IID) as Extreme Value Type I. In RUM, the assumption is that the individuals calculate the utility of each option and choose the one with the highest utility.

Mode choice models are estimated using BIOGEME (Bierlaire, 2003). The general model accounts for travel time and cost, and is formulated as:

$$V_{m,i} = \beta_t \times TT_{m,i} + \beta_c \times COST_{m,i} + ASC_m \tag{10}$$

where V_m is the utility of mode m, which is either car or public transport (pt), for individual i, ASC_m is the mode specific constant for mode m, β_t and β_c are the coefficients of time and cost respectively, $TT_{m,i}$ is the duration of travel by mode m for individual i, and $COST_{m,i}$ is the cost of travel by mode m for individual i. The travel time for each alternative is obtainable directly from the above-mentioned sources. The cost for public transport is set to an average of AU$4.1, according to the current fares in Melbourne, Australia. The cost of travel by car is calculated according to:

$$COST_{car,i} = 0.66 \times DIST_{car,i} + PKG_i + TOLL_i \tag{11}$$

where $DIST_{car,i}$ is the distance individual i travelled by car in kilometres, 0.66 Australian dollar per kilometre is the reimbursement rate set by Australian Taxation Office[5], PKG_i is the parking cost, which is calculated based on the trip destination and purpose (Table 14), and $TOLL_i$ is the toll for travelling in certain corridors in Melbourne, which is set to an average amount of AU$5 for those travellers passing through toll roads.

Furthermore, to capture the value of travel time across various levels of household income Koppelman and Bhat (2006) suggested the following model:

$$V_{m,i} = \beta_i \times TT_{m,i} + \beta_{costInc} \times \frac{COST_{m}, i}{Income_i} + ASC_m \tag{12}$$

where $\beta_{costInc}$ is the coefficient for the interaction of travel cost and income, and $Income_i$ is the household income for individual i in thousand dollars per year ($1000/$year$).

5 https://www.ato.gov.au/Individuals/Income-and-deductions/Deductions-you-can-claim/Vehicle-and-travel-expenses/Car-expenses/

4.4.1 *Value of Travel Time*

Value of travel time (VOT) is the most important value for cost-benefit analysis in transportation infrastructure projects (Beck et al., 2017; Small, 2012), and represents the monetary value that travellers are willing to pay for travel time saving. Many national and international organizations define standard values to be able to consistently evaluate related projects and policies (Mackie, Worsley, and Eliasson, 2014). Furthermore, VOT is an indicator for testing the reasonableness of a RUM-based estimated utility model (Koppelman and Bhat, 2006).

There are two main parametric methods for estimating VOT: Random Utility Model (RUM), and Random Valuation (RV). The former assumes that the random component of the model represents the utility differences of alternative travel options, while the latter assumes it reflects the variations of "the actual value of travel time and a suggested valuation threshold" (Ojeda-Cabral, Batley, and Hess, 2016, P. 231).

Numerous studies compare the two methods (Ojeda-Cabral, Batley, and Hess, 2016), or use them for national studies in different countries (Börjesson and Eliasson, 2014; Fosgerau, Hjorth, and Lyk-Jensen, 2007; Ramjerdi et al., 2010). However, since the choice of method is empirical (Börjesson and Eliasson, 2014), and in this study the main objective is to compare the datasets, not investigating VOT, simple definition and methods of VOT estimation are utilized to analyse the soundness of the estimated models.

VOT is defined as the marginal rate of substitution between travel time and money. The implied VOT can be obtained from an estimated choice model as:

$$\mathrm{VOT} = \frac{\frac{\partial V}{\partial TT}}{\frac{\partial V}{\partial COST}} \tag{13}$$

Accordingly, for the general model, VOT is calculated in a straightforward fashion by dividing the coefficient of time (β_t) by the coefficient of money (β_c) from Equation 10. For the income-dependent model, given the presence of income in the model specification, VOT is calculated as:

$$\mathrm{VOT} = \frac{\beta_t}{\beta_{costInc}/Income_i} = \frac{\beta_t}{\beta_{costInc}} \times Income_i \tag{14}$$

The calculated VOT using Equation 14 is income-dependent and can demonstrate the changes of value of travel time across various income levels. In this work, the household income quintile is considered for calculating the value of travel time.

4.5 MODEL ESTIMATION RESULTS

Table 15 summarizes the results of the general mode choice model estimation for all trips. The estimated coefficients and their t-test values are presented in the table with all being significant at 95% confidence level. The improvement in the models, based on the log likelihood

Table 15 Estimated multinomial logit model for all trips.

	G	GV	MO	MOV	M	MV
Variables	Estimated Coefficient (t-test)					
Travel time coefficient (β_t)	-1.01 (-27.22)	-1.15 (-27.85)	-0.767 (-26.72)	-0.673 (-25.58)	-0.689 (-19.63)	-1.00 (-27.73)
Travel cost coefficient (β_c)	-0.0722 (-49.14)	-0.0859 (-56.76)	-0.0766 (-46.97)	-0.0793 (-53.03)	-0.0847 (-44.14)	-0.103 (-59.95)
alternative specific constant						
Public transport (ASC_{pt})	-2.35 (-110.2)	-2.39 -106.14	-2.25 (-93.43)	-2.42 (-106.65)	-2.43 (-96.69)	-2.38 (-102.34)
Log likelihood at zero	-46644	-46682	-47352	-47323	-45173	-45368
Log likelihood at constants	-19293	-19427	-19511	-19409	-18563	-19258
Log likelihood at convergence	-18073	-17759	-18379	-18011	-17462	-17308
LL ratio-test Results ($\chi^2_{(2)d.f.} = 35.9$)	2440	3336	2264	2796	2202	3900
ρ^2	0.61	0.62	0.61	0.62	0.61	0.62
Number of observations	67294	67348	68315	68274	65172	65453
Number of individuals	20394	20410	20533	20530	20313	20345
Implied average VOT ($/hr)	13.99	13.39	10.01	8.49	8.13	9.71

values and LL ratio-test (see Hensher, Rose, and Greene (2005) for explanation), is significant for all data sets, and is the highest using a mixture of MATSim generated and the VISTA data ($\Delta LL = 1950$ for MV).

Table 16 and Table 17 present the results of the general mode choice model estimation for commuters and non-commuters respectively. The coefficients are all significant at 95% confidence level, and there is a significant improvement in log likelihood of the estimated models for all data sets. As expected, commuters' VOT are generally higher than the ones of non-commuters. Li, Hensher, and Rose (2010) estimated the VOT for commuters and non-commuters in Sydney to the respective values of AU$22.69 and AU$8.01 per person per hour. In comparison, the implied VOT of the commuters in GV, M, and MO datasets have the lowest difference ($\sim \pm 10\%$), among which the estimated model for the M dataset has the highest significance improvement ($\Delta LL = 438$). For non-commuters, the single lowest VOT difference belongs to MV with 4% and the significance improvement of $\Delta LL = 1235$, which is the second highest improvement (the highest is for the G data set, which is $\Delta LL = 1267$).

Furthermore, Australian Transport Assessment and Planning guidelines report the VOT for commuters and non-commuters in the Australian urban context equal to AU$48.63 and AU$14.99 per person per hour [6]. However, this is the average value across entire Australia and only for those travelling by car. Thus, it is advisable not to compare or validate the results against them.

The slight reduction of the ASC value from general model (average of -2.37 in Table 15) to more specific models (average of -1.86 in Table 16 and Table 17) suggests that considering the trip purpose reduces the unknown factors in the choice model, as expected. The lower ASC average in Table 16 (-1.74) compared to the average in Ta-

6 https://atap.gov.au/parameter-values/road-transport/3-travel-time.aspx

Table 16 Estimated multinomial logit model for commuters.

	G	GV	MO	MOV	M	MV
Variables	Estimated Coefficient (t-test)					
Travel time coefficient (β_t)	-4.44 (-28.72)	-2.09 (-21.01)	-2 (-22.23)	-1.02 (-15.09)	-3.03 (-23.02)	-1.63 (-18.59)
Travel cost coefficient (β_c)	-0.12 (-27.75)	-0.0837 (-23.26)	-0.0996 (-22.45)	-0.0734 (-20.15)	-0.15 (-24.69)	-0.0972 (-23.2)
alternative specific constant						
Public transport (ASC_{pt})	-1.15 (-16.41)	-1.97 (-28.26)	-1.47 (-20.44)	-2.07 (-28.71)	-1.63 (-22.62)	-2.13 (-29.6)
Log likelihood at zero	-5799	-5803	-5762	-5776	-5455	-5491
Log likelihood at constants	-3615	-3626	-3565	-3601	-3453	-3547
Log likelihood at convergence	-2895	-3229	-3185	-3355	-3014	-3203
LL ratio-test Results ($\chi^2_{(2)\,d.f.} = 35.9$)	1440	794	760	492	878	688
ρ^2	0.50	0.44	0.45	0.42	0.45	0.42
Number of observations	8367	8373	8314	8333	7871	7923
Number of individuals	6936	6941	6876	6891	6536	6582
Implied average VOT ($/hr)	37.00	24.97	20.08	13.90	20.20	16.77

ble 17 (-1.99) confirms the existence of a more homogenous group in the former.

The final set of results in Table 18 reports the estimated models for different household income quintiles. Similarly, the estimated coefficients and the improvement in the log likelihood of the models are all significant. Consistent with previous results (Table 15, Table 16, and Table 17), the implied VOTs from the Google Maps driven data sets (G and GV) are considerably higher than the other values in Table 18. Moreover, comparing the average VOT of the five quintiles in Table 18 with the VOT figures in Table 15, data sets MOV and MV have the lowest difference, with MV having the second highest significance improvement in the estimated model.

The literature suggests that a ρ^2 of higher than 0.3 means a reasonable fit for the model (Hensher, Rose, and Greene, 2005). The observed ρ^2 for all estimated models is in the reasonable range of 0.42 and 0.62, representing a decent model fit.

4.6 DISCUSSION

Here, agent-based simulation and web-based routing services are employed to synthesize the attributes of non-chosen travel alternatives in a travel mode choice study to compare the outcomes of different methods. Although there have been other studies focusing on the comparison of different modelling methods or various SP datasets (e.g., Hensher, Rose, and Li, 2012), to the best of the authors' knowledge this is the first documented study that explores the implications of using various methods, particularly simulation, for estimating travel attributes in travel behaviour modelling based on RP data.

Estimating the attributes of unobserved alternatives has several implications, one of the most important ones is estimating the choice models and, in turn, value of travel time, which is the most important

Table 17 Estimated multinomial logit model for non-commuters.

	G	GV	MO	MOV	M	MV
Variables	Estimated Coefficient (t-test)					
Travel time coefficient (β_t)	-2.55	-1.27	-1.28	-0.652	-1.42	-1.02
	(-37.14)	(-24.77)	(-29.02)	(-18.64)	(-22.62)	(-21.29)
Travel cost coefficient (β_c)	-0.108	-0.0931	-0.102	-0.0908	-0.127	-0.122
	(-48.09)	(-45.25)	(-42.59)	(-44.34)	(-37.54)	(-48.03)
alternative specific constant						
Public transport (ASC_{pt})	-1.54	-2.14	-1.81	-2.3	-1.93	-2.2
	(-48.11)	(-78.36)	-53.6	(-77.77)	(-52.56)	(-75.99)
Log likelihood at zero	-33478	-33598	-34768	-34849	-31315	-31606
Log likelihood at constants	-14198	-14621	-14351	-14641	-13334	-14343
Log likelihood at convergence	-12932	-13607	-13401	-13693	-12565	-13108
LL ratio-test Results ($\chi^2_{(2)\text{d.f.}} = 35.9$)	2532	2028	1900	1896	1538	2470
ρ^2	0.61	0.60	0.62	0.61	0.60	0.59
Number of observations	48299	48473	50160	50277	45178	45599
Number of individuals	18998	19042	18997	19054	18086	18240
Implied average VOT ($/hr)	23.61	13.64	12.55	7.18	11.18	8.36

Table 18 Estimated multinomial logit model across various levels of household income.

	G	GV	MO	MOV	M	MV
Variables	Estimated Coefficient (t-test)					
Travel time coefficient (β_t)	-2.06	-1.08	-0.949	-0.525	-0.785	-0.706
	(-38.06)	(-25.07)	(-28.21)	(-17.85)	(-18.93)	(-18.64)
Travel costInc coefficient ($\beta_{costInc}$)	-2.83	-2.57	-2.56	-2.49	-2.66	-2.95
	(-47.03)	(-44.72)	(-41.82)	(-43.37)	(-36.56)	(-44.85)
alternative specific constant						
Public transport (ASC_{pt})	-1.52	-2.02	-1.8	-2.19	-2.02	-2.11
	(-54.74)	(-83.76)	(-62.05)	(-83.71)	(-68.35)	-84.33
Log likelihood at zero	-39278	-39403	-40531	-40625	-36771	-37099
Log likelihood at constants	-17988	-18406	-18102	-18424	-16965	-18047
Log likelihood at convergence	-16593	-17347	-17134	-17472	-16271	-16974
LL ratio-test results ($\chi^2_{(2)\text{d.f.}} = 35.9$)	2790	2118	1936	1904	1388	2146
ρ^2	0.58	0.56	0.58	0.57	0.56	0.54
Number of observations	56666	56846	58474	58610	53049	53522
Number of individuals	19276	19317	19242	19302	18843	18930
Household Quintile (Disposable Income$/year)	Implied average VOT ($/hour)					
Quintile 1 (18,000)	13.10	7.56	6.67	3.80	5.31	4.31
Quintile 2 (30,000)	21.84	12.61	11.12	6.33	8.85	7.18
Quintile 3 (40,000)	29.12	16.81	14.83	8.43	11.80	9.57
Quintile 4 (55,000)	40.04	23.11	20.39	11.60	16.23	13.16
Quintile 5 (94,000)	68.42	39.50	34.85	19.82	27.74	22.50
Average	34.5	19.92	17.57	9.99	13.99	11.34

criterion in evaluating transportation projects. Despite the theoretical and practical advances in modelling travel choices, the limitations in estimating attributes of the non-chosen alternatives undercuts the improved capacity of the choice models (Balakrishna, Sundaram, and Salvin, 2010).

The synthesized data demonstrates a satisfactory correlation with the RP data obtained from VISTA. While the travel distances from VISTA were almost identical to calculated travel distances using all three tools (when applicable), the calculated travel times showed more variations. Overall, MATSim performed slightly better in terms of generating travel times with the highest correlation with VISTA.

The estimated coefficients and models were all significant at 95% confidence level, and the fitness of the models was reasonable. However, there were considerable variations in the implied values of travel time across data sets, demonstrating the sensitivity of the model outcomes to the variation of travel time.

Further, the model estimation results showed that, in a number of occasions, mixing other data sources with VISTA improves the significance of the estimated model. Also, combining VISTA data (except for one occasion) leads to a decrease in the implied VOT. Since the cost is almost constant due to the high similarity of travel distance across data sets and estimated models, the decrease in the VOT is due to overestimation in the VISTA travel time data, or underestimation of travel time in the other methods. VISTA contains self-reported trip attributes from participants. Previous research on comparison of GPS data and self-reported values trip attributes has demonstrated a tendency among participants to round up their travel time, which leads to a systematic overestimation (Stopher, FitzGerald, and Xu, 2007; Tenenboim and Shiftan, 2018). On the other hand, car travel times obtained from Google Maps Direction API and MATSim do not include the time of searching for parking or walking from the car to the final destination, which cause an underestimation in the travel times. Thus, deeper analysis is required in the future to judge the case, which is out of scope of this work.

