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Supply-side Behavioural Dynamics and Operations of Ride-sourcing Platforms

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Supply-side Behavioural Dynamics and Operations of Ride-sourcing Platforms

Dissertation

For the purpose of obtaining the degree of doctor
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Dedicated to

The ones who have always been there for me, my family.

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With profound gratitude,

Peyman Ashkrof,
Delft, October 2023.

Contents

Chapter 1: Introduction

1.1 Research Motivation

Digitalisation has facilitated the emergence of new mobility solutions to fulfil transportation needs and alleviate existing and potential issues such as traffic congestion, climate change, and hyper-urbanisation. Receiving considerable attention in recent years, ride-sourcing is one of the prime examples of innovative transport services in the shared mobility space where service-based models are promoted instead of the ownership-based system. Ride-sourcing is a digital platform supplied by independent car providers to offer on-demand door-to-door transport services to ride requesters. A ride-sourcing system acts as a two-sided platform that connects end-users, i.e., passengers and drivers. Passengers submit ride requests with specific origins and destinations to the platform. Then the operator attempts to assign each request to a nearby idle driver, who offers their privately owned/leased vehicle.

As pioneers in the sharing economy, ride-sourcing companies - also known in the North-American context as “Transportation Network Companies (TNCs)” - play a crucial role in the transportation industry. Providing flexible, fast, reliable, and convenient services, ride-sourcing platforms can be used for performing either first/last mile trips or the entire trip. Therefore, it can potentially meet passengers’ mobility needs by providing seamless and effective mobility solutions. On the other hand, there are fierce debates over the counter-productivity of ride-sourcing systems and their significant contributions to traffic congestion, vehicle kilometres travelled, inequity, and air pollution (Henao and Marshall, 2019; Tengilimoglu and Wadud, 2021; Tirachini, 2020). This highlights the major issues that may obstruct ride-sourcing potential social welfare.

The ride-sourcing system involves stakeholders with diverse objectives and decisions: drivers, riders, platforms, and policymakers. Each of which pursues different and potentially conflicting objectives. Ke et al. (2019) argue that passengers’ utility mainly depends on the trip fare and quality of the service, while drivers’ willingness to join the system is based on the expected profit. In this complex system, the identified goals might be (partially) attained at the expense of the other parties. For instance, the average waiting time for passengers is probably lower in an oversupplied system where the number of drivers is excessively higher than what is needed to satisfy the requests with a minimum level of service. This increases the satisfaction of the passengers but leads to high competition between drivers which in turn results in a lower income and consequently job dissatisfaction.

It should be noted that ride-sourcing drivers are not only chauffeurs but (semi-)independent fleet providers, i.e. service suppliers, consisting of one vehicle. Following the gig economy principles, they are not hired by ride-sourcing platforms but instead labelled as independent partners. Thus, drivers have the freedom to decide whether and when to join the system, accept/decline ride requests, and about their relocation strategies. Such freedom, recognised as drivers' primary motivation to enter the system, offers a range of choices that can dynamically impact the system performance and restrain the direct control of platforms over drivers. For example, unavailability or low acceptance rate of drivers in a region may lead to more unserved requests and higher waiting time for riders (i.e., lower level of service), resulting in the client's dissatisfaction. This stresses the pivotal role of the service suppliers and their corresponding decisions in accomplishing the system goals.

The large-scale strikes of ride-sourcing drivers and the worldwide lawsuits highlight drivers' widespread dissatisfaction with the system operations (Reuters, 2022; The Guardian, 2021). They believe that their interests are seriously compromised for the benefit of the other parties. This illustrates an atmosphere of tension between the ride-sourcing platforms and their service suppliers who are at the heart of the system as independent decision-makers. Such conflicts may hinder the potential benefits associated with ride-sourcing.

The literature on the supply side has covered various topics including the estimated travel time (Wang, Fu, & Ye, 2018), pricing strategies (G.P. Cachon et al., 2017; Zha et al., 2018a), matching strategies (Zha et al., 2018b), repositioning guidance (Vazifeh et al., 2018), policies and regulations (Zha et al., 2016). Nevertheless, they share an underlying assumption about ride-sourcing drivers to be either fully compliant with the platform (i.e., no independent decision-making) or considering merely optimum earning without including their behavioural reactions to the platform strategies (e.g., information sharing policy, matching, and pricing strategies). This is arguably resulting from a lack of insight into the factors taken into account by drivers when making relevant decisions such as accepting or rejecting a request or relocating in the network.

Another relevant research stream is associated with the emergence and implications of the on-demand mobility services operated by a centrally operated fully automated fleet (Levin, 2017; Liang et al., 2018; Wang et al., 2022; Winter et al., 2016; Zhang et al., 2016). Currently, automated fleets (level 5) are in an experimental stage (e.g., Cruise and Waymo) and seem not to be commercially available in fully deployed operations earlier than the 2040s. (Litman, 2022; SAE International, 2021). Therefore, considering drivers' roles and the aspects that affect their behaviour are essential for developing state-of-the-art system operations, especially given that already prevalent tensions between suppliers and the platform are rising owing to the dissatisfaction of drivers (Nicolas Vega (New York Post), 2019).

There is a growing body of literature on the realm of the supply side of this business such as elasticity, wages, and incentives. A key objective of modelling driver supply is to investigate why drivers join the system. Hall & Krueger (2018) identify flexibility in working hours and operations as the key factor attracting drivers to the ride-sourcing market. The impacts of monetary incentives on drivers' working shifts are investigated in supply elasticity studies. Cahuc et al. (2014) conclude that income rate impacts both strategic (i.e., joining the system) and tactical (i.e., working hours) decisions of drivers. Using the New York City taxi driver data, Farber (2015) argues that drivers stay online for more hours once their income rate is higher (positive elasticity). Concerning the impacts of wages and incentives, comparing the reaction of drivers to financial promotions offered by two competing mobility-on-demand platforms in China, Leng et al. (2016) reported an increase in the number of trips per day and a decrease in idle time during the promotion.

A critical supply-related factor that has hitherto remained unexplored in the literature is drivers' behaviour. As platforms do not have direct control over the drivers, a set of strategies need to be mapped out in order to direct drivers' decisions toward specific targets benefiting all the stakeholders. The key step in designing the corresponding strategies is to unravel drivers' behaviour and decisions based on the system functionalities which is a topic that remains relatively unexplored in the literature. The primary reasons behind this limited knowledge are:

- Revealed preference data is seldom accessible due to the reluctance of platforms to share such sensitive data.
- Stated preference data collection is quite costly given the hard-to-reach target group.

A deep understanding of drivers' choices and reactions to platform strategies (e.g., matching and pricing strategies) can provide an opportunity to raise and possibly address the issues of ride-sourcing drivers. This may in turn contribute to decreasing the existing tensions. Next, drivers' interactions with service algorithms should be considered in the design of user (supplier) interfaces. To this end, in contrast to the previous studies which have mostly neglected the behavioural dynamics of ride-sourcing supply-side, we examine the decisions of ride-sourcing drivers using a bottom-up approach and investigate the implications of accounting for drivers' behaviour on system operations of ride-sourcing platforms.

1.2 Research Scope and Theoretical Background

This PhD research is part of the CriticalMaaS project which consists of several work packages intending to investigate and model the performance of a two-sided Mobility-as-a-Service market at strategic, tactical, and operational levels with considering behavioural, organisational, and operational aspects of the mobility ecosystem. This research is mainly focused on the bottom-up operations of the supply side of the flexible on-demand mobility market. We develop models explaining and predicting the supply-side behaviour in a two-sided ride-sourcing platform.

In general, drivers' behaviour can be categorised into the strategic, tactical, and operational levels as illustrated in Figure 1-1. At the strategic level, drivers decide whether to join the platform. According to labour economy theory, workers are willing to accept a job if their minimum expected wage rate is satisfied (i.e., reservation wage). In addition to reservation wage, other factors such as market competition and evolution may impact the decision of ride-sourcing drivers to join the system. Forming an expectation of potential income, drivers who decide to work with the platform benefit from the flexibility of choosing the desired working shift at the tactical level. In order to hit the financial target, they need to predict demand and its corresponding characteristics for taking operational decisions including ride acceptance and relocation strategies. Ride acceptance is associated with drivers' reactions to ride requests that can be accepted or declined. Relocation strategies are employed when a driver becomes idle (i.e., drops off a passenger or starts the shift) and intends to continue his shift by seeking a higher probability of getting a ride.