The last main difference between the datasets with and without the VISTA is related to their estimated ASC. The absolute value for the ASC almost always increases when the VISTA data is combined with the synthesized data sets (G, M, and MO), suggesting an increase in unknown factors affecting the travellers' choice.

Overall, the models estimated using G dataset consistently show the highest significance improvement, ρ^2 (although minimally), and the lowest ASC. In other words, the G dataset provides the best model fit.

Furthermore, VOT was calculated and used as an indicator for reasonableness of the estimated models. The linear utility functions, similar to the ones in this study, indicate a fixed VOT across all respondents and allow for straightforward calculation of VOT. However, many researchers have worked on more complex methods to study the random variation of VOT across travellers. To this end, β is assumed to be randomly distributed, which arises three main issues:

decision on the parameters to be randomly distributed, what distribution to chose, and their economic interpretation (Hess, Bierlaire, and Polak, 2005). While there are consensus on the random taste heterogeneity of travel time for the first issue (Algers et al., 1998; Cirillo and Axhausen, 2006), the second and third are still under ongoing dispute.

Normal is the most investigated distribution (Hess, Bierlaire, and Polak, 2005), which presents issues in calculations. Assuming normal distribution will cause the model to show a probability of having negative values of travel time, meaning that the traveller is happy to choose a longer and presumably more expensive alternative. While any linear model producing such result is dropped "on the grounds of model misspecification (or lack of explanatory power in the data)" (Hess, Bierlaire, and Polak, 2005, p.224), a non-linear model cannot be so easily dismissed as there is literature suggesting that this counter-intuitive result is actually true for people who do activities during their travel (Jain and Lyons, 2008; Redmond and Mokhtarian, 2001).

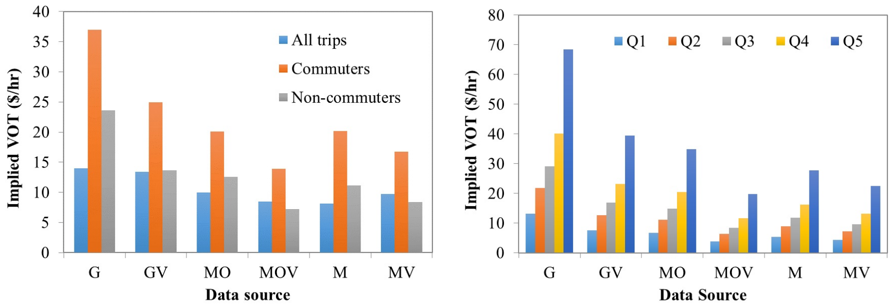
The alternatives to normal distribution are distributions with fixed or variable bounds. While a distribution with fixed bounds, such as Lognormal, stops the model from producing positive travel-time coefficient, it also prevents the exploration of their actual existence, which leads to a poor model fit and loosing information in the data. Hess, Bierlaire, and Polak (2005) suggested that variable bound distributions provide the best alternative and presented a detailed discussion on the importance of distribution selection and its consequences. Since the focus of this study was not to investigate the value of travel time, but to use VOT as an indicator of the reasonableness of the estimated models and investigate its overall sensitivity to the data source, the authors assumed constant VOT across all individuals and utilized basic methods for its calculation.

Figure 12 represents a comparison of the estimated VOTs for different market segments and across different household income levels. Since the ground truth, i.e. the real value of travel time, is unknown, it is challenging to assess the validity of the estimated VOT. However, the high correlation of data sets with the RP data and the closeness of the obtained VOT to those of previous studies is reassuring.

The sensitivity of the implied VOT to the selected sources of data should be considered and highlighted by the modeller. One approach is to provide a range for the implied VOT rather than a single value. This may help with a better understanding of the possible benefits of a transportation project, specifically toll road projects that are known to be highly sensitive to the estimation of VOT and thus, sensitive to the source of data used to estimate the choice models.

4.7 CONCLUSION

Here the sheer impact of using different methods in estimating travel times was demonstrated in the context of choice modelling. The significant variations in the implied VOT, drawn from various meth-



(a) (b)

Figure 12: Comparison of the estimated VOTs ($/hr) (a) for different market segments: all trips, commuters, and non-commuters; and (b) across different household income levels

ods, were revealed, which in turn can have significant implications for major transportation infrastructure planning, especially toll roads. Furthermore, it was shown that an agent-based model, even without intensive calibration, is capable of producing reasonable data for choice model estimation. One important implication of this conclusion is the applicability of the approach in travel behaviour studies involving new travel modes, such as demand responsive transport and autonomous ride sharing.

There were two main limitations to this work: First, the lack of ground truth on real cost of travel, which made the concrete validation of estimated VOT impossible. Second, the lack of proper calibration of the MATSim model, which if done, might contribute to the improvement of the model estimation results for the data obtained from MATSim.

The future work will first address the latter to provide more robust results, which will, in turn, result in better estimation of VOT. This will also provide further opportunities for a detailed investigation of VOT across respondents or using more advanced methods. Moreover, another topic for future work is to perform a comparison of VOT from this work with those coming from a calibrated static assignment, to potentially challenge/verify the conventional methods.

5 TOWARDS IDENTIFYING THE CRITICAL MASS IN SPATIAL TWO-SIDED MARKETS

This chapter is adapted from the manuscript with the same title accepted at journal *Environment and Planning B: Urban Analytic and City Science*. As the first author, I designed the research, implemented the experiments, analysed the results, and wrote the majority of the paper. My supervisor, Prof. Stephan Winter, proposed the idea, helped in literature review, edited the paper, and contributed to the discussion. Our collaborator, Prof. Kai Nagel, helped with content planning and research design, and contributed to the discussion and conceptual models. He also assisted in result analysis.

5.1 OBJECTIVE AND CONTRIBUTION

As explained in Chapter 1, demand responsive transport systems' market mechanism can be studied using the principle of multi-sided markets. Multi-sided flexible shared transportation platforms, similar to any other multi-sided platforms, need to address the notorious *chicken-and-egg* problem. However, the main difference between the two groups of platforms is that location matters as well in the flexible shared transportation platforms, not only the number of drivers (or vehicles) and passengers. For the passengers, the vehicles need to be there at the right time, and for the vehicles large demand elsewhere is irrelevant. This means an extra dimension of space in studying and identifying the critical mass and critical mass frontier of multi-sided transportation markets.

This chapter addresses this challenge for the first time and clarifies the role of spatial configuration of a ride-sourcing system in its success. The hypothesis here is that in spatial multi-sided markets, other than in non-spatial markets, there is not a single critical mass frontier that needs to be reached to make the system self-sustained, and that this frontier is varying from one location to the next, depending on the density and distribution of the demand and supply over space and time.

The rest of the chapter is organized as follow. In Section 5.2, the conceptual model is elaborated and the expectations are framed, which set the scene for describing the experiments in Section 5.3, including the model, simulation configurations and scenarios. Then, the results of the experiments are presented in Section 5.4 and thoroughly discussed in Section 5.5. Section 5.6 lays out the conclusion alongside with the limitations of the work.

5.2 CONCEPTUAL MODEL AND EXPECTATIONS

The interest in this chapter lies in two-sided flexible and shared transportation markets: markets where the platform itself does not directly control drivers (supply) and customers (demand). Some systems seem similar, e.g., bicycle sharing systems, but in general are not, since the platform provider and the supplier are often the same. They could, however, be converted into a two-sided market, for example, in a station-based bicycle sharing system, where stations would be provided by persons and institutions, and not by the platform provider itself.

In order to make this concrete for a spatial approach, assume that the area of interest is divided into regular cells. It is now plausible to assume that there will be the dynamics similar to Figure 3 (Section 2.3) *at each grid cell*. However, there will additionally be an infection process: If one cell is far in the UR corner, it will infect its neighbours because both the high demand and the high supply will radiate into the neighbouring cells. Similarly, if a cell is far in the LL corner, this cell will not help its neighbours to become served, and thus effectively inhibit them. Overall, the dynamics becomes quite similar to that of the well-known Ising model (Chandler, 1987; Ising, 1925), where spins, which are either "up" or "down", try to align to each other, but are also subject to some random noise. There is an elaborate theory of what happens when the noise is larger or smaller; here, small noise is assumed, and thus have a so-called first-order phase transition between "most spins up" and "most spins down". The model can also be used to describe aspects of segregation (Müller, Schulze, and Stauffer, 2008); translating this to the two-sided transport market, "up" would correspond to "served", and "down" to not-served.

From this theory, one can come up with predictions. For the following, it is assumed that each individual cell follows the dynamics according to Figure 3, and the same plot can be considered, but in which all cells' demand and supply values are averaged over the whole system. For *homogeneous* systems (same population density everywhere), one would expect the following:

- In a system of ***infinite*** **size**, one would expect that the dashed line in Figure 3 divides the dynamics deterministically into two basins of attraction: If the system starts to the lower left (LL) of that line, it will deterministically go to zero demand and supply (sub-critical); when starting in the upper right (UR), it will deterministically go to high supply and demand (= super-critical = "served").

- In a system of ***finite*** **size**, one would assume that boundary to become blurred, and the deterministic behaviour becomes replaced by probabilities: When starting the system somewhere inside the LL region, one would still expect a non-zero probability to become super-critical (= served); that probability would be 50% at the dashed line, and become smaller with increasing distance from it. Conversely, when starting somewhere inside the UR region, one would still expect a non-zero probability to become sub-critical; again, that probability would be 50% at the dashed line, and become smaller with increasing distance from it.

- One would expect that the **transition region (in state space equal demand over supply space) becomes more narrow with larger systems**. That is, for small systems, the transition from small to large probability to become super-critical is slow and smooth; for large systems, it is fast and steep; and in the limit of infinite system size, it becomes a deterministic switch. Plots that demonstrate this are the NU and UU plots in Figure 15, from left to right.

  This also implies that a two-sided market of infinite size could not become super-critical, since the starting point is in the LL corner. Becoming super-critical is thus only possible through some special pathway, typically given by some inhomogeneity in the system (e.g., starting with a specific subset of the population, e.g., only computer-affine people).

In general, however, real-world systems are expected to be inhomogeneous. Figure 3 shows, by the dotted lines, a possible market where the reachable densities of demand and supply are smaller than what they could be in an urban core. One clearly sees that a transition to the UR area would be more difficult to achieve. With such information, it would be possible to delineate regions that could potentially become super-critical, and others that cannot – the latter being regions where the dotted rectangle does not extend into the UR area at all.

The pathway of an area, consisting of many cells, into super-criticality will, in general, not be a homogeneous transition, but rather some spatial location becoming super-critical, and then **infecting its neighbours**. This also implies that connected areas that can potentially become super-critical are either all together super-critical, or all together they are not. As an illustration, an already served urban core will "infect" all neighbouring suburbs as long as they are potentially super-critical. Once the borders of that connected region have been reached, the growth of the service area will stop. From then on, improvements in the cost structure will make additional areas super-critical, and the service area will then grow into those regions. This will somewhat resemble invasion percolation (Wilkinson and Willemsen, 1983), except that spatial densities are not distributed randomly, but according to population densities and people's preferences.

5.3 EXPERIMENTS

The hypothesis and discussions in this work are illustrated and tested with simulations, which are made increasingly more realistic. The simulations are coded in Java language and the important aspects of them are:[1]

- An assumed fixed population, which in general will be distributed non-homogeneously in space. Of this fixed population there will be different shares of people interested in the market.
- Initial supply will either be homogeneously or normally distributed (cf. Figure 13).
- In general, both demand and supply will "drift" with a small rate into the market. Whether they remain in the market will depend on the utility of the service for the customer and on the profit for the supplier.

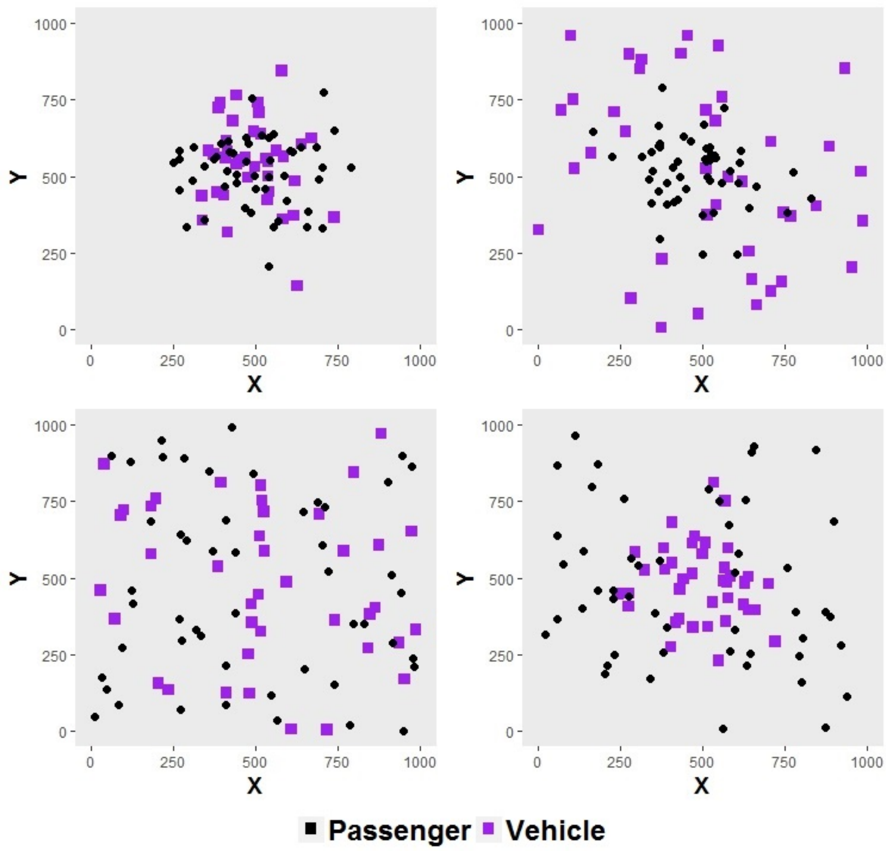


Figure 13: An example of different distributions of vehicles and passengers. Upper left: Both passengers and vehicles are normally distributed (NN). Upper right: Passengers normally distributed, vehicles uniformly (NU). Bottom left: Both passengers and vehicles uniformly distributed (UU). Bottom right: Passengers uniformly distributed, vehicles normally distributed (UN).

5.3.1 *Model and Simulation Configurations*

The simulation consists of an environment and two types of entities: passenger and vehicle. The environment is the area that contains all

1 Full code is available on https://github.com/zahra-n/CriticalMassFinal

the entities in space. A passenger i has three individual characteristics: Number of Neighbours (N_i), Interest (TS_i), and Utility (U_i). N_i is counted for each passenger and is equal to the number of vehicles around i that are within the Acceptance Threshold (AT_i). TS_i can be either 1, meaning Passenger i is interested in being matched with a vehicle, or 0, meaning otherwise. U_i is calculated inversely proportional to the distance of Passenger i to their matched vehicle, if applicable. The vehicle entity j has only one individual characteristics: Utility (V_j), which is equal to the utility of the respective matched passenger, or 0.

The simulations work iteratively. In each scenario, which are explained below, the iterations start after the population generation (described in Section 5.3.2). In each iteration, first, a certain number of vehicles are randomly generated within the environment, which are either normally or uniformly distributed (again cf. Figure 13), and added to the already existing vehicles. This number of additional vehicles decreases by 10% for the next iteration if the average utility of all vehicles is below a certain threshold (VT), and stays the same otherwise.

Second, the passengers' interests, with default values of 0, are updated based on the availability of vehicles or their past experience (utility from the previous iteration). More technically, TS_i becomes 1 if either N_i in the same iteration is higher than a defined threshold (the Neighbour-based Interest Threshold NTST), or if U_i from the previous iteration, if it exists, is bigger than a Utility Threshold (UT).

The changes in the number of vehicles and interest of passengers replicate their interdependence. If there are more vehicles, more people will get interested, so the chances for a vehicle to be matched and keep the overall utility higher is bigger, which results in more vehicles in the next iteration.

Then, all the vehicles within the acceptance threshold (AT) of each interested passenger are identified and the closest one is matched with that passenger, the passenger's and the vehicle's utilities are updated based on their distance and the matched vehicle is removed from the pool. Finally, all the vehicles with utility below VT are deleted (they lose interest) and the rest stay for the next iteration. Each scenario is run for 100 iterations.

Further, since in the systems of finite size the system's success is associated with a probability, each 100 iterations of one scenario is repeated 100 times to calculate the probability of the success. Success is defined as at least one passenger having interest. Furthermore, since the focus is only on the concept of critical mass, for the sake of simplicity Euclidean distances are computed and not network distances. As Hua, Xie, and Tanin (2018) have demonstrated recently, the differences between the two distance measures on spatial queries (e.g., on ordering) are not necessarily relevant. Moreover, network distances make a difference when there are either strong physical barriers such as mountains, lakes or rivers in the area of investigation, or singularly fast transportation infrastructure, such as motorways without speed limits. Neither of these occur in the (populated parts of the) study area. Also, the model assumes "success" when a match is within 100 metres (AT threshold); it is expected that instead using a network distance of, say, 150 metres, would yield similar results.

5.3.2 *Scenarios*

First, the scenarios are designed in an artificial environment to show the impact of the spatial distribution of entities, their density and the size of the area on the critical mass frontier in a controlled environment. In these scenarios, the overall population is static and fixed in terms of their location, and in turn density and distribution. However, the demand, i.e., people interested in using the ride-sharing system, is dynamic and uncontrolled, as it depends on the number of available vehicles nearby. In terms of supply, there is a controlled starting point in terms of distribution and density, however, only distribution is controlled in the iterations and density may get higher or lower. Then simulations are run on a real-world scenario, where not all of these parameters can be controlled any longer.

5.3.2.1 *Artificial Environment*

The scenarios in this category happen in a square area and include variations of area size, and the density and the distribution of entities. Three area sizes, 1 km^2, 9 km^2, and 25 km^2, and Normal and Uniform distributions have been considered. Combining these parameters comprises the twelve different cases presented in Table 19. According to Section 5.2, the system is expected to have different behaviour based on its size, therefore, three different sizes are chosen to test the hypothesis. The specific numbers are based on the suburb sizes of Melbourne, Australia, the metropolitan area of the real-world scenario (see below). One square kilometre is close to the smallest suburbs. Nine is considered a medium size suburb and 25 km^2 is among the large suburbs. There are bigger suburbs in the metropolitan area; however, since the test runs proved that 25 is sufficiently big to test the impact of size, larger areas were not modelled.

For each case 100 scenarios are run which includes variation of both entities' densities from 10 per km^2 to 100 per km^2 with an increment of 10 per km^2. The maximum density for the vehicles are 100 per km^2. In all scenarios the acceptance threshold (AT) and neighbour interest threshold (NTST) are the same for all individuals and are set to 100 meter and 5 neighbours, respectively. Moreover, the utility thresholds for people to loose interest and for vehicles to decrease their number for the next iteration are the same and equal to 2.0. In Section 5.4.2, the impact of changing these thresholds on the results is explained and discussed.

5.3.2.2 *Real-world Scenario:*

Yarra Ranges, Australia, is a local government area (LGA), located in the outer northeastern suburbs of Melbourne (Figure 14). Yarra

Table 19: Artificial environment scenarios

Area Size (km^2)	Population Distribution	Vehicle Distribution	Case Code
1	Normal	Normal	1_NN
1	Normal	Uniform	1_NU
1	Uniform	Uniform	1_NU
1	Uniform	Normal	1_UN
9	Normal	Normal	9_NN
9	Normal	Uniform	9_NU
9	Uniform	Uniform	9_UU
9	Uniform	Normal	9_UN
25	Normal	Normal	25_NN
25	Normal	Uniform	25_NU
25	Uniform	Uniform	25_UU
25	Uniform	Normal	25_UN

Ranges consists of 14 suburbs, one of which includes only national parks and no resident. Figure 19 presents the population density of the residential suburbs at 10% of the total population. Mooroolbark has the highest density and is surrounded by other high density suburbs, namely, Kilsyth, Montrose, and Chirnside Park. In contrast, Upwey-Tecoma with the second highest density is surrounded only by low density areas. This provides an opportunity to study the impact of boundaries and neighbouring suburbs on the transition to super-criticality.

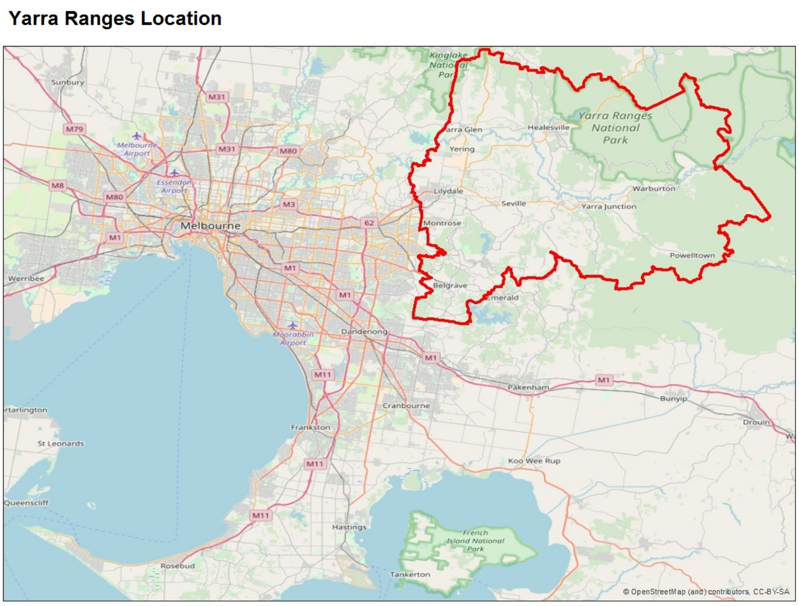


Figure 14: Yarra Ranges, Victoria, Australia

The population generation is based on the census data of 2016 (StatisticS, 2016), which reports the number of people living in an area on a granularity of *Mesh Block*, the smallest area defined by Australian Bureau of Statistics (ABS) for statistical data reporting and analysis [2]. To generate the population various percentage of the whole population is considered, and sufficient points are created in each mesh block to represent the location of one person. The simulations are run with 5% to 100% of the total population. All other parameters and vehicle densities are the same as the scenarios from artificial environment. There is only one difference in the method for adding vehicles. While in the artificial environment all vehicles are treated as one pool, in the Yarra Ranges scenario, the vehicles are divided into 13 different pools based on the 13 occupied suburbs of Yarra Ranges. At the end of each iteration, the average utility of all vehicles in each suburb is calculated, and if it is lower than VT, in the next iteration that suburb receives 10% fewer vehicles. However, the passengers are able to look for a vehicle globally, i.e., they do not care if they are in the same suburb as the matched vehicle.

5.4 RESULTS

The objective of this work is to investigate how the spatial characteristics of demand and supply affect the critical mass frontier in a spatial two-sided market.

As explained previously, the expectation is that the critical mass frontier to be a blurred area showing the transition from sub-critical to super-critical conditions. To this end, the results are presented as heat maps, where the horizontal and vertical axes represent passengers' and initial vehicles' densities in the area respectively, while the colors represent the probability of the system's success and ranges from dark red, representing 100% probability of the system's success, to dark blue, meaning its 0% probability.

5.4.1 *Artificial Environment*

Figure 15 demonstrates the results for cases in the artificial environment. In all graphs inside this figure, the transition region is visible, which is the area between the dark red and dark blue in each graph.

Let us start with the **UU case** (third row), which is closest to the theoretical situation of Section 5.2. One can make the following observations:

- The outcome is probabilistic: For the same initial conditions, different outcomes are possible.
- For very low densities of both passengers and vehicles, the probability to become supercritical is close to zero. Conversely, the probability is close to one for large densities of passengers and vehicles.

2 http://www.abs.gov.au/websitedbs/censushome.nsf/home/meshblockcounts

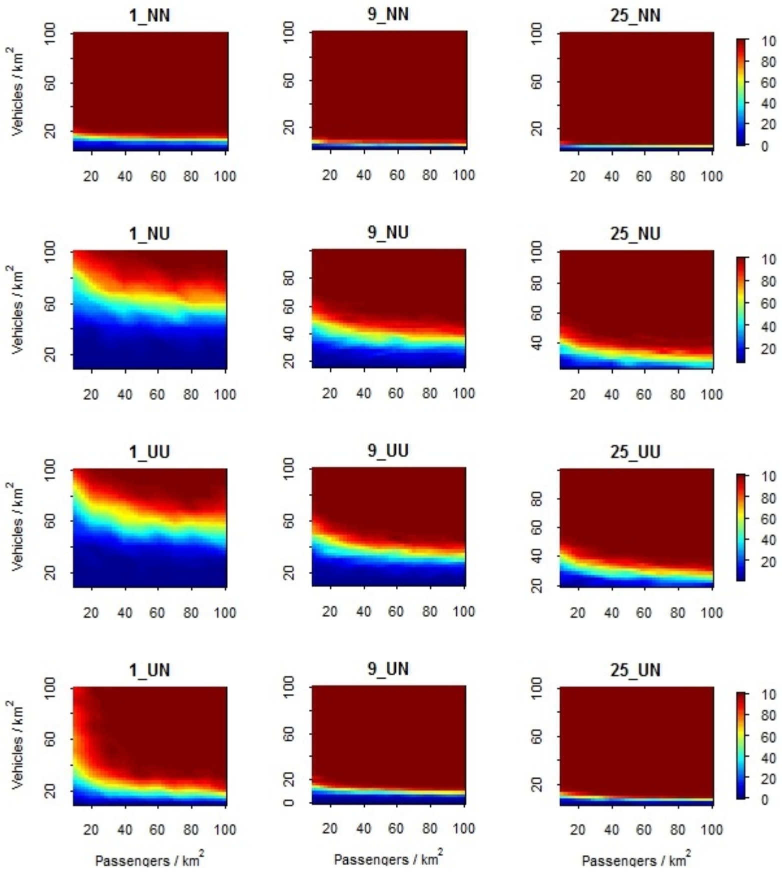


Figure 15: The success probability of systems with different sizes, densities, and distributions. The x-axis denotes the density of potential passengers (boundary condition), while the y denotes the initial density of vehicles.

- The width of the transition region (from blue to read) becomes smaller with larger system sizes. This is consistent with the theory from Section 5.2.

The **NU case** (2nd row) is similar to the already discussed UU case (3rd row). In contrast, **both** ***N** cases (1st and 4th row) are similar to each other, but different from the two *U cases (2nd and 3rd row). This implies that the initial vehicle distribution (second letter) has a stronger influence on the outcome than the distribution of the population. Initially, concentrating the vehicles in a smaller area (the *N cases) yields a much higher probability of overall success than spreading them out. This implies that whoever wants to make the system a success should concentrate its seed vehicles into small initial service areas rather than spreading them out.

5.4.2 *Sensitivity Analysis*

In designing the scenarios, a number of assumptions were made, namely acceptance, neighbour-based interest, and utility thresholds, to be able to demonstrate and discuss the results. Understanding how the variations of these numbers changes the system behaviour is critical, and makes sensitivity analysis a requirement.

The sensitivity analysis is performed on the 9 km^2 area for two reasons: First, according to the results presented in the previous section, too small or too large system may exaggerate or eliminate the impact of parameters on the transition area, thus, it is important to conduct the sensitivity analysis in a medium size area. Second, 9 km^2 is a reasonable approximation of many suburbs in the study area.

The analysis hardly showed any observable change in NN cases when changing the parameters. But unlike the NN cases, some behavioural changes were manifested in the NU and UU cases due to parameters variation, which includes mostly the width (or shape) and the position of the transition area. Width, here, means how fast the systems changes from dark blue to dark red; while, position, here, means how high the area is in the graph. For example, the transition area in 1_NU case is higher and wider than the one in 25_NU case in Figure 15.

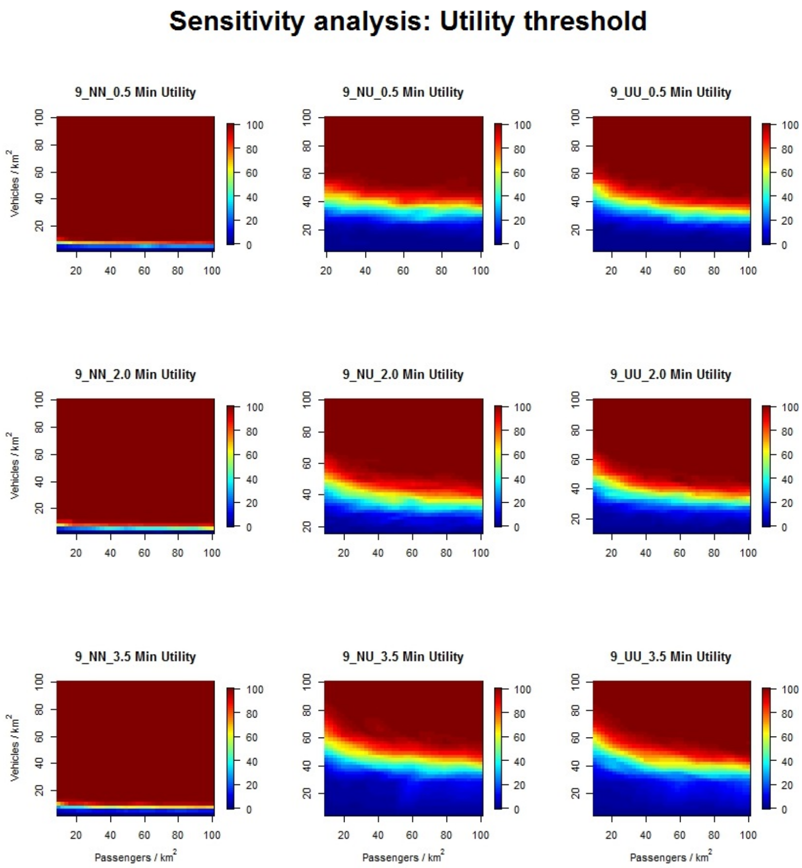


Figure 16: The success probability of systems with variations in utility thresholds. The x-axis denotes the density of potential passengers (boundary condition), while the y denotes the initial density of vehicles.