In the opposite direction, drivers adjust their upper-level decisions based on their experience. According to the characteristics of the served demand at the operational level, drivers can assess the profitability of the selected working shift. Then, they choose either the same shift or change it or may quit the platform if the actual income cannot meet the reservation wage during a certain period of time.

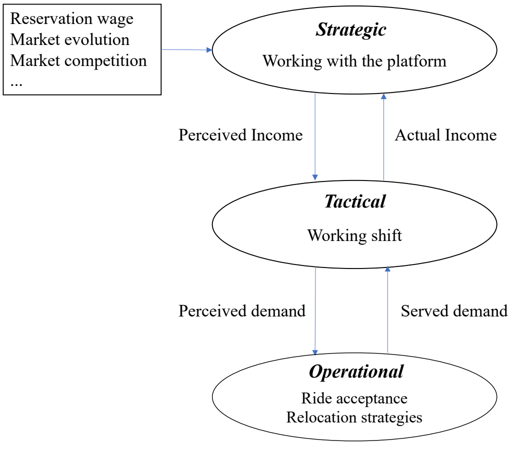


Figure 1-1: Drivers' decisions hierarchy

The strategic level pertains to drivers' long-term decision, which relies on several external factors such as reservation wage, market evolution, competition, and regulations. The tactical stage is mainly concerned with mid-term decisions affected by both strategic and operational decisions over time. Given the considerable knowledge gap in ride-sourcing supply-side behavioural dynamics and their consequences for system operations, a bottom-up approach is used to model individual drivers' real-time interactions with the platform. To this end, we primarily focus on the operational decisions of drivers as a key determinant in the within-day system operations.

A conceptual model is proposed in Figure 1-2. The box and arrows indicated by the dotted line are out of the scope of this research. As depicted, the operational decisions of ride-sourcing drivers are affected by drivers' understanding of the system operations, their socio-demographic characteristics, attitudes, experience, upper-level decisions, and interactions with the other parties. Operational decisions of drivers include ride acceptance and relocation strategies. The former refers to the drivers' choice of accepting/declining ride requests based on the given information, driver's experience, shift status, etc. The latter is associated with the decisions of drivers about repositioning while being idle. Although platforms provide drivers with some repositioning guidance, other factors such as characteristics of the previous ride, current location and time, and drivers' experience may also play a role in the relocation strategies of ride-sourcing drivers. In general, drivers prefer to increase the occupancy rate (i.e., the ratio of driving with passengers to the total working shift) which is governed by their operational decisions.

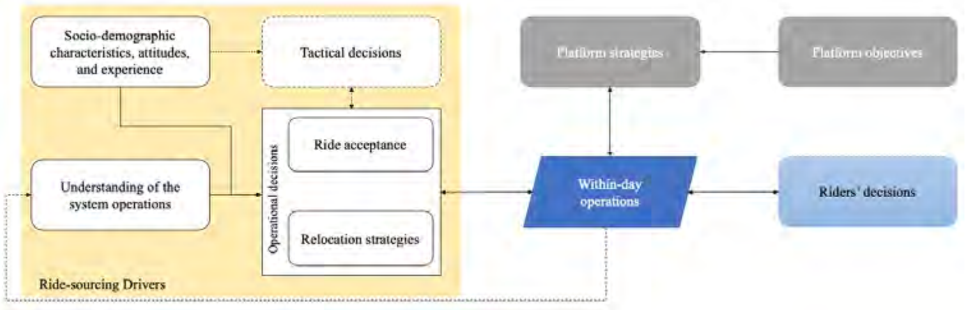


Figure 1-2: Research Conceptual Framework

The platform has several objectives formulated either by themselves or imposed by policymakers. In order to accomplish them, a set of strategies should be adopted to translate the policies into system operations. Platform operational strategies such as information sharing policy, matching algorithm, pricing strategies, repositioning guidance, and rating system impact both drivers' and travellers' behaviour and vice versa. For instance, if a ride-sourcing company shares more information (e.g., trip fare and final destination) about ride requests with drivers, then they can make more informed decisions about the requests. On the other hand, if drivers decline many short-distance ride requests, then the company could limit the information provisioned preventing drivers from seeing the total ride distance before accepting the request. As another example, devising incentive schemes such as surge pricing for drivers stimulates them to join the system given that they are the fleet owners in the ride-sourcing setting. It may result in a larger fleet size, higher acceptance rate, and level of service.
Overall, the objectives of a two-sided platform can be achieved through a set of strategies only if the behaviour of both drivers and travellers is taken into account. In other words, if the needs and expectations of one side are overlooked, system goals, such as profit and social welfare, are less likely to be achievable. In general, research into this topic and especially the relevant theories about ride-sourcing drivers' behaviour and the respective consequences are lacking. The following sections describe the research questions and approach adopted for delving into the above-mentioned issues in this thesis.

1.3 Research Questions

Based on the research scope, real-world operations and network features, literature review, and the identified research gaps, the following main research question is formulated:

To what extent does the behaviour of ride-sourcing drivers influence the within-day system performance and the operational strategies of ride-sourcing platforms?

In order to answer the main research question, the following key questions need to be addressed:

1. What are drivers' perception of and their interactions with ride-sourcing platforms? (Chapter 2)
2. What components govern the relationship between the information sharing about a ride request and the decision of ride-sourcing drivers on accepting/declining requests? (Chapter 3)

3. What factors, and to what extent, affect the relocation strategies of the ride-sourcing drivers? (Chapter 4)
4. To what extent does drivers' ride acceptance behaviour play a role in ride-sourcing system operational performance with/without surge pricing? (Chapter 5)
5. What is the difference in performance between a fully centralised (automated/fully compliant) and a decentralised (human-driven/choice-based) fleet once accounting for ride acceptance? (Chapter 5)

1.4 Research Approach

In this section, the research approach for addressing the research questions based on the proposed theoretical framework is presented. Figure 1-3 summarises the steps undertaken in this thesis and shows how they relate to each other. This research consists of both behavioural and operational modelling as well as quantitative and qualitative methods.

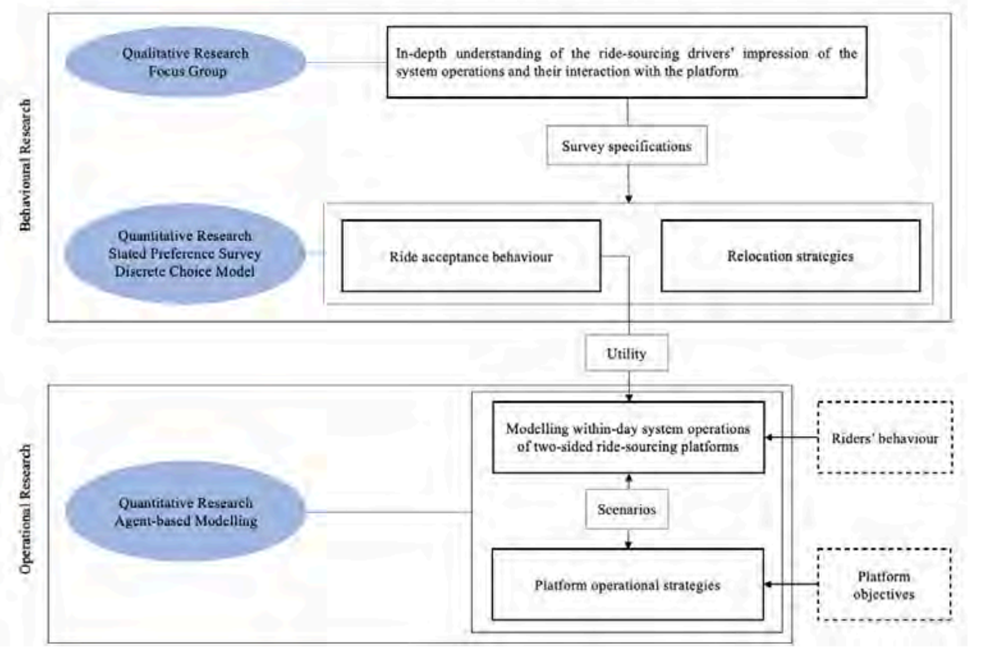


Figure 1-3: Research approach

The behavioural research, which aims to answer research questions 1-3, starts with a qualitative exploration of drivers' opinions about the system operations and their interaction with the platform by conducting focus group interviews with ride-sourcing drivers. Findings from this study are then used to design a set of novel stated choice surveys to quantitatively investigate the operational decisions of drivers by collecting unique data from ride-sourcing drivers and analysing them using discrete choice modelling. The rationale for using both qualitative and quantitative methods is that investigating the working pattern and behaviour of ride-sourcing drivers needs to be built on a deep insight into drivers' understanding of the system operations and their interaction with the platform, especially when there exists little guiding theory.