Figure 16 demonstrates that the variations of the utility threshold are not impactful. In other words, if the threshold increases or decreases by up to 30% the difference in the transition area is minimal, i.e., there is no observed change in its shape and only minimal changes in its position. Since the utility is only a function of distance, variations in acceptable distance thresholds have been investigated as well. According to Figure 17, unlike the changes in utility threshold, alterations in the acceptance threshold appear to be critical to a certain extent. While relaxing this threshold from 100 meter to 200 meter results in a much narrower and lower transition area, and changing it up to 400 meter converts the transition area to one deterministic line in all three cases (9_NN, 9_NU, and 9_UU). This sensitivity to changes in acceptance threshold but not to the utility threshold shows that the system behaviour's sensitivity to the distance is discrete. It also makes sense in the real world, as people are indifferent to small changes in their walking distance, e.g., no one would walk 100 meters to the station, but not 120 meters.

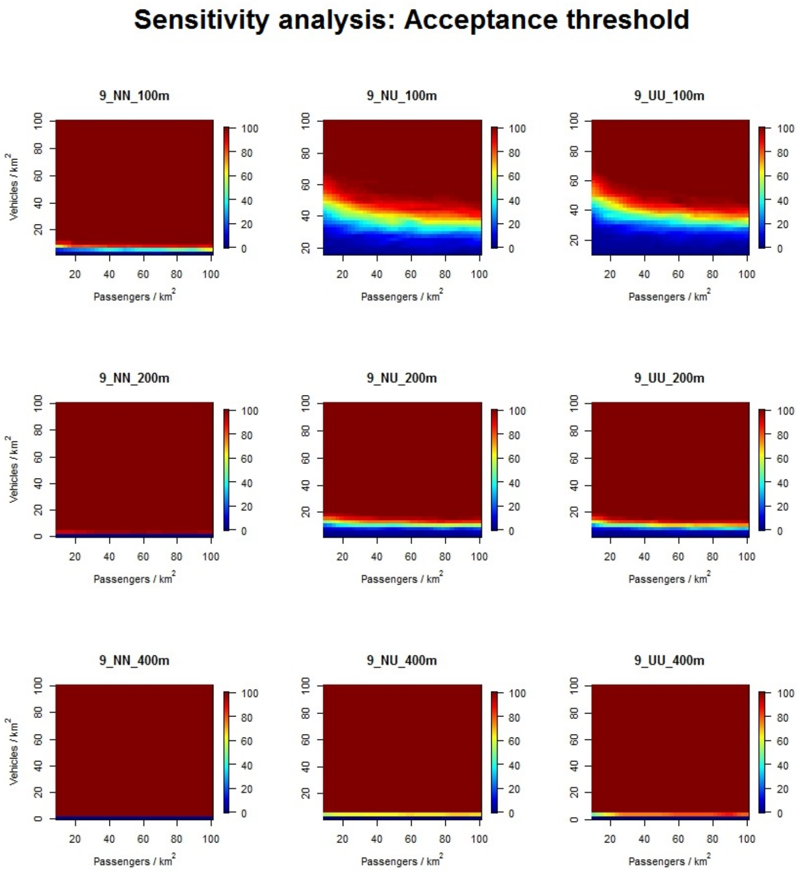


Figure 17: The success probability of systems with variations in acceptance thresholds. The x-axis denotes the density of potential passengers (boundary condition), while the y denotes the initial density of vehicles.

The last parameter is the number of neighbours sufficient for a passenger to get interested in being matched with a vehicle (NTST). Figure 18 shows that increasing this threshold (i.e., more neighbours are required, stricter threshold) makes the transition area slightly wider but significantly higher, and vice verse. This means, while people's tendency to use the system may play a crucial role in a faster potential success of the system (lower transition area), it is less critical to the certainty of the system's success (slight changes in the shape).

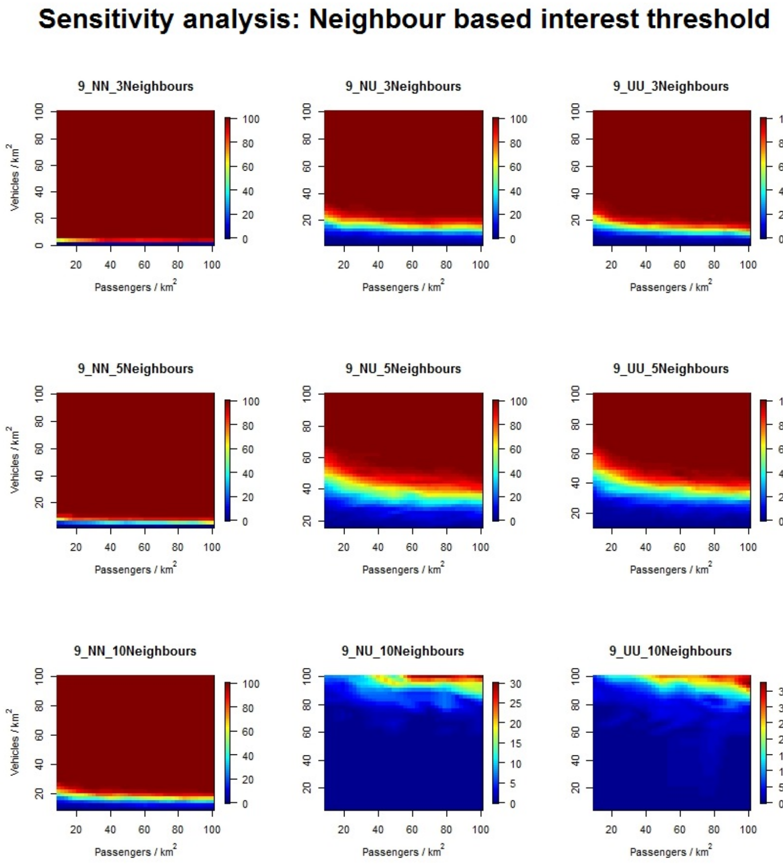


Figure 18: The success probability of systems with variations in sufficient neighbour thresholds. The x-axis denotes the density of potential passengers (boundary condition), while the y denotes the initial density of vehicles.

Overall, the more relaxed any of the thresholds is the wider or the lower the transition area becomes. Furthermore, there is always a threshold at which, regardless of the density, the system is always successful (e.g., $AT = 400meter$) and one at which the system cannot succeed (e.g., $NTST = 10$).

5.4.3 *Real-world Scenarios*

According to Figure 19, the population distribution in this area is similar to a normal distribution, thus, its heat map is expected to follow the trend from the 25 km^2 cases in Figure 15 and have a more deterministic and narrower transition area than the one in 25_NU case, which is assumed to be the most similar theoretical scenario. Figure 20 shows the success heat map of Yarra Ranges scenarios next to the one from 25_NU case, which fulfils the expectation.

However, more detailed analysis is required for a better understanding of the system's behaviour towards super-criticality. Thus,

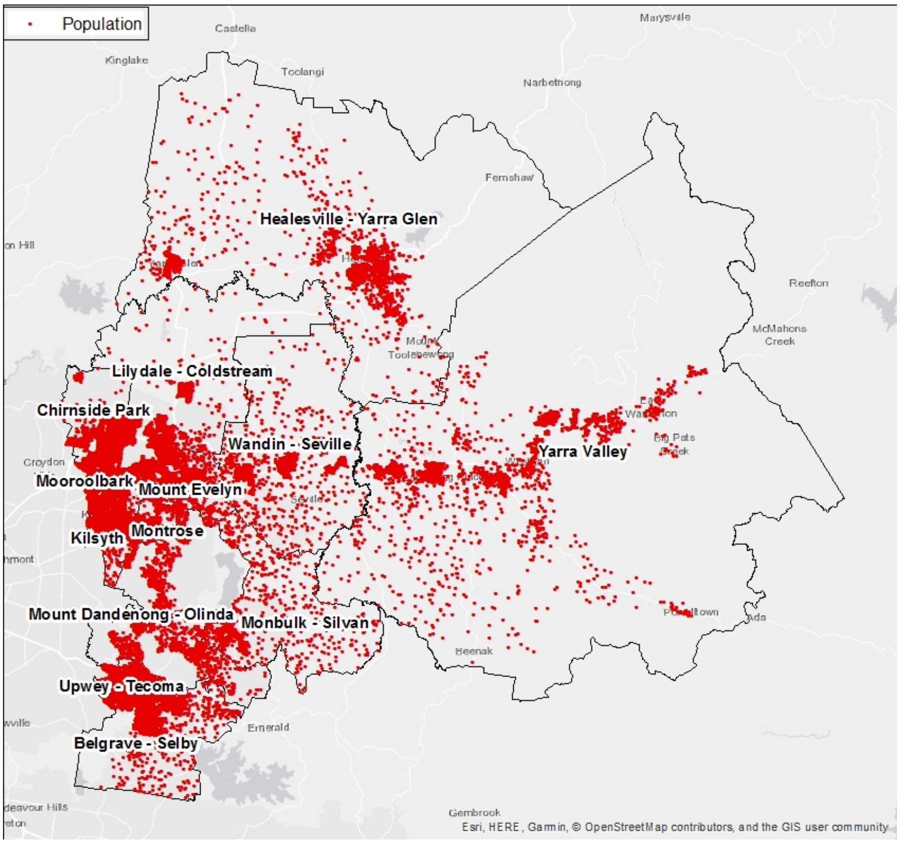


Figure 19: Population distribution of Yarra Ranges demonstrating 10% of the whole population

the super-criticality is visualise and investigate in a number of suburbs in Yarra Ranges.

A number of Yarra Ranges scenarios are run up to 1000 iterations to be able to provide a better understanding of the system's behaviour in the longer run and allow time for changes to happen. Figure 21 illustrates the results from Yarra Ranges scenario with initial vehicle density of 60 per km^2 and 10% of the population (these numbers are chosen as an example, simulations of other combinations show the same level of consistency with the theoretical expectations) through iterations. The passengers' utilities are aggregated and illustrated in hexagonal cells.

Mooroolbark, Upwey-Tecoma, and Kilsyth, in this order, with population densities over 100 people per km^2 and area sizes between 8 and 13 km^2, are expected to have relatively similar results, as they all fall in the UR area of their most similar theoretical case, 9_UU. However, Figure 21 reveals that on an aggregated level the passengers utilities in Upwey-Tecoma are significantly lower than in Mooroolbark and Kilsyth. Moreover, it shows that Mooroolbark becomes super-critical in the early iterations (100) and starts infecting the surrounding suburbs[3], while Upwey-Tecoma stays in the same stages of success as the early iterations. Although the process of infecting the neighbouring slows down as it gets closer to the boundary of the

3 An animation of the changes will be made available online as supplemental material.

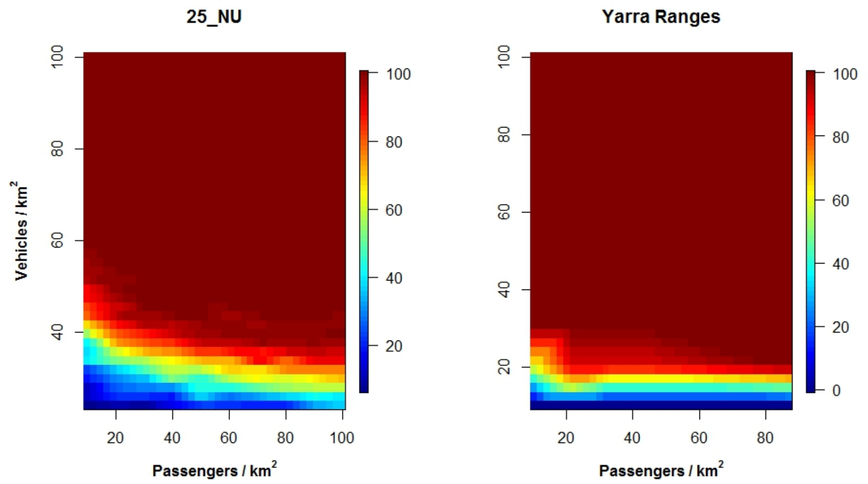


Figure 20: System's success probability in Yarra Ranges compared to 25_NU scenarios

high density areas, it does not stop as there is still connections to the neighbouring areas.

This does not mean that there is no one with high utility in Upwey-Tecoma. The system in this suburb behaves as expected from graphs in Figure 15 and contains a number of passengers that are interested and has been matched with vehicles around them. However, since the number is not as high as in Mooroolbark and the passenger's density is relatively high, the average stays low and in the blue spectrum.

5.5 DISCUSSION

In this work, first, the impact of different spatial characteristics of an area on the critical mass frontier is investigated in an artificial environment, which allows for a strict control of the parameters. Further, to evaluate the theoretical results, the system is also implemented in a real-world scenario.

The results from the artificial environment demonstrated the importance of spatial characteristics of an area in forming the critical mass frontier for a spatial two-sided market. It was shown that a densely populated spatial core significantly impacts on the critical mass frontier and helps any system become viable much faster. In all NN cases, the LL areas are significantly smaller than their counterparts in other cases. This means that the UR area is bigger and includes more $\vec{p}(x, y)$, resulting in more certainty of the system's success.

The outcome of the real-world scenarios strongly supported the results from the theoretical experiments and further provided insights on the impact of neighbouring areas. In line with the expectations, the results demonstrated that if there are a number of areas in the UR region of their relative graphs, they all become super-critical together and start infecting the neighbouring areas. This process slows down or stops at the border of these areas and may advance again with changes in pricing or other characteristic of the system, which is beyond the scope of this work to illustrate and investigate.

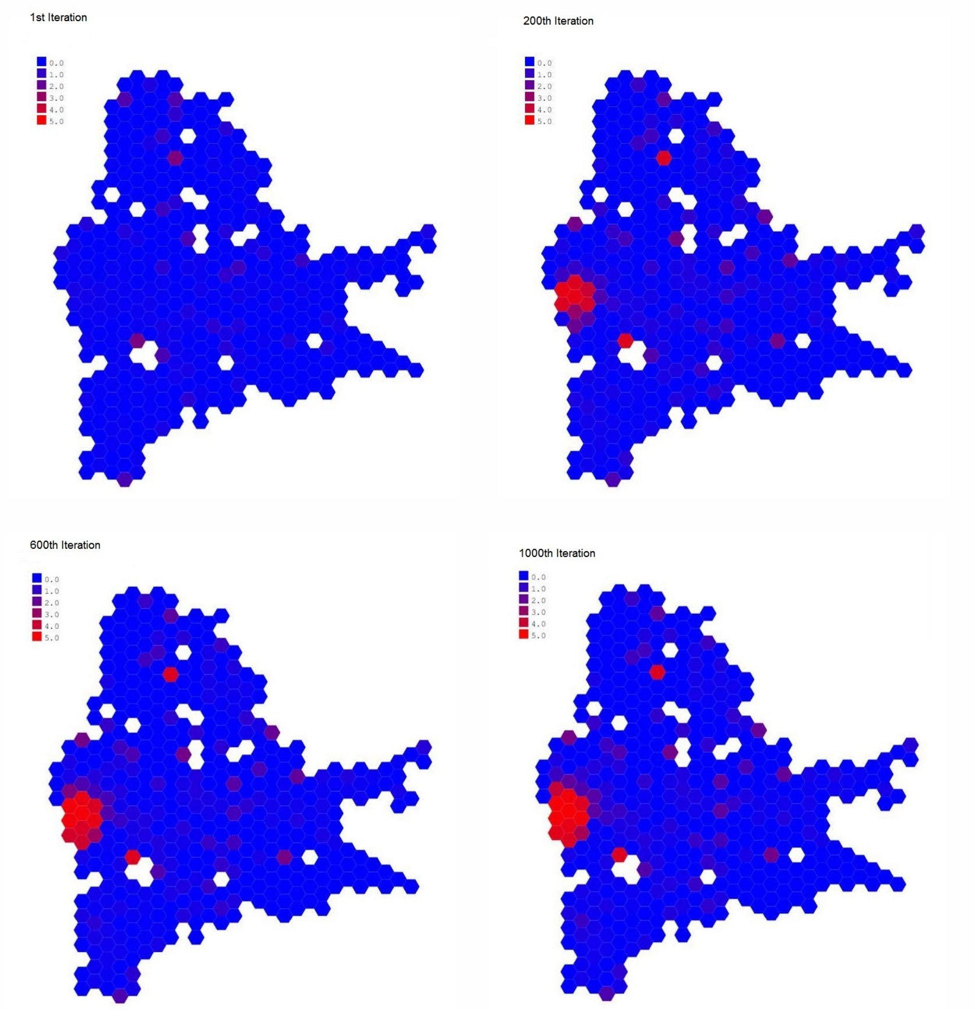


Figure 21: The changes in passengers' utilities through iterations, spreading high utility from the dense center to the surroundings. Also note that spreading eventually stops, confirming that there are areas that cannot be made super-critical even when they have a super-critical neighbour.