In the operational study which is designed to address research questions 5-6, the identified factors regarding ride acceptance behaviour are incorporated into the system operations using an agent-based simulation framework to assess their impacts on the system performance. Then, various scenarios are tested through the designed framework, which includes the parties' behaviour and decisions. The reason for focusing on ride acceptance decisions over relocation strategies is that ride acceptance is a relatively new concept in the gig economy environment which has not been adequately addressed in the literature. In comparison, there is extensive operational research into repositioning, mainly for taxi drivers.

1.5 Thesis Contributions

This thesis makes both scientific and societal contributions, which are briefly discussed in Sections 1.5.1 and 1.5.2.

1.5.1 Scientific Contributions

This research mainly contributes to understanding and modelling the supply-side behavioural dynamics of ride-sourcing platforms and their consequences on system performance. Integrating both behavioural and operational aspects of the ride-sourcing supply side in the system operations is the novel theoretical contribution of this dissertation. The main specific scientific contributions of each chapter are listed as follows:

- **Gaining in-depth empirical knowledge of the ride-sourcing driver's perception of system operations and unravelling their needs, expectations, and preferences (RQ 1, Chapter 2)**

This study offers deep insights into ride-sourcing drivers' perception of system operations and their interactions with the platform. We also explore the needs, expectations, and preferences of drivers as service suppliers. Consequently, a conceptual framework is presented to map the relationship between the decisions of drivers and then qualitatively identify the factors influencing those decisions. The output of this research constitutes the foundation of the subsequent studies in this thesis.

- **Identifying the key factors affecting the ride acceptance behaviour of ride-sourcing drivers based on platforms' information sharing policy (RQ 2, Chapter 3)**

We disentangle the ride acceptance decision of ride-sourcing drivers based on the existing and hypothetical platform strategies regarding information sharing. First, the impacts of the components of the current information dissemination strategy are estimated, and then the potential factors that may influence the ride acceptance decision of drivers are identified using hypothetical scenarios. Given that the study was conducted during the COVID-19 pandemic, the implications of the outbreak are also analysed.

- **Quantifying the main determinants of ride-sourcing drivers' relocation strategies based on the platform repositioning guidance (RQ 3, Chapter 4)**

We identify the key factors influencing the relocation behaviour of drivers based upon real-time information provisioned and the related platform strategies. We also examine drivers' reactions to novel strategies and the corresponding information provided. Finally, various platform strategies to design more tailored and effective repositioning guidance using the findings of this study are discussed.

- **Examining the implications of ride-sourcing drivers' ride acceptance decisions on system operations of two-sided ride-sourcing platforms in which the parties interact with each other (RQ 4 and RQ 5, Chapter 5)**

Integrating the ride acceptance behavioural components of drivers into the ride-sourcing system operations in which both riders and drivers interact with other through the platform, we analyse the platform's within-day performance in terms of passengers' waiting time, drivers' income, and platform revenue. First, new insights into supply-demand intensity are provided. Then, the performance of a centralised (similar to automated vehicles) fleet consisting of fully-compliant drivers is benchmarked against a decentralised (human-driven) fleet where individual drivers make ride acceptance decisions. Next, the implications of the acceptance rate are discussed at the disaggregate level. Finally, we introduce surge pricing as one of the most prominent and controversial platform strategies and examine its impacts on the acceptance behaviour of drivers and consequently on riders' and the platform's objectives.

1.5.2 Societal Contributions

This thesis contributes to gaining a deep understanding of the behaviour and needs of ride-sourcing drivers. Research findings can help design policy/operational frameworks to alleviate the (major) problems of drivers (as part of the society) in this complex system explained in Chapter 2. Given the role of drivers as service suppliers, their decisions have significant consequences. For instance, ride rejection results in an increase in the waiting time of passengers and idle time of drivers that can be limited using the findings of Chapter 3. Idle driving due to relocation strategy contributes to traffic congestion and air pollution that can be controlled by more tailored platform repositioning guidance as discussed in Chapter 4. Underestimating drivers' choices in the system operational design leads to miscalculation and misrepresentation of the implications of ride-sourcing systems as demonstrated in Chapter 5.

Understanding such dynamics can help improve the ride-sourcing system performance, which may lead to a higher market share. This can have double-sided effects on the transport system due to possible modal shift. For instance, shifting active mode travellers or public transport users to ride-sourcing results in adverse outcomes (e.g., more vehicle kilometres travelled and higher traffic congestion). On the other hand, the ride-sourcing system can benefit society by attracting private car owners, potentially reducing the demand for parking space. To this end, the performance of ride-sourcing companies should be rigorously monitored and regulated by transport authorities to ensure their operations are in line with social welfare from multiple perspectives (e.g., drivers, riders, and the general public).

1.6 Thesis Outline

This thesis comprises six chapters. The research presented in this thesis can be categorised into three components: qualitative insights, behavioural modelling, and simulation model experiments research. An overview of the chapters and their relations is presented in Figure 1-4.

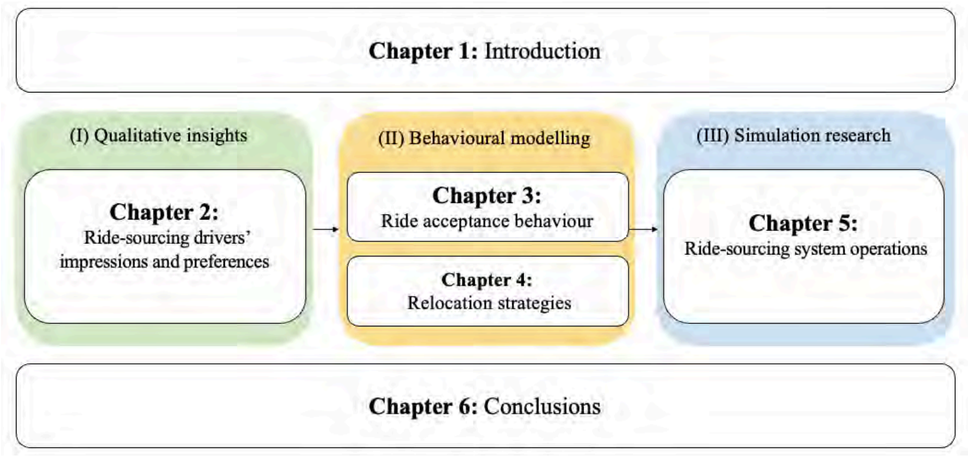


Figure 1-4: Overview of the thesis outline

Part I – Qualitative insights in Chapter 2 shed light on the perception of ride-sourcing drivers of the system operations and their interaction with the platform using a focus group study. This chapter proposes a framework explaining the tactical and operational decisions of drivers, their relationships with each other, and the factors which may affect those decisions. This framework is used in the experiment design and interpretation of the results of the following chapters.

Part II – Behavioural modelling consisting of two studies, presented in Chapter 3 and Chapter 4, delves into the operational decisions of drivers using two stated choice experiments. First, Chapter 3 analyses the ride acceptance behaviour of ride-sourcing drivers and explore the implications of the platform information-sharing policy on drivers' choices. Then, the relocation strategies of drivers are studied in Chapter 4 where the influential determinants are identified, and their effects are estimated.