As a consequence of the experiments, one can conceptually delineate a spatial region into areas that are "potentially super-critical" and other ones that are not:

- Areas inside such a potentially super-critical area *and* connected to an urban core can expect to eventually be served (e.g., Kilsyth and Montrose).
- Areas inside such a potentially super-critical area but not connected to an urban core may eventually be served, or not (e.g., Upwey-Tecoma).
- Areas outside the potentially super-critical area will not be served, except when the overall costs for the service become lower.

This has, in fact, important consequences for policy, in particular for regulation. When left to itself, super-critical areas will be served by commercial companies, while sub-critical areas will not. The surplus of the super-critical areas will, depending on the competitive situation, either go to the suppliers or to the customers; and it is in fact quite plausible that it will go to the suppliers since platform markets are not highly competitive, since they are difficult to invade Katz and Shapiro, 1985. Sub-critical areas would, in consequence, not be served at all, or only with taxpayer subsidies.

An alternative scenario would be to give out regulatory licenses that would force a licensee to serve the complete market, including the sub-critical areas. Surplus on super-critical areas would thus be used to cross-subsidize sub-critical areas. Clearly, this will make the super-critical areas either more expensive to customers, or less profitable for suppliers; presumably the latter. It would, however, also either decrease the taxpayer burden or improve services to sub-critical areas. Clearly, this is a regulatory intervention. It is, however, an intervention that is quite standard in infrastructure markets (water, electricity, telecommunications), where the connection cost is regulated to be the same for all locations. Thus, a public debate is needed if certain mobility services should be treated in a similar way. This debate is even more necessary since dynamic transport systems bear the promise of being a much better system for sparsely populated areas than the current systems, and thus the question becomes if a society wants to realize these promises or not.

It also becomes clear that in strongly super-critical areas, prices will be such that they are either much higher than cost, or much smaller than the users' willingness to pay. It may thus make sense to use a strategy also used in other areas of infrastructure engineering, which is to enforce a more uniform service provision by giving out licenses. For example, in water, electricity or telecommunication, it is often normal that the connection fee is the same for everybody, no matter where they are located. This effectively spreads revenues from relatively-easy-to serve densely populated areas to more-expensive-to-serve less densely populated areas, and forces suppliers to supply at those prices even in areas where these do not cover costs. In Germany, such schemes are enforced by a certain interpretation of its constitution, which demands "equality of living conditions" across the country. Other countries may have similar norms in place; such schemes may also be seen as a measure to help spread economic and technology gains from the urban centers to other areas. Australia has no comparable legislation.

The mechanism to achieve this would thus be to give out licenses for regions that include urban cores but also rural areas (e.g. for all of Victoria). At the same time, one would demand minimum service standards across the full region. Platform providers could, for example, set incentives for suppliers in rural areas in order to reach them. If the precise details of such a license cannot be determined by government, it could do what it also does in other infrastructure markets: the licenses could be auctioned off.[4]

5.6 conclusion

Critical mass frontier is the border of success and failure in a two-sided market. Its identification prior to implementation is highly crucial for any platform in such market. The main hypothesis here is that unlike in non-spatial markets, e.g., media sharing, news media, and credit card platforms, there are certain platforms, whose success highly depends on the location of their members.

Using simulations, the hypothesis is confirmed by demonstrating that spatial characteristics of an area, namely size, the density and distributions of demand and supply, have significant impact on the critical mass frontier of an implemented spatial platform based on two-sided market. Here, the aim is to draw overall insight on how the spatial characteristics of demand and supply may help or hinder an area achieve super-criticality, not at providing a concrete number as the required number of vehicles or passengers to create a self-sustained two-sided spatial market. Moreover,it is illustrated that the critical mass frontier is almost never a deterministic line and there is always specific uncertainty in achieving success.

This work is the first step towards developing a framework for identifying critical mass frontier in spatial two-sided markets. One main shortcoming of this work was the lack of time consideration in matching vehicles and passengers, which makes the results more optimistic than reality. However, since the focus of this work is neither optimizing the dispatching algorithm nor finding specific solutions for specific condition this shortcoming has been neglected.

In future work, it is necessary to make more realistic assumptions, e.g., considering a street network, time dependency of demand and supply, and build a more comprehensive simulation platform that allows for investigating more specific scenarios.

4 This is not an argument that, at this step of the understanding of such system, the authors are recommending governments to auction off such licenses. Rather, it is intended to point out that there exists a large body of literature for how to deal with such markets.

6 COLLABORATION OF RIDE-SOURCING PLATFORMS

This chapter is adapted from the manuscript with the same title submitted for peer review. As the first author, I designed the research, implemented the experiments, analysed the results, and wrote the majority of the paper. My supervisor, Prof. Stephan Winter, proposed the idea, helped in literature review, edited the paper, and contributed to the discussion and collaboration concept.

6.1 CONTRIBUTION

An avoidable element of DRT systems' market mechanism is the competition between the operators, which has posed disadvantages to the users. Despite the regulatory interventions of authorities in certain markets, there are still strong competition in transportation markets causing passengers monetary and non-monetary losses. MaaS as a relatively new concept brings the promise of solving this problem by uniting all operators to join forces and offer their services through the same platform. However, the studies on the collaboration of operators are limited and this work intends to fill in this area.

The hypothesis here is that operators feeding into a single meta-platform will bring benefit to all customers (passengers and drivers) and thus also the operators. The following questions are investigated:

1. How does the spatial separation of the fleets of participating operators impact an individual operator's success, particularly for small operators?

2. How does the spatial separation of the fleets impact the minimum market share for an operator to survive?

3. Will customers, i.e., passengers and drivers, benefit from a meta-platform?

In particular, this research investigates the potential benefits of operators' collaboration using simulation. The simulation model is agent-based and represents all the relevant spatial elements of a ride-sourcing system. The impact of platform collaboration is studied in scenarios. These scenarios vary the spatial distributions of passengers and drivers, and the different operators' market shares. The potential advantages to all the stakeholders, i.e., operators, passengers, and drivers are measured and investigated. It is intended to shed light on the value of collaboration of operators from a spatial point of view and highlights the role of the spatial characteristics of competing ride-sourcing systems; not investigating possible pricing strategies and their implications in competition or collaboration.

The rest of this chapter is organised as follows. Section 6.2 provides the context of platform collaboration to the research problem. Section 6.3 details the simulation and its components. Section 6.4 lays out the scenarios that have been designed to comprehensively cover the influence of spatial heterogeneity and distribution of market shares in the investigations. The results are presented in Section 6.5 and discussed in Section 6.6. Finally, the conclusions and the future directions are summarised in Section 6.7.

6.2 COLLABORATION

The recent progress in ICT and the ubiquity of smart devices have made it possible to revolutionise transportation systems in a potentially disruptive manner (Meyer and Shaheen, 2017). Online matchmaking platforms enable a sharing economy of scale on real-time transport solutions. For example, companies such as Uber, Lyft and DiDi offer *ride-sourcing* services through online platforms, breaking into the traditional taxi business models. *Ride-sharing* companies offer now matching private drivers and passengers along the drivers' trips in real-time, which so far had been a matter of planning ahead or of social conventions, i.e., has become more convenient and safer. *Car-* and *bike-sharing* have become possible through online platforms, as well as *sharing parking places*.

Ride-sourcing, ride-sharing and park-sharing are multi-sided, i.e., platforms connecting two or more groups of customers, here *drivers* and *passengers*, or *drivers* and *owners of parking places*, respectively. Usually, the success of multi-sided platforms depends on the number of customers on all sides, and on the rate at which they achieve a critical mass of these customers. The critical mass of multi-sided platforms is a point or a set of points (i.e., a 'frontier') at which the platform has achieved enough customers of all groups to continue their growth (Evans and Schmalensee, 2010). Critical mass is a complex consequence of external network effects of its customer groups (Evans and Schmalensee, 2010). For ride-sourcing, for example, the critical mass frontier is where new drivers find passengers, and new passengers find drivers.

Moreover, as mentioned in Chapter 1, one-sided platforms, such as for car-sharing or bike-sharing, are subject to the same network effects, and thus are also calling for a critical mass.

Transportation-related platforms are prime examples of platforms that have a strong spatial and temporal component in their matchmaking. Demand and supply, in order to be matched for an imminent service delivery, need to be in the vicinity of each other at the time of matchmaking. Already Evans and Schmalensee (2016a) recognise this fundamental component in their leading platform example, a restaurant table booking system. While restaurant bookings are typically made in advance, and for intended locations (not current locations), ad-hoc transportation platforms operate under much stricter spatial and temporal constraints. For example, ride-sourcing requires from a driver and a passenger to be near to each other in order to be matched. In addition, ride-sharing requires from a passenger to have a destination on or near to the route of the driver in order to be matched. A park-sharing service requires a parking space be located near the destination of the driver. In all cases, nearness is expressed in utility functions that measure waiting times and detour times typically in minutes (Agatz et al., 2011). In this utility function, space and time are equivalent. For example, a vehicle far away requires for a passenger to wait in the same way as a close vehicle starting later.

The competition among platforms also add to this complexity for the customers. Platforms try to form a monopoly by attracting all customers and rendering their competitors, i.e., platforms offering the same service, redundant. In such competitive market of shared transportation systems, where each platform offers their services separately, the customers are obliged to search each individual platform to find the service that suits their need at that moment. Although multi-homing brings advantages to both customer groups – passengers and drivers in a ride-sourcing system – it is a time-consuming and error-prone task to be performed on a regular basis.

While drivers anecdotally can afford to operate several smartphones in parallel, for passenger customers search is rather sequential. They need to enter their origin and destination in each individual application, and wait several seconds (up to minutes) to receive the available offers. Then, keeping those in mind, they need to check the next application with similar (or rather contradictory) procedure and interface. With unlikely assumption that they remember all the details correctly for a precise comparison of platforms, they may lose the option they conclude to have been the best during this search process. Consequently, many passengers content themselves with using one application, for example, the one that has offered the best service at some point in the past, or the one that the passenger finds easier to interact with. Platform providers also add to customer binding by incentives.

Such a competitive market dynamic does not allow entrants to achieve the critical mass and become successful, despite the potential superiority of their services, because the competition is not among the current service offerings, but among platforms.

Here is where collaboration can come into play. While by pure numbers of customers newcomer platforms find it challenging, and established platforms would fight for every customer, it is imaginable that collaboration benefits both. The reason for this assumption is the spatial and temporal component, or the strict spatiotemporal constraints, of each transport service. Thus, it is not a matter of numbers, but a matter of distribution of the customers of each platform. A small ('newcomer') platform could attract customers in an area where an established platform is under-represented, for example. In that case, collaboration leads to flexible sharing of customers, and thus larger customer satisfaction of both drivers and passengers. This, in turn, leads to market growth benefiting also the platform providers.

Platform collaboration and sharing is fundamentally different from a platform monopoly (such as the regulated taxi market). First, the collaborating platforms keep their autonomy in pricing, customer service, or driver payments. This means the market has to deal with various customer experiences. Secondly, each of the collaborating platforms is looking for their own benefit. This means if the spatiotemporal component does not provide an advantage for the smaller platforms collaboration reverts to competition and the smaller platforms will disappear (due to the network effects).

Platform collaboration can be technically realised by a meta-platform that merges all current supply and demand from participating transport platform providers.

6.3 SIMULATION DESIGN

The hypothesis will be investigated using an iterative simulation. In each iteration a proportion of the population would like to use ride-sourcing as their transportation mode, and looks for a driver. This subset is the group that either had a previous good experience with a platform, or observes now on a platform abundant available offers nearby. The drivers, however, appear randomly at the beginning of the iteration. They may stay and continue offering their services in the next iteration, or may leave at the end of an iteration because of insufficient benefit. Moreover, in each iteration it is assumed that there are a number of operators with certain shares of the market, that is, a certain percentage of all drivers are registered with that operator. This market share evolves over the iterations since drivers may withdraw from the pool.

This study is focused on the spatial aspects of the market and the temporal aspect will be simplified by assuming that a short term simulation, in which all market participants aim to travel at the same time. However, the waiting time, which is a determinant component of ride-sourcing system is implicitly considered in the utility of the passengers (See Section 6.3.1). As explained in Section 6.2, time and space can be considered equivalent as they may impact the utility in the same way. In the following, demand and supply modelling are detailed, and the simulation platform and its configurations are explained.

6.3.1 *Demand*

Demand is represented by the transportation needs of a synthesised vehicle-less population with N_p members. While members are homogeneous, i.e., they have the same threshold for accepting an offer from a driver in terms of distance from the driver, they decide to use the offered services individually. Every time a member of the population – passenger i – is matched with a driver, the member calculates and stores the utility (U_i), which is inversely proportionate to their distance to the matched driver. This reflects the waiting time for the passenger: the lower the distance, the lower the waiting time, the higher the utility.

Another attribute of the passenger i is their interest (NT_i), which can be 1, meaning they are looking for a ride, or 0, meaning they are not interested. This attribute is a function of U_i from the previous iteration (if any) and the number of neighbouring drivers, which is the number of drivers in the acceptable distance (AT) from the passenger. Moreover, each passenger has an initial default operator (O_i).

6.3.2 *Supply*

The supply side consists of a pool of independent and homogeneous drivers. The former means that each driver decides based on their own interest (represented by utility) to either continue offering services or to stop and become unavailable, and the latter means they all have the same threshold to make the decision on their availability.

Each driver (j) is registered with only one operator (O_j) and, unlike the passengers, do not have the possibility of multihoming. Literature has shown that multihoming in all groups of customers is not a reasonable assumption (Armstrong, 2006). Also, each driver has only one attribute: a utility (V_j), which is either zero or the same as the matched passenger (if any). The utility of the driver reflects the necessary driving distance to the passenger, while the passenger is waiting. Drivers make decisions about their availability based solely on their utilities: if V_j is higher than a certain threshold, called driver lower utility threshold (T_l^d), they stay available; otherwise, they become unavailable. This setting reflects the flexibility of such systems in real world for the drivers, who can be available as long as they choose.

Note that the utility functions of demand as well as supply are specific for ride-sourcing. Other services would compute utilities according to their service models.

6.3.3 *Platform*

The simulation of each scenario starts with the generation of the passengers randomly distributed through the area. The form of this random distribution depends on the scenario (see next section); normal and uniform distributions have been chosen in this work.

Each iteration of a scenario starts with the generation of the drivers randomly distributed. The form of this distribution and the number of drivers depend also on the scenario (see next section).

Then each passenger (i) is allocated to their default operator, which is the operator with the most vehicles within an acceptable distance. If there are operators with the same number of drivers within this distance, then the closest driver's operator becomes the passenger's default operator. If the passenger either finds at least a certain number of drivers, defined by a neighbour-based interest threshold ($NbTS_i$), in an acceptable distance, or her utility from the previous match (if any) is higher than (T^P), then the passengers interest turns to 1 ($NT_i = 1$).

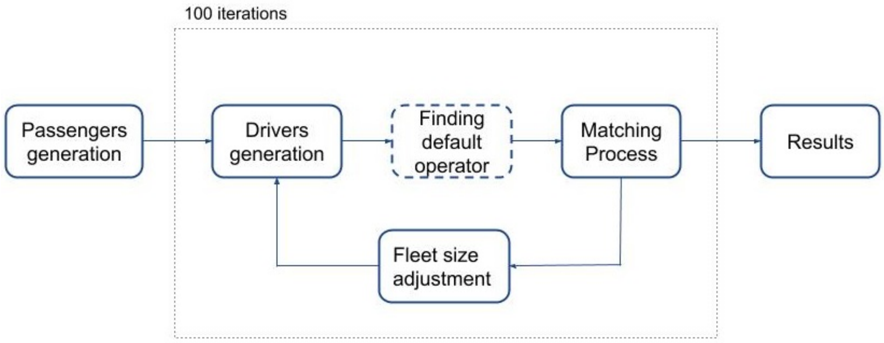


Figure 22: The work flow of the platform

This passenger looks for a match. If the scenario includes multiple platforms (instead of a joined meta-platform), only the drivers with the same operator as the passenger's default operator are considered for counting the neighbours and for matching. If there are drivers in the acceptable distance of the passenger, the nearest one is matched. Both calculate their utility. The matched driver is no more available for other passengers. The matching process does not take into account the destination of the passenger as it is not possible for drivers on such platforms to see the destination of the passengers before they accept to give a ride. Note that this is a simulation of ride-sourcing platforms not ride-sharing platforms, where the drivers have a destination and take detours to pick up/drop off someone.

At the end of each iteration all vehicles that have utilities lower than T_l^D will become unavailable, i.e., they are deleted from the simulation (In a real-world setting, it means that if a driver is not happy with her/his income they leave the platform temporarily). Further, an average utility ($\bar{V}_o$) is calculated for each operator. Those operators with average utility lower than T_l^D will have 10% fewer vehicles, and those with average utility higher than a new threshold called driver higher utility threshold (T_h^D) will have 10% more vehicles to add to their surviving pool in the next iteration. This mechanism reflects the growth or shrinkage of operators' size resulted from their success or failure. The overall work flow of the platform is illustrated in Figure 22.

Each scenario is run for 100 iterations, sufficient to form an equilibrium. Figure 23 demonstrates that this equilibrium is reached in one of the scenarios for drivers and passengers. At the end of the 100^{th} iteration, the success is measured, which is the number of passengers using the system (which is equivalent to the number of rides, or the business the ride-sourcing system has generated). This process is repeated 100 times for each scenario to derive the success probability of that simulation's conditions.

6.4 SCENARIOS

Here, two main groups of scenarios are examined: The first group of scenarios models the currently observed *multi-platform* markets,

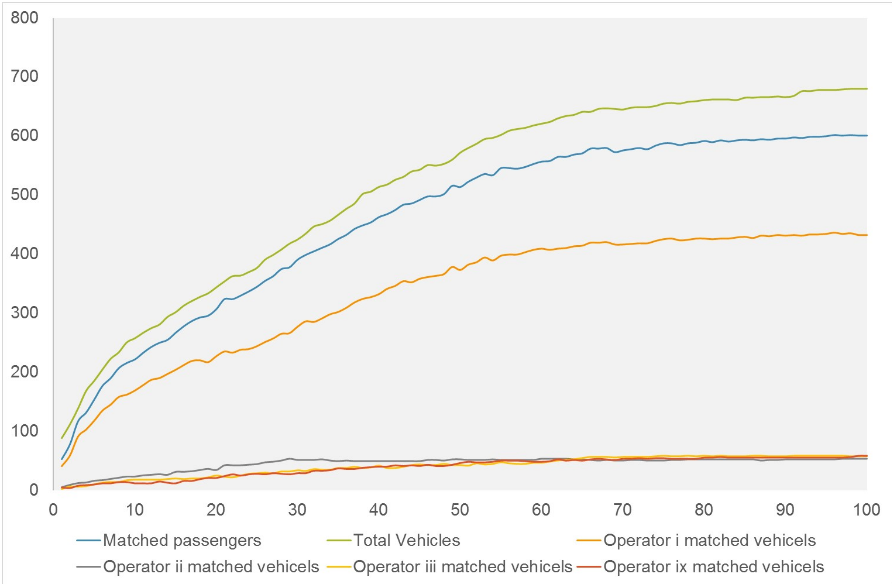


Figure 23: An example of the equilibrium state of the simulations

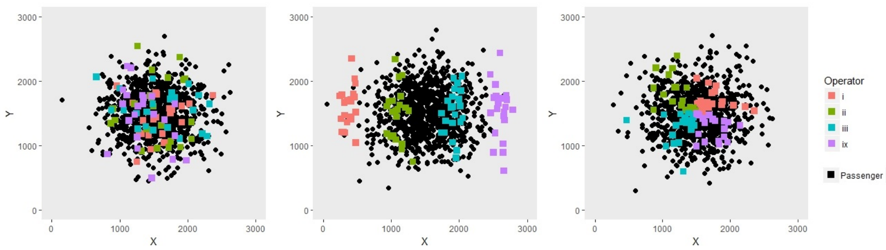


Figure 24: Various spatial separations: The operators are in the same space (left), separated in elongated bands (middle), and separated in pie-pieces (right).

where there are several operators offering their services on separate platforms and passengers only choose the vehicles from their default preferred operator (platform competition). The second group models the hypothetical situation of a *meta-platform*, where all the operators offer their services in one single platform, and passengers' default operators do not matter (service competition, or operator collaboration). The objective here is to identify the potential consequences of these joint meta-platforms. Moreover, competition and collaboration are tested for various spatial separations of the operators, including the following:

- all operators have their fleets in the same space (Figure 24, left)
- the operators have their fleets in separate spaces in elongated partitions (Figure 24, middle)
- the operators have their fleets in separate spaces in pie-piece-shaped partitions (Figure 24, right)

These variations allow for a systematic comparison of consequences of having a meta-platform against operating in a specific area. These six variations (Figure 25, platform and spatial separation level) represent the attributes of the platforms (operators). To understand the role

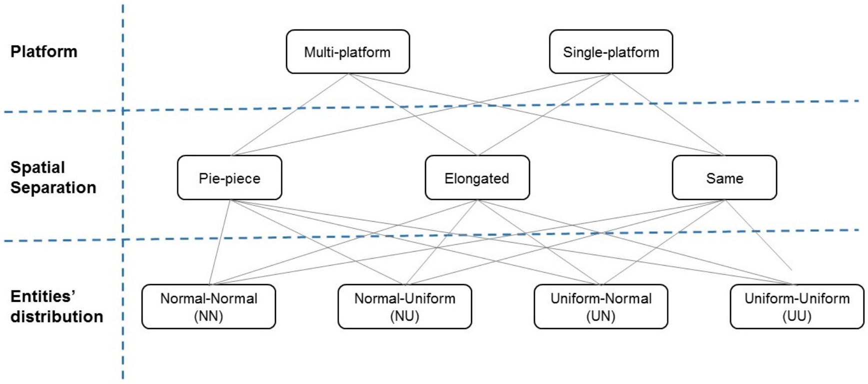


Figure 25: Specification variations for scenario designs.

Table 20: Operators' market shares in different scenarios.

Operators	Scenario 1	Scenario 2	Scenario 3
i	70%	52%	25%
ii	10%	16%	25%
iii	10%	16%	25%
iv	10%	16%	25%

of spatial distribution of the passengers and drivers, various spatial distributions of them are also investigated. In each case, both passengers and drivers will have either normal or uniform distribution (Figure 25, bottom level – passengers first, drivers second). In total, Figure 25 specifies the 24 cases of investigated platform operations. Further, defining market shares in each case completes the process of scenario design (not shown in Figure 25).

Table 20 presents the three scenarios that are investigated in each case, all involving four competing or collaborating operators. Scenario 1, with one operator with significantly larger market share than the others, is designed to investigate the impact of a meta-platform on dominating operators (e.g., Uber nowadays). Scenario 2 allows investigating the situation where one operator has a much larger share than the others but their market share is too small to be considered dominating. Finally, Scenario 3 is to test the situations with operators of equal market share. The thresholds are the same in all scenarios. A sufficient number of drivers to make a passenger interested (NbTS) is set to 5. The acceptable distance threshold (AT) is set to 100 meters for the results presented here in detail, and also to 200 meters and 500 meters for thorough comparison in Section 6.6. Note that these distances are Euclidean, such that actual travel or waiting times in network distance are longer. Literature suggests a willingness of walking to public transport up to about 500 meters, and there are reasons to assume that this distance is shorter for private transport such as ride-sourcing. A too short acceptable distance threshold, however, leads only to an underestimation in the results, which is considered acceptable in this research.

6.5 RESULTS

All presented results are for scenarios with $AT = 100m$. The changes in the results caused by increasing this threshold are discussed in Section 6.6. The outcome of the simulations are presented in three subsections. First (Section 6.5.1), the potential advantages to the operators are measured by their success probabilities and matching rates in the various scenarios to identify the most viable combination. Also, the changes in minimum viable market shares is reported and discussed in this subsection. Secondly (Section 6.5.2), the passengers' benefits are studied through their weighted utilities and overall number of matches. Finally (Section 6.5.3), the changes in drivers' benefits are detailed using their weighted utilities to make sure that all sides of the system have been considered.

6.5.1 *Operators' gain*

The results show that with several operators in the market, operating in the same space significantly reduces the chance of success for the operators. In the current situation with each operator having their own platform (platform competition), even an operator with 70% of the market share struggles to survive under any distributions of passengers and drivers. After joining a meta-platform (platform collaboration), the situation becomes slightly better and almost any NN scenario has a chance to succeed.

The results for operating in separated elongated spaces show almost the same outcomes for both multi- and meta-platform groups: with passengers and drivers normally distributed, there is a fair chance of success for any platform operating in the dense middle (e.g., operators i and ii in Figure 24, middle).

However, the results for the pie-piece separation of the operators are different. The difference demonstrates the impact of spatial separation on the success probability of the operators. In other words, certain spatial arrangements can have significant impacts on the operators success, and a pie-piece separation leads to high competition or collaboration in the center of the area.

Figure 26 shows the difference in success probability in different scenarios between multi- and meta-platform situations. For example, the blue bars in Scenario 1 represent the difference of success probability for the respective operators when both passengers and drivers have normal distribution. The high differences for small operators (those with 10% market share) mean that the operators' chances for success significantly increase if they offer their services on a meta-platform without decreasing the chances of the larger operator. Overall, Figure 26 illustrates that there is always either no change or a positive change with platform collaboration, meaning that offering services on meta-platform do not hinder any operator, if not help them. Moreover, it shows that the spatial distribution of drivers and passengers have distinct impact on the difference it makes whether the

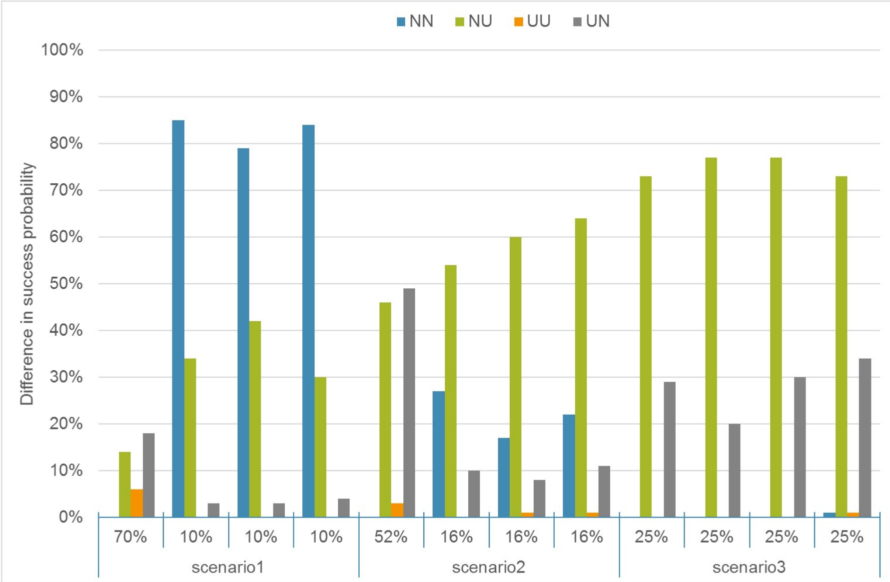


Figure 26: The difference in operators' success probabilities resulted from operators joining a meta-platform in pie-piece spatial separation scenarios.

operators offer their services on a meta-platform or not, as different trends are visible for different sets of distributions. For the NU and UN scenarios (scenarios with different distributions for drivers and passengers), the closer the companies' market shares are the higher the difference is that the collaboration makes (grey and green bars in Figure 26). This trend, however, is exactly reversed when both passengers and drivers have normal distributions (blue bars in Figure 26). There is hardly any changes in UU scenarios, as they are in general unsuccessful, and even forming a meta-platform cannot help them much.

Another measure important to the operators is their matching rate, i.e., the percentage of their available fleet that is matched. Since they charge for a percentage of the ride price, the more matches they have the higher their profit will be. The number of matches sometimes varies significantly for each operator if they join a meta-platform. The results of these changes are presented in Figure 27. There is a positive change in the majority of the cases, specially in NN and UN cases. Moreover, pie-piece spatial separation of the operators facilitate this improvement in almost all cases. Although the success probabilities of the operators never decrease when they join a meta-platform, their matching rates may decrease in rare situations.