Part III – Simulation model experiments research containing Chapter 5 integrates the behavioural components of drivers' acceptance decisions into the system operations through an agent-based simulation framework. In this chapter, the with-day operation of ride-sourcing platforms is simulated, and the identified KPIs are analysed from multiple perspectives: supply-demand intensity, centralised versus decentralised fleet, ride acceptance rate implications and surge pricing.

Finally, the answers to the research questions are given in Chapter 6. This chapter draws the primary conclusions, discusses and reflects on the potential applications of the findings. We also discuss the limitations of this research and provide recommendations for future studies.

Chapter 2: Ride-sourcing Drivers' Behaviour and Preferences

In the two-sided platform of ride-sourcing, the supply-side dynamics are driven by drivers' working behaviour and their interactions with the platform as service providers as well as fleet owners. The study of bottom-up operations requires gaining empirical knowledge of the labour supply experience with the system operations, which is largely unknown in the literature.

In this chapter, a focus group study is conducted to qualitatively explore the ride-sourcing drivers' impressions of the system operations and acquire an in-depth understanding of their needs, expectations, and preferences. We also dig into drivers' decisions and their relationships with each other. The chapter is structured as follows: First, background information on the ride-sourcing operations and the role of service suppliers is given in Section 2.1. Then, the methodology for designing and implementing the focus group sessions and data analysis is presented in Section 2.2. The findings are categorised and discussed in Sections 2.3 and 2.4. The conclusions are drawn in Section 2.5.

This chapter is based on the following papers:

- Ashkrof, P., de Almeida Correia, G. H., Cats, O., & van Arem, B. (2020). Ride-sourcing drivers' behaviour and preferences. *Presented at the ISTS2020 conference in October 2020 (online).*
- Ashkrof, P., de Almeida Correia, G. H., Cats, O., & van Arem, B. (2020). Understanding ride-sourcing drivers' behaviour and preferences: Insights from focus groups analysis. *Research in Transportation Business & Management*, *37*, 100516.

2.1 Introduction

Technology development in the transportation sector has changed the mobility boundaries and introduced new transport possibilities to address transport-related issues such as traffic congestion, parking scarcity, climate change, hyper-urbanization, and also demographic and societal changes. Ride-sourcing companies, also known as "Transportation Network Companies (TNCs)", have emerged as one of the frontiers in the shared mobility space and can potentially shift mobility from a vehicle ownership model to service-based operations. By definition, ride-sourcing is a digital platform supplied by private car owners to offer on-demand door-to-door transport services to users requesting rides. Therefore, it is able to possibly address the transportation needs of travellers by offering seamless and efficient mobility solutions. Notwithstanding, there are also intense debates concerning the deficiencies and pitfalls of ride-sourcing services such as their contribution to traffic congestion, discrimination, and air pollution (Shen et al., 2020). This raises awareness of the possible system issues and the relevance of these services as well as the operations and potential regulation thereof for developing a sustainable urban mobility policy.

From the supply-side perspective, drivers are not only chauffeurs but semi-independent fleet owners. Given that working relationship in the gig economy (i.e., a labour market system supplied by independent contractors/freelancers) between the platform and digital workers is characterized by mistrust (Wentrup et al., 2019), drivers are in the heart of these two-sided platforms since they offer their private cars to transport passengers.

Previous studies on the supply side have covered various topics including estimated time of travel (Z. Wang et al., 2018) pricing strategies (G.P. Cachon et al., 2017; Zha et al., 2018a), matching strategies (Zha et al., 2018b), repositioning guidance (Vazifeh et al., 2018), policies and regulations (Zha et al., 2016). They have mostly assumed that drivers are fully compliant with the platform or considered a few monetary variables including hourly income as the factors influencing their choices though many variables such as the cumulative revenue, working shift, the aversion to long working hours, driving costs, information sharing and incentives may presumably impact the decisions of drivers, yet remaining hitherto unexplored in the literature. This arguably stems from the lack of knowledge on the aspects considered by drivers and their potential impact on their behaviour and decisions. Furthermore, many studies have hypothesized that on-demand transport services are operated by a centrally fully automated fleet of vehicles, so-called taxi robots (Ciari et al., 2020; Hörl et al., 2019; Levin, 2017; Liang et al., 2020; Oh et al., 2020; Winter et al., 2020). Current fleets are not automated at this time and the literature suggests that automated vehicles seem not to be introduced to the market in the near future (SAE International, 2018).

Furthermore, literature is increasingly focusing on driver supply properties such as elasticity, wage, and incentives. Wang and Smart (2020) analysed an extracted sample of 18,399 for-hire vehicle drivers working in the United States from 12-year Integrated Public Use Microdata Series data. They report that the hourly income of for-hire vehicle drivers has decreased since the entry of Uber to the market. The key objective of modelling driver supply is to investigate the main reasons why drivers join the system. Analysing the characteristics of Uber drivers through the Uber administrative data and surveys, Hall & Krueger (2018) conclude that flexibility is the main factor attracting drivers to work for Uber to start with. With regard to supply elasticity, the effects of monetary measures such as hourly income on the working shift of drivers are studied. Cahuc et al. (2014) argue that income rate impacts both the decision to join the platform as well as the number of working hours. Using New York City taxi driver data, Farber (2015) found out that drivers have a positive elasticity which means that they typically work longer hours when income rates are higher in line with expectations. Moreover, several studies have investigated the effect of wages and incentives on the supply-side operation of ride-sourcing platforms. For instance, Leng (2016) analyses the response of drivers to monetary promotions given by two competing ride-sourcing platforms in China. They reported that the number of trips per day increases and the idle time decreases during the promotion.

Most of the abovementioned studies are based on several assumptions concerning drivers' behaviour which have not been insofar thoroughly studied. In general, drivers are free to decide whether and when to join the system, to accept/decline ride requests, and about their relocation strategies in order to cover more profit/satisfying periods. This freedom provides drivers with a range of choices that can directly influence their income level as well as the system performance. For example, the low ride request acceptance rate of drivers in a region might increase the waiting time for riders in that area (lower level of service). In another scenario, if no driver accepts an incoming ride request or to be available at a particular location/time, the request is aborted resulting in the dissatisfaction of the client. This highlights the fundamental role of service suppliers in the ride-sourcing environment. Hence, in order to control the supply-side dynamics, the drivers' behaviour and perceptions toward the platform strategies need to be unravelled. This also provides an opportunity to address the issues that drivers face which could lead to decreasing the existing tensions with the platforms and thus break the barriers to fully realize the potential benefits of ride-sourcing. To this end, this study aims at gaining in-depth knowledge about ride-sourcing drivers' decisions and their relations with system functionalities.

We conducted three focus group interviews with Uber drivers in the Netherlands. In our analysis, we classify the results into drivers' (i) understanding of the system operations, (ii) behaviour and (iii) expectations in order to shed light on the ride-sourcing drivers' role. In the following sections, details on the focus group execution (section 2) are given, followed by a discussion of our findings (section 3). We propose a conceptual model for drivers' main behavioural elements and their connections in section 4 and conclude with a discussion of this study's implications pointing also for directions for further research (section 5).

2.2 Methodology

2.2.1 Focus Group Characteristics

Given that the knowledge about the social reality of ride-sourcing drivers is limited due to the non-transparent characteristics of the gig economy practices, focus group as a form of empirical qualitative research is adopted as the research method in this study. This approach allows gaining deep insights into drivers' perspective of the system operations and unravelling their interactions with the platform in order to comprehend their views and behaviour.

Focus groups enable the exploration of the topic of interest by providing qualitative information by means of a focused discussion between a limited number of people who on one hand possess certain common characteristics and on the other hand exhibit diversity with regard to other key characteristics (Krueger and Casey, 2014). In the context of transport innovations, focus groups have mostly been used for studying the views of travellers and policymakers concerning emerging mobility technologies (Carvalho et al., 2016; Davison et al., 2012; Faber and van Lierop, 2020; Ferrer and Ruiz, 2018; Jacobsson et al., 2017; Li, 2018; Nikitas et al., 2019; Pudāne et al., 2018).