Finally, the results demonstrate a high dependency of the minimum viable market share on the spatial distributions of the entities, particularly the drivers, and how spread the fleet of an operator is. Figure 28 summarises the viability results across all scenarios. Here, the assumption is that an operator has a viable market share if it has a success probability of higher than 50%. Accordingly, when the operators are in the same space, only normally distributed passengers and drivers provide the opportunity for a viable market share. In the multi-platform situation, only an operator as large as 70% may sur-

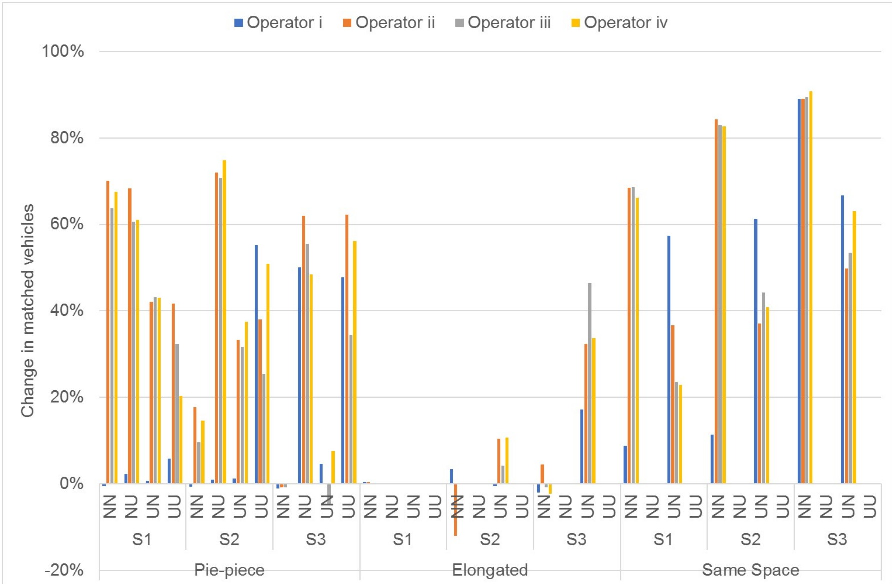


Figure 27: The difference in operators' matching rates resulting from operators joining a meta-platform.

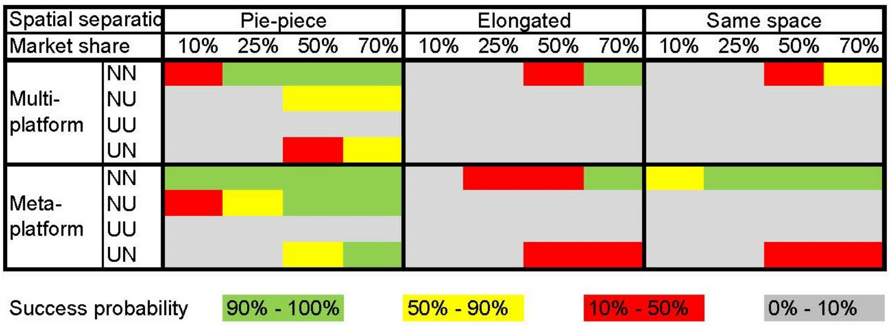


Figure 28: The different success probability levels.

vive, but there are hopes for the smaller operators, as small as 10%, in the meta-platform situation scenarios. Elongated separation of the operators makes the viability slightly worse, and only large (70%) operators may survive, and only in NN scenarios. The results are more promising in the pie-piece separation scenarios. Here, apart from NN scenarios, in NU and UN there are good chances for smaller operators to succeed. Finally, Figure 28 shows that, in rare cases, joining a meta-platform may impact the viability of an operator and change it from a completely inviable one to a viable one. However, operator collaboration (by joining a meta-platform) clearly benefits small and large operators and increases their chances of success.

Overall, the importance of a densely populated center is demonstrated in the results. Particularly a dense population of the drivers seems to be more critical than a dense population of people, as UN scenarios always show more successful results compared to NU scenarios. This is also highlighted by the complete lack of success in all UU scenarios.

6.5.2 *Passengers' benefits*

To investigate the passengers' benefits, their average utility, weighted by the percentage of matched passengers, in each scenario has been considered. Figure 29a demonstrates the results in the form of differences of percentages of weighted passengers' utilities between the multi- and meta-platform situations in various scenarios (Table 20). It shows that only in pie-piece separation or when operating in the same space, with both entities normally distributed, there are chances for passengers to gain benefit if all operators join a meta-platform. The reason for no improvement in the elongated separation scenarios lies mostly in the lack of success in this arrangement. In other words, in both multi- and meta-platform situations the elongated separation scenarios do not provide a good service condition for the passengers.

Figure 29b demonstrates the comparison of weighted passengers' utilities in separated spaces (elongated and pie-piece) and same space scenarios. It shows that the elongated separation of operators mostly has no impact on the passengers' benefits, except for NN scenarios with same platform, where the passengers' weighted utilities may decrease by almost 40%. However, separating the operators into pie pieces significantly improve the passengers' weighted utilities by up to almost 60% in NN scenarios in both situations.

Figure 30 illustrates the difference operator collaboration makes to the total percentages of the matched passengers. According to the figure, the most prominent changes happen in NN scenarios when all operators are in the same space. Also, there are noticeable improvements in pie-piece separation scenarios, particularly with both passengers and drivers normally distributed.

6.5.3 *Drivers' benefits*

The changes in the average utility, weighted by the number of matched drivers to the total vehicles, of each operator's drivers when the operator joins a meta-platform is illustrated in Figure 31. The figure shows that the average utility decreases for larger operators, and increases for smaller ones with a direct correlation, i.e., the larger the operator the larger the reduction and vice versa. While this happens mostly when the operators have pie-piece spatial separation in scenarios with $AT = 100m$, with increasing AT to 200 and 500 meters this impact is emphasised and seen in other spatial settings (same space and elongated separation).

This reflects the initiated opportunity for smaller operators to have a chance in service competition, or operator collaboration, and prevents a monopoly.

6.6 DISCUSSION

The main objective of this work is to investigate the impact of collaboration of ride-sourcing platform operators on the different involved parties (i.e., operators, drivers, and passengers) and to shed light on the role of their spatial characteristics. To this end, a simulation platform was designed and the output of several scenarios was investigated in terms of consequences for operators (to identify their potential gain), passengers (to identify incentives for authorities to intervene via regulations), and drivers (to identify their potential gain or loss). Although a simulation has been designed and used in this work, the contribution here is not the simulation design, but the outcomes and conclusions, derived from it.

The success probability of an operator proved to be strongly dependent on spatial separation of all operators, having the maximum probability in the pie-piece separation. While joining a meta-platform rarely increases the chance for the operators in elongated and same space spatial arrangement, it may significantly increase the success probability of the operators in pie-piece spatial separation presumably because of the tight neighbourhood in the central area. Moreover, the importance of spatial distributions of passengers and drivers was accentuated by illustrating that a dense population of either passengers or drivers (NN, NU, and UN cases) affect both the success probability and its potential increase. It was also shown that a dense center of drivers (i.e., UN and NN scenarios) is more effective, which implies that operators may solve their critical mass problem by focusing on specific suburbs and increasing their registered drivers via various types of incentives.

The analysis of changes in the average weighted utility of passengers in different scenarios showed that both pie-piece spatial separation of operators (compared to same space spatial separation) and a meta-platform situation result in an increase in certain cases, and no change in others. Interestingly, the former has a bigger impact than the latter. The overall matching rates are also positively influenced by operators' collaboration, particularly in pie-piece spatial separation.

Although the changes for operators and passengers are almost always positive, the case for the drivers is different. In certain scenarios, their average weighted utility decrease, specially for the drivers registered with the larger operators. However, since the results in scenarios with equal operators show no significant change in the average weighted utility of drivers, certain measures can be suggested to prevent or eliminate this reduction. For example, the drivers can multi-home, i.e., register with more than one operator, as some actually do in the real world. From the drivers' perspective, multi-homing is equivalent to service competition, or operator collaboration, but not from a passenger perspective. Effects of multi-homing should be studied in future research to identify the point of equilibrium. This mechanism automatically prevents forming monopolies.

Overall, NN scenarios prove to be the most successful, as expected, and the UU ones show the lowest potential for success or changes. Although this was expected as in the real-world transportation sharing systems are more successful in densely populated centres, and less thriving in the suburbs, its systematic illustration provides the opportunity to also identify the solutions and test them.

The overall outcome of this work demonstrates a definite positive trend for the collaboration of operators, particularly for small operators and passengers. There are limited negative impacts, which should be studied in more detail for identifying individual solutions. The outcome shows promising implications for emerging schemes of *MaaS*. First MaaS schemes, however, work with preferred operators per transport mode, and do not yet realise single-mode operator collaboration. Vice versa, none of the shared mobility operators has suggested or tried operator collaboration with competitors.

Finally, one critical assumption in this work is the AT limit, which was set to 100 meters for all the reported results. To ensure that this limit does not cause systematic bias in the results, all the scenarios were run with limits of 200 and 500 meters as well. The results proved to have similar but amplified trends as the ones reported hitherto, i.e., if there is an increase observed in a comparison that increase is even bigger in 200 meter scenarios, and again bigger in 500 meter scenarios. Moreover, although the UU scenarios seemed mostly unsuccessful with scares potential for improvement in scenarios with $AT = 100m$, increasing AT results in improvement even for them, mostly in line with NU scenarios.

6.7 CONCLUSION

This work has investigated the impact of collaboration of ride-sourcing platform operators and the role of spatial components of the system using simulation. It has two main outcomes carrying important messages to operators and the authorities.

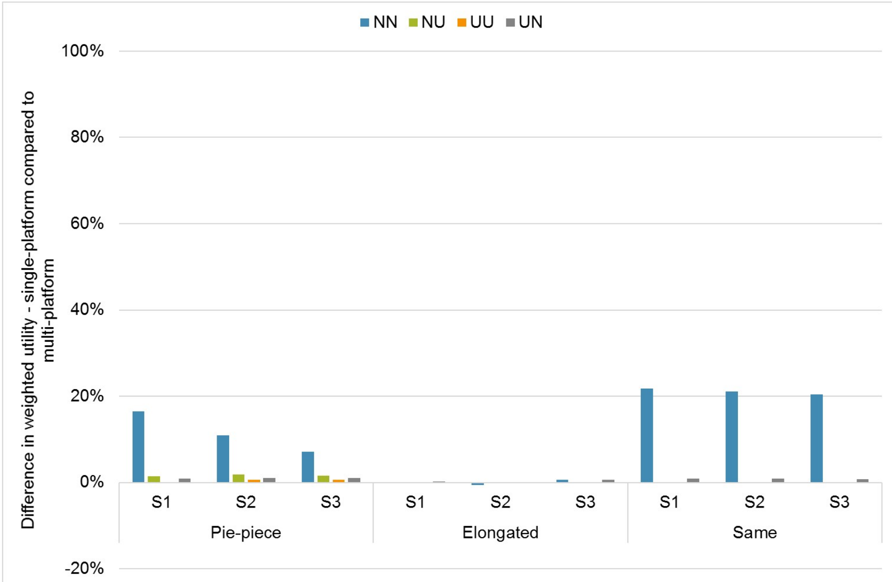
First, collaboration (i.e., joining a meta-platform) of the platform operators is beneficial to the operators, by increasing their success probabilities and matching rates, and lowering their viable market share (to certain extent), and to passengers, by increasing their chances to get a match and thus decreasing their waiting time. Its occasional negative impacts on drivers are possible to be prevented or eliminated as discussed in Section 6.6.

Secondly, with more than one operators in the market, a certain spatial segmentation of the market has potential advantages to all parties. Although this may seem difficult to achieve by agreement among the operators, it can be facilitated with governmental regulatory interventions. However, in operator collaboration such an agreement is easier to imagine.

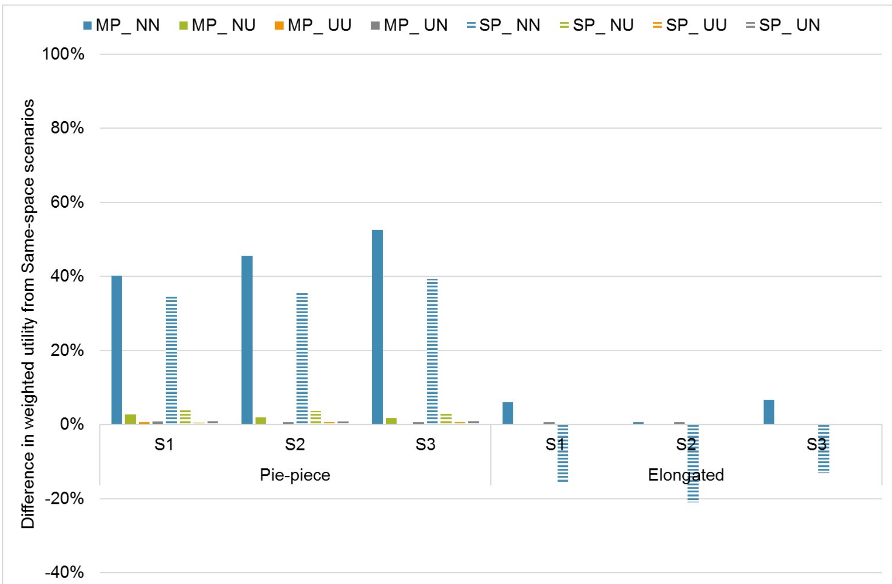
The focus of this work was on ride-sourcing market; however, the results are easily extended to other similar markets of the shared mobility economy, such as car- or bike-sharing, or ride-sharing. What changes with the market is the utility of the passengers (and drivers if they exist). For car-sharing, for example, the utility of the passengers reflects their walking time/distance to a vehicle, while the vehicles' utilities render irrelevant. Ride-sharing, on the other hand, requires additionally an extension of the simulation as it is necessary to account for destinations, and thus routes travelled. Collaboration in these markets can be investigated in future work.

Finally, the main limitation of this work is the lack of time in the consideration in the demand and supply. The simulation rendered supply and demand as concurrent. Although temporal differentiation of supply and demand is an important component of any transportation system, its omission was deemed acceptable as the focus was on spatial features and collaboration. The future work could include a more complex simulation platform capable of creating and investigating spatio-temporal events and produce more nuanced results.

In favour of repeatable research, the simulation code has been published on https://github.com/zahra-n/OperatorsCollaboration. With the code all results can be reproduced to the degree of impact of random seeds. In particular the results for $AT = 200m$ or $500m$ can be reproduced, and other thresholds can be varied. Most importantly, however, the code can be re-used for the future work laid out in this section.



(a)



(b)

Figure 29: (a) Difference in weighted utilities of the passengers resulting from operators joining a meta-platform. (b) Difference in weighted utilities of the passengers resulting from spatial separation of the operators (as opposed to all operators perform in the same space.

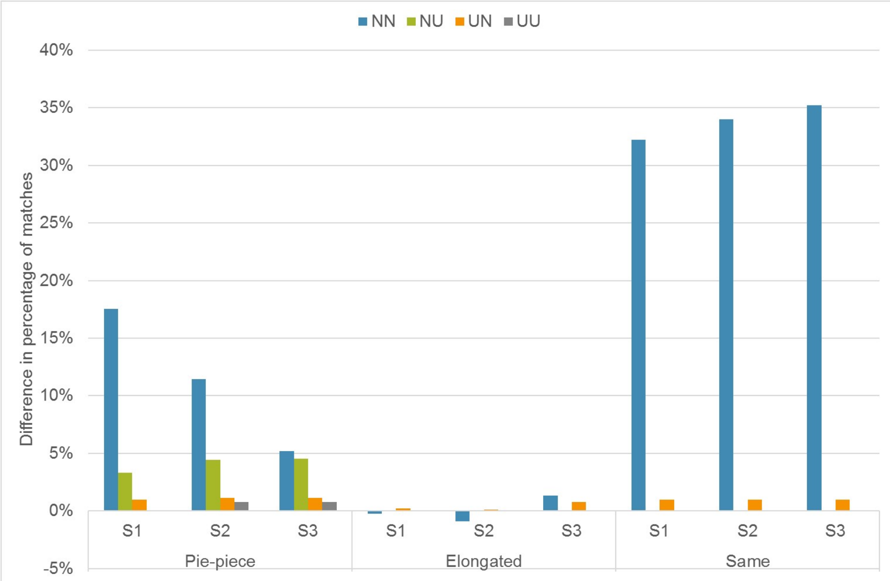


Figure 30: Difference in percentage of all matches resulting from operators joining a meta-platform.