The method of focus group strives to provide a dynamic informal group discussion amongst participants to freely share their ideas and learn from or contrast each other's perspectives thanks to the sense of cohesiveness as being a member of a group (Peters, 1993). This enables the researcher to consider the variation in the opinions, generation of new ideas as well as possible solutions, the evolution of the ideas during the discussion, and evaluate the discussed topics in order to efficiently capture the main themes. The main potential pitfalls of focus groups

are potential participants/moderator bias, ungeneralizable outcomes and time-sensitive results (i.e. dependent on the time of the study).
The main reasons for adopting a focus group as the research method in this study are: i) The knowledge about drivers' perception of the system operations and their interactions with the platform is limited and scarce; ii) Qualitative research can explore the opinions and feelings of drivers; iii) The focus group findings can facilitate the prioritization and design of future quantitative research.

2.2.2 Focus Group Design and Sessions

Before describing the focus group set-up, it is important to provide a brief description of the research context. This study is conducted in the Netherlands in which high-quality public transport services are provided and two ride-sourcing companies, namely Uber and ViaVan, are currently active. Uber started operating in Amsterdam in 2012 and currently provides two private-ride products, i.e. UberX[1] and UberBlack[2] in more than five cities. ViaVan has only recently entered the market (early 2018), offering solely shared rides and its operations are limited to the Amsterdam area resulting in a smaller pool of available drivers. Ride-sourcing is generally more regulated in Europe than elsewhere, especially in the Netherlands where drivers need to be registered as professional drivers. Therefore, Uber drivers working in the Netherlands were identified as the target group.
Placing emphasis upon the individual heterogeneity, Wang et al. (2020) concluded that classifying the taxi users into different groups is necessary when studying their behaviour. Given that this heterogeneity may exist between drivers, several categories can be investigated. As ride-sourcing drivers are free to decide about their working patterns, it is assumed that full-time and part-time drivers have distinctive behaviour given that part-time drivers might have some other scheduled activities limiting their freedom. Part-time drivers are defined as the ones who have other occupations while full-time drivers spend their whole working time in the platform. Furthermore, more experienced drivers are expected to decide differently compared to beginning drivers. Hence, working full-time/part-time and being an experienced/beginning driver were defined as the screening criteria for the participants.
Based on the findings of Krueger et al. (2014), focus group sessions should be small enough to enable the participants to share their ideas yet large enough to provide a diversity of perceptions. On the other hand, since dominant participants may influence others within the group, it is recommended to have more than one group session. Moreover, collecting data from several group discussions enables the researcher to compare and contrast data across groups. To this end, we decided to hold three sessions with 4-7 drivers in each group.
The focus group meetings took place in Amsterdam on 22, 25, and 29 July 2019 in a standard meeting room where the conversations (in Dutch) were audio-recorded. Each session lasted two hours and was led by a professional moderator hired for this purpose who was not involved with the research beforehand. This was a deliberate choice to minimize the moderator bias which could unnecessarily redirect the discussions into the moderator's topics of interest. On the other hand, prior knowledge of the moderator can have some added value to foster the group dynamics. In order to obtain a balance between the moderator bias and having enough background knowledge, we had several joint meetings with the independent moderator to brief her and also provided her with a semi-structured moderation guide to ensure the research objectives could be achieved. Besides, the author of this thesis followed all the focus groups'

[1] UberX is Uber's basic ridesharing service that provides private, cost-effective transportation options using a variety of vehicle types.
[2] UberBlack is a premium ride service offered by Uber, characterized by professional chauffeurs and high-end vehicles.

discussions in an observation room in real-time. He was able to see and hear the participants while they could not see him thanks to a one-way mirror. In several situations during the sessions, he contacted the moderator for asking some follow-up questions. However, she was fully authorized to refuse to ask any leading questions raised by him during the discussions. It should be noted that at the beginning of each session, participants were informed about his presence (as a researcher from a Dutch university) behind the one-way mirror and the relevant reasons for that. Figure 2-1 indicates the meeting room from the perspective of the first author in the observation room.

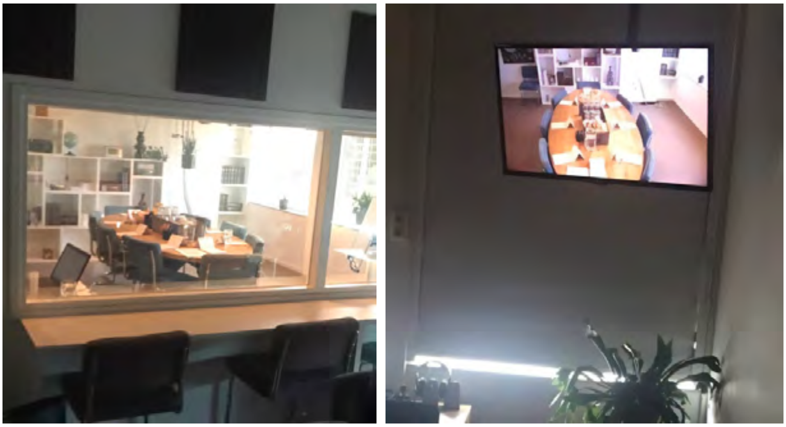


Figure 2-1: Focus group meeting room, two perspectives taken from the observation room

Each session started with a short introduction to the topic. Although the identity of the research team was not revealed, it was emphasized that the research is conducted by a Dutch university for academic purposes. The idea behind this was to prevent potentially underlying concerns by participants that may hinder them from expressing themselves freely and possibly giving biased and strategic responses.
After the introduction, the focus group rules and conditions including confidentiality, having no right or wrong answers, respecting the opinions of each other, the session duration, and eventual incentives were explained. Then, the drivers were asked to introduce themselves and summarize their perception of the platform performance in one word as an icebreaker. Following the group introduction and based on the moderation guide, the general open-ended questions were asked to initiate the discussion and then follow-up questions, probes, and prompts were raised to saturate the topic. Table 2-1 shows the topics and the main associated questions.

Table 2-1: Main questions of the moderation guide

No.	Main Questions*	Topic Category
1	How happy are you on a scale 1-10 (10 is the highest) as a driver?	Starter
2	Why did you choose Uber?	Background
3	What are the differences between a taxi driver and an Uber driver?	Taxi vs Uber
4	Describe a typical workday, what are your activities?	Working pattern
5	How many of you have a fixed/flexible working shift and why have you selected this working shift?	
6	How much time do you ride with and without a passenger within a weekday? What about weekends?	Empty rides
7	Is there any way to reduce your empty trips? How?	
8	What kind of information are you shown when a request comes?	Requests
9	Based on what factors do you consider accepting or rejecting a request?	
10	What is your opinion about having a menu of trip requests to select between them?	
11	Did you ever feel uncomfortable during working hours? Or experience any passengers' misbehaviour? If yes, in what way?	Safety
12	When you finish up a trip during your shift, what do you do? (Do you stop there and wait for the next possible passenger?)	Relocation
13	What have you figured out about the platform pricing mechanism?	Pricing
14	What would be the minimum hourly net income that you expect to earn?	Minimum income
15	What do you think about providing service in low demand areas such as suburban or offering rides in the middle of the night?	Incentive
16	Imagine you will be the CEO of Uber as from tomorrow, what are the first things you would change?	Expectations
* Each main question had a set of what-if scenarios, follow-up questions, and probes in order to ensure the topic is saturated.		

2.2.3 Sample Characteristics

A panel provider was hired to reach out to the target group. Using snowball sampling, they recruited 16 Uber drivers complying with the screening criteria (full-time/part-time and experienced/beginning drivers). Even though the focus group sample is not required to represent the population in terms of neither socioeconomic characteristics nor working behaviour (Marshall, 1996), Table 2-2 contains information about the drivers' profile to allow for additional insights when discussing the findings.