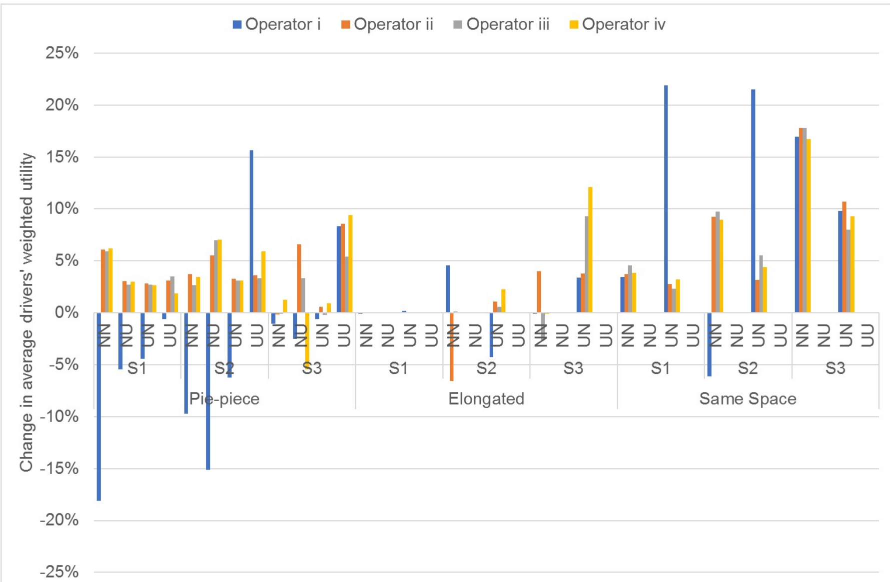


Figure 31: Changes in average weighted utilities of drivers associated with each operators resulted from operators joining a meta-platform.

7 DISCUSSION

The discussion presented in this chapter revisits the research questions and results of each chapter, and reviews the progress this thesis has made towards understanding the implementation challenges of DRT systems.

Chapter 3 began the research by providing evidence for the superiority of DRT systems over conventional public transport (CPT) systems in terms of travel time for the demand side, and costs for the supply side. Although these are not the only factors in decision making of either side, they play key roles. The research questions were:

- Can a microtransit service provide shorter travel time than the CPT system for passengers in low demand areas?
- Will a microtransit system that provides shorter travel time than the CPT cost more than it?

The comparisons were done in general network shapes (grid and star shape) and the results showed transferability to real-world networks, as the results for the Belgrave scenario were comparable to the similar hypothetical scenario. While the travel time showed reduction for the majority of people (a minority group suffered from high waiting times) in all scenarios, the costs did not follow the same trend. The results showed that as the demand grows the costs increase linearly, which could be considered evidence for a low sharing rate in the simulation. In all low-demand scenarios the cost of DRT was lower than CPT.

Looking back at the questions and the outcomes of Chapter 3, where these questions are answered, two points are noteworthy: first, all these results highly depend on the matching algorithm used in the model, as the algorithm allocates vehicles to passengers using an exhaustive search based on passengers' planned and direct travel time (see Section 3.2.2). This algorithm is not the state-of-the-art at the moment. State-of-the-art algorithms help with a higher sharing rate, which results in lower costs to operators. However, there is always a trade-off between increasing sharing rate and decreasing travel time for passengers. In other words, an algorithm that allows for longer detour time or distance to pick up a second/third/forth passenger will increase the travel time for the previous ones. Therefore, in a real world implementation of such systems, care should be taken that optimising the operators' expenses does not lead to increasing travel time beyond passengers' detour tolerance.

Second, although the research questions were answered to the full extent with conclusive evidence, the results do not account for many real-world factors, such as the actual traffic situation, or the possibility of changing mode or of not travelling. On one hand, such assumptions eliminate the impact of unknown factors and make the results clearer to interpret. On the other hand, however, with such assumptions, the model does not replicate people's behaviour and the innate dynamicity of DRT systems in the real world, which may make the results more optimistic than desired.

The dynamic nature of DRT systems means more volatile demand and supply compared to the conventional modes. An example that can explain this volatility in a microtransit market is as follows. A microtransit service such as described and demonstrated in Chapter 3 will provide a convenient service to the users compared to CPT and people may shift their mode to the microtransit. The simple network effect of "word of mouth" (which these days happens mostly in the digital world, e.g., forums and social media) may result in people with other mobility habits shifting to microtransit as well. To cope with this demand growth, the operator may increase their fleet size. If the former happen much faster than the latter (which can be imagined as people may one day decide to start trying the new system in their area, but the process of purchasing vehicles and hiring drivers may take weeks or months) the current services will be overpopulated resulting in various inconveniences, such as higher waiting time, and longer detours, which means longer travel time overall. Consequently, some users may leave, reducing the demand, followed by an increase in the quality of the rides again, which can potentially attract new customers and a part of the old ones. This loop is expected to happen in long term and it is highly dependant on the local context. While in this example the demand was volatile, in other DRT systems, such as ride-sourcing, the supply can also become volatile, which was briefly discussed in Chapter 6. This phenomenon is similar to the Gartner hype cycle[1], except that more than one "peak of inflated expectation" can be expected.

One crucial element of the above mentioned interaction model is a contextualized mode choice model, preferably based on RP survey data, due to the biases associated with SP data (Section 2.2). Identifying this shortcoming became the basis of the next step of the research, i.e., developing a mode choice model based on available RP data. Two questions had to be answered before progressing to mode choice model estimations:

- What is the best application or software package to synthesize the attributes of non-chosen alternatives in a travel mode choice model?
- Is RP data always diverse enough to develop a detailed travel mode choice model?

Chapter 4 answered these questions by comparing three recent methods for synthesising the attributes of unobserved alternatives and establishing simulation as one of the legitimate tools to synthesise data for this purpose.

The estimated models in Chapter 4 include only travel time and distance, while an appropriate model that can be used in such re-

1 https://www.gartner.com/en/research/methodologies/gartner-hype-cycle

search need to include at least waiting time, walking time, and number of transfers as well. However, adding those attributes to the estimated model resulted in statistically insignificant models, which implies lack of sufficient variability in the available RP data. Therefore, more data, in terms of volume and variety, is required to estimate a model that is well representative of people's travel behaviour. Considering the ubiquity of portable smart devices, one solution is using the data available from such devices to tackle the problem of data variety and volume shortage. However, accessing such data has been proven to be problematic and not always possible, mainly due to privacy and commercial sensitivity of such data.

Another key outcome of this chapter was demonstrating the sheer difference in calculating value of travel time (VOT) resulting from various methods of data synthesis. Since VOT is a determinant component in evaluating any transport infrastructure projects, this sheer difference should be taken into account by modellers and decision makers. Assuming DRT systems as motorized public transport, an unrealistic highly estimated VOT by public transport can have a positive impact on evaluating policies that facilitates DRT systems. This can result in large government investment in systems that may just add to the burden of public transport costs. Another example would be road pricing, in which a much higher or lower estimated VOT can result in failure of such schemes too.

An alternative method to study the dynamicity of DRT systems can be exploiting the concept of multi-sided markets, which set the course of the rest of the research. The main question to be answered here is:

- How do the spatial components of a ride-sourcing system impact its critical mass frontier?

DRT systems fall into the crisply defined subcategory of spatial multi-sided markets, which are delineated by their prominent spatial characteristics. Chapter 5 demonstrated and discussed that the spatial configuration of DRT systems and their context have significant and inevitable impacts on their critical mass, the pivotal element of self-sustainability, and established the concept of *spatial critical mass*.

One key point of Chapter 5 is that spatial critical mass is not deterministic, but a probabilistic phenomena. In a real-world context this means that compared to aspatial systems, higher risk can be associated to success of spatial systems, including DRT systems, in business planning.

Furthermore, spatial critical mass is not only impacted by the spatial characteristics of the area in study, but also the neighbouring areas. This means that although deployment of DRT systems may seem easier in limited sized areas, which may make it the business of local councils to handle, planning on a strategic level is required to ensure the positive impact of areas on one another. Proper policies and regulatory interventions are to be carefully identified to ensure that all areas are served, supercritical and sub-critical alike. An example of such interventions could be a licensing method discussed in Section 5.5.

Securing critical mass is the objective of every new multi-sided business, including DRT operators. Many of them are start-ups, which leads to bitter competition bringing disadvantages to the customer. Mobility as a service (MaaS) is believed to be a powerful solution to this issue, which requires collaboration of numerous public and private organizations, including government, public transport providers, and other transport network companies (TNC) such as ride sourcing, car/bike sharing, and microtransit operators. The lack of analytical investigation for the potential benefits of such scheme provoked the research questions of Chapter 6 as follows:

- How does the spatial separation of the fleets of participating operators impact an individual operator's success, particularly for small operators?
- How does the spatial separation of the fleets impact the minimum market share for an operator to survive?
- Will customers, i.e., passengers and drivers, benefit from a meta-platform?

This chapter presented quantitative evidence establishing the benefits of such collaboration to all involved parties. While the potential advantages to the operators may be of interest of TNCs and transportation start-ups, the potential benefits to passengers and drivers (both considered to be customer groups of multi-sided platforms) can be notable for organizations and governments with regulatory powers. Moreover, the results showed the benefits of a market spatial segmentation, with each segment including high and low population density areas, in achieving success for collaborating operators. These benefits were decreasing viable market share and increasing matching rate for these operators. Such segmentation could be done by government via various interventions. This can directly be linked to the interventions required for achieving the equality of service in supercritical and sub-critical areas. Despite all the benefits such interventions bring in implementation of DRT systems, their impact on other aspects of urban context must be thoroughly investigated. Particularly, land use and land/house pricing are two crucial elements that are likely to be affected.

The main impediment to realisation of MaaS is not its technical feasibility, as proved by the successful experiments around the world (Smith et al., 2019; Sochor, Strömberg, and Karlsson, 2014), but lack of proper policies. Literature suggests that government can play a key role in MaaS success by being agile and flexible in adopting and imposing the right regulations (Docherty, Marsden, and Anable, 2018; Lyons, Hammond, and Mackay, 2019; Nuttall and Arbuckle, 2018). This piece of work could be an initial evidence base to nudge governments towards fully integrated transport systems, in which DRT systems play a key role.

8 CONCLUSION

This chapter first summarizes the major findings and lessons learned from this research and then lays out the direction of future research.

8.1 SUMMARY

The main objective of this thesis is to shed light on the implementation of DRT systems through investigating four hypotheses:

- A microtransit in a small low-demand area is capable of providing a better option compared to the CPT system.
- It is possible to develop a mode choice model based on existing RP survey and synthetic data.
- In spatial multi-sided markets, other than in non-spatial markets, there is not a single critical mass frontier and that this frontier is varying from one location to the next, depending on the density and distribution of the demand and supply over space.
- Operators feeding into a single meta-platform will bring benefit to all customers (passengers and drivers) and thus also the operators.

The progress of research through Chapter 3 to Chapter 6 have provided evidence to support these hypotheses, culminating in the following key lessons learned for implementation of DRT systems:

- Microtransit systems are suitable solutions to improve the mobility for people in low-demand suburbs, and save costs for operators.
- In identifying spatial critical mass for a prospective DRT system a risk factor needs to be identified based on the spatial configuration of the area to factor in the probabilistic nature of spatial critical mass.
- Since successful or failed implementation of a DRT system in a suburb can impact its neighbouring suburbs, planning on strategic level for a city-wide (or in an ideal case state-wide) implementation can ensure the long-term prosperity of the implemented systems.
- A collaboration among transport operators and providers to offer their services on one meta-platform is in the collective interest of all involved parties. Therefore, governments and authorities as the regulators and of the market can accelerate unlocking all the benefits by right policies and interventions.

8.2 FUTURE WORK

Areas of further research stemming from the results and conclusions of this work are identified and can be categorised in three groups.

8.2.1 *Assessment tool*

Models are one of the main tools that help researchers and decision makers understand and predict the outcome of new transport systems. Therefore, development of a tool capable of representing the dynamic interactions between the demand and supply sides of DRT systems over many days, as described in Chapter 7, is a necessity in the future research. One main challenge to be addressed for such tool is developing a mode choice model that accounts for not only all the standard attributes of travelling, such as time and distance, but also all the nuances of new modes, such as willingness to share, detour tolerance, and willingness to travel in an autonomous vehicle.

With such tool, it would be an interesting research topic to investigate the equilibrium of DRT systems and their conditions. It is possible that a stable state is never reached due to the highly dynamic nature of these systems. Ronald, Thompson, and Winter (2015b) have developed a preliminary model to study the demand of a microtransit over many days, which showed a fluctuation in demand under various circumstances. However, certain shortcomings, such as lack of mobility options and mode choice, leave the results open to scrutiny.

Furthermore, it is expected that such tool can be utilised to identify the best spatial configuration for achieving spatial critical mass for DRT systems and help the operators with solving the infamous *chicken-and-egg* problem. One aspect of such implementation is optimisation of the initial condition of a DRT system, i.e., fleet size and their location distribution.

8.2.2 *Policy and pricing*

Considering the impact that areas can have on one another in success or failure of DRT systems, and the impediments that lack of proper regulations bring on the way of the success of MaaS, identifying apt policies to address these issues could be a compelling topic for future research in transportation policy and planning. Such policies should be carefully scrutinised in regard to their impact on land use, and their interactions with the existing regulations. While the promising features of DRT systems and MaaS indicates better mobility options, it may not improve the accessibility in certain regions.

With the right infrastructure and proper regulations in place, evaluating and identification of viable business models for MaaS platforms, and their impact on travel behaviour in different contexts will be topics for further research. One main challenge in such studies will be finding the right pricing structure, considering the interest of several stakeholders, which are occasionally contradicting. This can become even more complex when considering the potential government subsidies and how they can be deployed to increase the social welfare.

8.2.3 *Spatial critical mass*

In this research, both drivers and passengers were considered customer groups with certain homogeneous preferences for focusing only on the spatial aspects of the studied systems. An interesting question for future work will be investigating the impact of heterogeneous customer groups on spatial critical mass.

It was also concluded that collaboration impacts platforms' viable market share and decreases it in certain scenarios. Linking this to spatial critical mass, it is expected that the critical mass changes its shape and position depending on the level of collaboration in the market, which can be studied in future research. Levels of collaboration can be determined by the number of operators offering their services on the same meta-platform, and the variety of the services they offer.

Furthermore, in the case that MaaS, despite all demonstrated and anticipated benefits, does not happen soon, research can focus also on the impact of competition of operators on their spatial critical mass and identify the right strategies to achieve success, which is of paramount importance for start-ups in their competition with incumbent operators to secure critical mass.

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DECLARATION

I declare that this thesis has been composed solely by myself Zahra Navidi Kashani. Some chapters are revised based on published or submitted manuscripts of which I am the first author and my contributions have been explained individually. Except where states by reference or acknowledgement, the thesis is entirely of my own. The thesis in whole has not been submitted in any previous application for a degree.

Melbourne, Australia, April 2019

Zahra Navidi