It can be seen that out of the 16 drivers, most of them were male whereas two females participated. The number of part-time drivers was slightly higher than the number of full-time ones (9 part-time drivers). Most of the participants were UberX drivers while one of them was working as UberX as well as UberBlack driver simultaneously. Their working experience differed from 1 month to 5 years. In this study, drivers with more than two years of driving experience with the platform are considered experienced drivers. Each driver is identified by a specific code which starts with D (driver) followed by the participant number within the respective focus group session (from 1 to 6), their employment status (F for full-time, P for part-time), the session number (from 1 to 3). For example, D2F3 refers to Driver number 2 who is a Female and participated in the third session.

Table 2-2: Sample characteristics

Driver code	Gender	Age	Employment status	Service	Experience
D1F1	Male	24	Full-time	UberX	6 months
D2P1	Male	41	Part-time	UberX	4 years
D3F1	Male	66	Full-time	UberX	4 years
D4F1	Female	28	Full-time	UberX	2 years
D5F1	Female	29	Full-time	UberX	2 years
D6P1	Male	28	Part-time	UberX	6 months
D1F2	Male	22	Full-time	UberX	6 months
D2P2	Male	22	Part-time	UberX	2 years
D3F2	Male	22	Full-time	UberX and UberBlack	3 years
D4P2	Male	22	Part-time	UberX	2 years
D1P3	Male	39	Part-time	UberX	3 years
D2F3	Male	36	Full-time	UberX	5 years
D3P3	Male	31	Part-time	UberX	3 years
D4P3	Male	42	Part-time	UberX	1 month
D5P3	Male	25	Part-time	UberX	1 month
D6P3	Male	25	Part-time	UberX	3 years

2.2.4 Data Analysis

The transcript-based analysis is considered as the most robust method of analysing qualitative data (Onwuegbuzie et al., 2009). The qualitative content analysis principle was used to analyse the focus group transcripts obtained from the audio-recorded conversations. Based on the research framework, this systematic bottom-up approach aims at providing a comprehensive description of the phenomenon at the theoretical level through inductive or deductive category development (Elo and Kyngäs, 2008; Mayring, 2000; Williamson et al., 2018). The collected data is the primary source of identifying concepts, themes, and categories in inductive analysis processes while deductive content analysis is carried out based on the prior formulated knowledge (Kyngäs, 2020; Mayring, 2000). In this study, the majority of analysis is conducted deductively because the existing literature contributed to defining the study assumptions and deriving most of the categories. However, some themes were identified independently of the literature given that background knowledge is limited and fragmented in this field.

The analysis process comprises three main phases including preparation, organizing and reporting (Elo and Kyngäs, 2008). The transcripts are scrupulously reviewed word for word several times for making sense of the data and ensuring accuracy. Then, the text is coded by writing notes and headings in shorthand words in the margin and also keywords and sentences are highlighted. After that, the data is classified into several groups in accordance with the identified categories in the literature. Next, those groups were categorised under higher-order headings in order to reduce the number of topics, extract the themes, and increase the understanding of the phenomenon. Finally, the identified categories and sub-categories are integrated, analysed, and interpreted in order to explain the drivers' decisions and behaviour using the relevant highlighted quotes. To increase the reliability of the findings, the moderator was also requested to provide a top-line report in order to enable the cross-checking of the identified themes with an independent coder, therefore, minimizing the researcher bias in the analysis process. The next section reports the focus group findings.

2.3 Findings

We report the findings in three main categories: system operations (3.1), drivers' behaviour (3.2), and drivers' expectations (3.3). The first section discusses the drivers' perspectives on ride-sourcing system components. Then, the decisions of drivers as well as the corresponding attributes are explained in the second section. The last part elaborates on the needs, preferences, and expectation of the focus group drivers.

2.3.1 System Operations

Here we describe the ride-sourcing platform functionality as experienced and perceived by the drivers. We structure the discussion of these findings into the following sections: ride requests, working shift and area, utilization rate, rematch, reputation system and tips, navigation, manipulation, and riders.

2.3.1.1 Ride requests

When a ride is requested by a rider, the app sends the request to nearby drivers. Drivers have the choice of either accepting or declining the request. If a driver decides to accept the request, he needs to pick up the rider at his pick-up point. Even after accepting the request, the driver can cancel it. However, the cancellation has some consequences (to be discussed below). In case of not accepting the request, the driver waits for the next possible request or ends his working shift. The main question is that what kind of information is shown to drivers when a request appears? In the focus group, we asked the drivers to clarify it and express their opinions. a) Information sharing policy: Currently, drivers are provided with limited information. They are able to see the pick-up point address, the distance and predicted travel time between their location and the pick-up point, and the rider's rating. Trip fare and the final destination are not shown to drivers. They cannot see the destination immediately after accepting the request. Instead, the destination pops up when the driver approaches the rider. This is presumably because the probability of cancelling the request by the driver decreases given that he has already driven some kilometers to pick-up the passenger. Thus, if he/she cancels the request at this stage, he/she has earned nothing. Most drivers stated that they found it difficult to make a decision about the request given the limited data available upfront.

> *"The given information is the distance from the client and the rate. That's it." D1F2*

> *"... you don't know where someone is going. But it can be hard to decide sometimes..." D6P1*

Many drivers said that having no information about the ride destination before accepting requests is problematic as they may end up with a short-distance ride which is even shorter than the distance between the drivers' location and the pick-up point.

> *"Prior to a ride, you don't know the destination. Sometimes you drive for 15 kilometers and find out someone only has to be 200 meters down the road. That's really a problem." D1F1*

There is also other information that is occasionally indicated such as surge pricing (dynamic pricing), trips longer than 30 minutes, and pre-booked rides. Surge pricing is a pricing strategy based on the local ratio between supply and demand. It results in higher fares for riders and thus

higher income for drivers. Both drivers and riders can see a multiplier applied on top of the standard rates in the application in case of surge pricing.
Moreover, a special icon (+30) appears in the driver's application to indicate in case a trip duration that is longer than 30 minutes. Drivers are also informed if a request is a pre-booked ride. Since they cannot see pre-ride requests much in advance, one of the drivers found this feature unnecessary. There is no difference for drivers whether a request is pre-booked or not when they are not able to see it in advance, so it does not have any effect on the drivers' decisions.

> *"[drivers can see] if they [riders] have booked it [the ride] in advance [pre-booked ride] ... It doesn't make a difference. It's unnecessary information." D4P2*

b) Declining and cancelling requests: There is a clear distinction between declining and cancelling requests. The former implies that the request is never accepted by drivers while the latter means that an accepted request is cancelled by either drivers or riders. In contrast to declining, which could be done without any ramifications for the driver, cancellation has some consequences. There is a threshold of a maximum three cancellations per day and drivers need to explain why an accepted request has been cancelled. If a driver exceeds the maximum, he/she gets a warning. After receiving three warnings, the application is deactivated and he/she needs to go to the headquarters to get briefed and in some cases, the driver may get blocked either temporarily or permanently.
The more experienced the drivers, the more selective they are with accepting requests. Experienced drivers believed that only some of the requests should be accepted based on several criteria depending on the driver's experience in order to maximize the profit. They usually stop somewhere and wait for the next trip. In contrast, beginning drivers prefer to accept most of the requests and then drive empty to receive a request.

> *"I think you can cancel three times a day. If you cancel more, you'll get a warning... You can decline as much as you want. But you can't cancel as much as you want... I used to accept everything as well, but after some time you learn how to work with Uber… it's better not to accept everything. Otherwise, you work really hard, and only take rides for 4, 5 or 6 euros. I'd rather wait for a ride of 30 or 20 [minutes]..." D2F3*

Drivers may also cancel a request if either the pick-up point seems to be risky in terms of getting fined or the rider looks problematic or the trip characteristics including trip distance/fare are not appealing. Risky pick-up point was the most typical reason for cancelling a request.

> *"Many cancellations. Because of the wrong pick up locations…" D3F2*

> *"You must also pay attention to the places where you are allowed to stand still or park. Pick up points. For example, if I look at Utrecht near the station… pick up points are really bad." D2P1*

If the request is cancelled by the rider after two minutes or by the driver because of the riders' issues (e.g., not showing up, too many people, etc.), the rider has to compensate for it.

> *"If you wait for the client... If the client is not there and you already called… Then you will get a refund for the waiting time... Not only that, but it's also when the client is with too many people." D2P2*

However, the cancellation feature could cause some disputes between riders and drivers when they try to shirk the responsibility for the cancellation. Many drivers believed that Uber supports the rider in all cases even if they are mistaken.

> *"During disagreements between drivers and clients, Uber always picks the side of the client. And even if they don't, they often make a double commitment. Then, they tell the client they chose their side, and they tell us the same. And ultimately, they give us compensation, but the customer won't get banned. So, clients will never have any consequences of their wrongful behaviour" D1F1*

c) Preferred destination: Drivers can set their preferred destination and have a higher chance of getting requests heading in the same direction as their destination. They are allowed to set their preferred destination twice a day. Most drivers were satisfied with this feature and use it when they intend to finish their shift. They usually set the destination to their home and get the filtered requests.

> *"It's like a bonus. Because I also think that there's a higher chance for you to get that ride, over other drivers. I don't know exactly how that works, but I think it's something like that." D1F2*

A few drivers did not find it helpful because they believed they might miss some profitable requests in other directions.

> *"...You won't get offered any rides that go in another direction. So, you'll be empty way more often…" D3P3*

2.3.1.2 Working shift and area

Gig-economy firms are renowned for giving the labour the freedom to choose their working shift due to the fact that they do not have direct employment relations but are rather considered as independent contractors.

a) Flexible working patterns: Flexibility, freedom, and independence were acknowledged by all drivers as the main motivation for joining Uber. Drivers can work as much or as little as they desire. They are able to independently decide when and where to start and finish their work without requiring to explain to an employer. The feeling of not having a boss can provide drivers with a sense of independence.

> *"You decide about your own working time. You decide if you are going to work at all or not. I don't have to call someone if I am not going to work... You get everything in control... It doesn't matter where you are in the Netherlands, you can always go online and work if you want to..." D4P2*

> *"You can more or less decide yourself how much you earn, how many hours you work... And you're independent." D5F1*

This option can enable labour supply to work dynamically based on their preferences. That is why many Uber drivers work as part-time workers meaning that they have another source of income at the same time.

b) Maximum working hours: A new rule has recently been made that sets a maximum of 12 working hours per day for drivers. Based on Uber, from May 2018, the driver application is deactivated after 12 hours of driving with Uber and will be activated after 6 hours of a continuous break. This working time limit excludes the period when the driver is offline or he/she stops somewhere and wait for the next trip. Some drivers pointed to this rule as a strict policy which reduces their flexibility, but it seems that there is a misunderstanding. They thought that the maximum working hours rule was applied even in the offline mode within the shift.

> *"I would also like those broken shifts. Often, I only have a couple of regular customers, but you are forced to use your driving time immediately." D1F1*

> *"Now you can work 12 hours from the moment that you are logged in... Sometimes I don't feel like working yet or there are no rides, but then I can't take an evening shift because I am then over the maximum number of hours. Because the clock just keeps counting. That has to do with the safety of the driver." D5F1*

It appears that Uber needs to adopt measures to adequately inform drivers about the new rules to avoid undesired consequences and allow drivers to effectively use the platform and schedule their working hours accordingly.

2.3.1.3 Utilization rate

The working shift duration includes all trips with passengers, empty trips (deadhead trips), and waiting time. As Uber drivers are paid based on the kilometres travelled with riders, it is crucial to draw a distinction between rides with passenger(s) and empty rides. That is why the utilization rate is an indicator that shows the percentage of mileage with passengers. It is calculated by dividing the amount of time the vehicle is occupied by the total working shift duration.

a) Weekday versus weekend: The most typical utilization rate reported in the focus group was 60%. Some drivers reported that their utilization rate was higher on weekends than weekdays while others stated that although the occupancy rate was the same on both weekend and weekdays, the riders' characteristics were distinct.

> *"For me, there is not really a real difference between the week or the weekend. The riders are different though. But the occupancy rate isn't." D2P1*

> *"During the week I have around two rides per hour, sometimes three. During the weekend it's almost always three per hour. On average one ride is around 15 minutes." D6P1*

b) Seasonality: A few drivers believed that driving for Uber could be a seasonal job when they have plenty of rides in the summer (high utilization rate) and not many rides in winter, especially in the period after Christmas (low utilization rate). Therefore, given that the utilization rate fluctuates during the year, they did not feel that the job was financially secure.

> *"During the summertime, there are so many tourists. And there's so much going on. But the period after Christmas… There's such a decline in income for those months… you almost can't compensate for it in the busier months." D1P3*

> *"It's not always secure. In the winter it can be that you will leave really early and don't drive a lot, and if you get a fine or get an accident... That can happen. You will have a lot of costs and no income." D4P2*

c) Ride-sourcing versus taxi: Despite the unstable utilization rate, one of the drivers who was working for normal taxi companies confirmed that the utilization rate of Uber is much higher than normal taxis.

> *"In a normal taxi, I'm empty way more. If I drive for Uber, I can have up to three customers per hour." D4F1*

This is in line with the findings of Cramer et al. (2016). Using data from five cities in the US, they concluded that the utilization rate of ride-sourcing platforms is higher than taxis due to the larger scale of ride-sourcing platforms, more efficient matching and pricing strategies and also flexible labour model. Contreras and Paz (2018) also confirm that ride-sourcing has negative and significant impacts on taxicab ridership.

2.3.1.4 Rematch

Rematch is a new matching strategy implemented in some airports to help reduce the number of cars in the terminals, riders' wait time, and the number of drivers waiting in the airport parking lots. When drivers drop off passengers at the airport, they can immediately receive an on-site pick-up request as available, so they do not need to drive to the parking lots and wait there for the next possible request. If no request pops up within a certain time window (2-3 minutes), they are no longer eligible for Rematch and can either go to the waiting queue or exit the airport.

Drivers who want to work in the Amsterdam airport (Schiphol) need to deposit 100 euros to receive a special pass called "Schiphol Pass". There is a virtual waiting queue in the airport for the drivers who have the pass. While many drivers were unaware of Rematch, a few drivers confirmed that Rematch can help them earn more money thanks to the higher utilization rate at the airport. They reported that when a trip is finished at the airport, the next ride request instantly appears, therefore, no waiting time.

> *"You don't have to wait there [Schiphol] anymore. I've had Rematch a couple of times. It's great for your income. If it works, it really makes sense to go there... Nowadays you have the rematch system which improves your chances of getting a ride back immediately." D3P3*

One of the drivers who had not noticed Rematch accused Uber of discriminating between drivers because he thought only some drivers (e.g., the ones joining the platform at early stages or drivers who accept more rides) would benefit from this feature. This, again, stresses the necessity of having effective communication between drivers and the platform in order to ensure drivers are fully updated about the new features and also the platform can receive drivers' feedback for further improvement. It helps eliminate possible misunderstandings and develop trust, as one of the main components in any sustainable business, between suppliers/workers and the platform.

2.3.1.5 Reputation system and tips

Drivers and riders are able to anonymously rate each other from 1 (the lowest) to 5 (the highest) to quantify the service quality based on the trip experience after finishing a ride through the application. This feature, which is the so-called two-way (bilateral) rating system or reputation system, can intensify the interaction between drivers and riders and may enhance trust-building between them, particularly since they usually do not know each other. On the other hand, the platform can use the reputation system to control drivers/riders and monitor their behaviour given that the working relationship between the platform and digital workers is characterized by mistrust (Wentrup et al., 2019). A beginning driver/rider starts with 5 stars and then the rating is adjusted according to the feedback, so the overall rating is an average of accumulated individual ratings. The reputational feedback mechanism can potentially influence the behaviour of both riders and drivers given the consequences of having a low rating, especially for drivers.

a) Unfair rating system: Many drivers stated that they perceived the rating system to be unfair because of two key reasons: Firstly, the riders' rating is less reliable than drivers' rating since most of the riders do not travel as much as drivers, hence their ratings are based on fewer records. Secondly, the riders' rating is not considered as important as drivers' rating given that drivers are banned by Uber either temporarily or permanently if their rating is below what is considered by Uber as a minimum rating in that region while a low rating does not have any consequences for riders. In other words, riders play the role of middle managers over drivers given that their feedback is a key element for drivers (Rosenblat and Stark, 2015), in a manner similar to other two-sided platforms such as Airbnb and TripAdvisor.

> *"If a client has a low rating, that doesn't carry any consequences. But, it does to us. And that client can keep behaving the same. That's a difference. Under 4.6, you can't even drive for Uber. But a client with a rating of 4.0 can still order an Uber." D6P1*

Analysing the data from ride-sourcing platform in India, Kapoor and Tucker (2017) argued that drivers are stimulated to leave the platform by an unfair rating system.
Some drivers mentioned that when heading towards riders with a poor rating they adjust their expectations and can experience anxiety.

> *"I'm really on edge when I see that my next client has a low rating. I make sure I'm ready for it and expect the worst." D3F1*

The reputation system can, therefore, be considered as a scare tactic to address the mistrust issue between all parties, particularly for drivers who are constantly under the risk of being deactivated.
Tipping: Riders can also give a tip to drivers in the application after each trip as they wish. Some drivers pointed out they did not rely on this option though and perceived it as a bonus promoted by Uber.

> *"Clients often don't have any cash with them. That's the concept of Uber as well, so it's a good thing that they can also give a tip digitally." D2P2*

Chandar et al. (2019) pointed to the gender differences in tipping and being tipped. They found that men leave more tips while women are tipped more.

2.3.1.6 Navigation

For drivers, the quality of navigation is crucial due to the fact that it is not only about getting from point A to point B, but finding and picking up their riders. Using the Estimated Time of Arrival (ETA), Uber navigates drivers through the fastest path between the driver's location and the pick-up point(s) as well as between the pick-up point(s) and the destination(s). Decreasing the travel cost for riders, energy consumption, and vehicular pollution, a reliable ETA can improve system efficiency. However, an accurate ETA depends on many factors such as spatial-temporal dependencies, traffic congestion and weather condition (D. Wang et al., 2018).
a) Unreliable ETA: Although Uber has recently redesigned its navigation system, a few drivers said that the ETA does not work precisely.

> *"It doesn't consider traffic. So, therefore arrival times often are incorrect in busy areas like the center." D3F1*

b) Re-routing issues: Uber recommends drivers to ask riders about their preferred route which may cause some problems for drivers. A few drivers said that if they re-routed the trip due to some justifiable reasons like the rider's preference, the platform did not automatically consider it. This was not desirable for drivers, especially when they had to take a longer route. In this case, drivers need to email the customer service to explain what happened in order to claim the extra kilometers travelled.

> *"They see the route you took and based on that they might think you should've done it differently. So, automatically if you have driven 5 kilometers too long, they will take that from your final earnings, even though you might have had a good reason." D2F3*

2.3.1.7 (Mis)information and asymmetric relations

a) Misleading: Many drivers claimed to be misled even before starting the job. They believed that Uber manipulated them. They were told that they could earn around 1000 euros per week.

> *"They made all these great promises, like earning 1000 euros per week and that all sounded great so I thought: let's do that... With these advertisements they've attracted drivers, that's really misleading." D6P3*

b) Many drivers emphasized that the application sometimes misleads them by showing the surge pricing areas or high-demand areas where they are supposed to have more demand while in many cases drivers who follow the application recommendations are not able to get any requests.

> *"There is a dynamic rate. But it is there for nothing because you don't get any rides. While it says it's really busy. You could be at home looking at the rate, and because you think it's busy you will go to work. But then it will be for nothing... You could be in an area that's very red. But then you could also have no rides for half an hour. These are the moments I get really annoyed." D1F2*

Although the mismatch information about surge pricing and high demand areas has caused a feeling of mistrust for many drivers, some more experienced drivers believed that this might be due to the fact that drivers compete with each other to reach the recommended areas, then those locations will no longer be undersupplied. They also stated that the platform might be aiming to attract drivers to a certain area for different reasons such as decreasing the passengers' waiting time.

> *"...I think everyone just has the same mentality. Everyone just goes there, if there's surge there." D6P3*

c) Strong competition: Some drivers believed that oversupply is one of the main reasons that they cannot earn more money as much as Uber promised. There exists a strong competition between drivers to get rides which leads to lower utilization rate and therefore lower income.

> *"There is a lot of competition... Uber does not have a maximum number of drivers, so anyone can register. And now the supply and demand are no longer at a good proportion. So, there's too much competition." D6P1*

d) Monopolization: Despite the low income and the feeling of mistrust as well as being manipulated, a few drivers stated that Uber has a monopoly position as there is no competing company receiving as many as Uber ride requests, so they felt forced to work with Uber.

> *"It's like you don't have a better option than Uber. They've taken over the complete market and just forced everyone to join them." D5F1*

2.3.1.8 Riders

a) Rider-oriented platform: Many drivers said that in case of any conflict between drivers and riders, Uber mostly takes the riders' side. Drivers believed that Uber is biased towards riders at the cost of drivers which can even lead to rider' misbehaviour. Some drivers mentioned issues caused by riders including vomiting in the car, eating or drinking, unpleasant smell, smashing the door, touching buttons, and hyper-critical people.

> *"They [riders] think they can do anything in the car… Not all of them. But there are a lot of clients who think they can do anything." D3F2*

b) Ride-sourcing riders versus taxi passengers: Some drivers pointed out that Uber riders were more cautious than passengers picked up at random from the street. This is because riders know that their identity can be traced if needed thanks to the cash-free transactions and self-identification procedure for activating the application.

> *"There are a lot of differences between Uber and Taxi clients because all Uber customers are registered. If a customer [Uber rider] gets into your car, they've already given their credit card details. So, the customer won't misbehave as much. Because they know Uber can find them…" D4P2*

c) The difference between taxi and ride-sourcing users is also highlighted by Rayle et al. (2016). Comparing the results of a survey of ride-sourcing users in San Francisco with a previous taxi survey and taxi trip logs, they conclude that younger and well-educated passengers who seek short waiting times and fast point-to-point trips tend to use ride-sourcing services.

2.3.2 Drivers' Behaviour

Drivers' behaviour stems from their operational and tactical decisions which are based on their understanding of the system operations and preferences/aversions. In general, drivers are able to make decisions about accepting/declining/cancelling requests, relocation (repositioning), working shift and area. Decisions related to requests and relocation can be associated with operational decisions while selecting the working shift and area are categorized as tactical decisions. This section describes the factors which are taken into account by the drivers when making decisions. The findings are presented in three sub-sections: ride acceptance, relocation strategies, working shift and area.

2.3.2.1 Ride acceptance

Once a request appears in the application, drivers are given a few seconds to decide whether to accept or decline (dismissing, not accepting) the request. Although the given information seems to be limited for making an informed decision, many requests are declined by drivers. Romanyuk (2016) argues that in a two-sided platform with a matching algorithm, the probability of rejecting a request by a seller is higher when the full information disclosure is available. Drivers are shown the pick-up point address, the distance and time between the driver's location and the pick-up point, and the rider's rating before accepting the requests which can lead to blind passenger acceptance when they do not have any information about the trip fare and the final destination. In case of accepting, the fastest route to the rider is given while the driver is still not able to find the final ride destination. The final destination is shown when the driver approaches the rider and pick him/her up. Some additive information is given as necessary, for example, if the request is within surge pricing, the trip is longer than 30 minutes, and the ride is pre-booked.
a) Pick-up point location: In the focus group meetings, the drivers discussed their criteria for making decisions with regards to incoming requests. All the drivers unanimously believed that

the requests with risky pick-up points located mostly in the city center should be declined due to the high risk of getting fined by police while there is no support from neither the platform nor the rider. Getting fined leads to increasing the operational costs, therefore, less profit.

> *"...you can't wait there [risky spots], so you'll get a fine. And then your customers get in and laugh while you get a fine. I don't feel like doing that. In the center there are a lot of places like that…" D3P3*

> *"...If I am not allowed to stand still, I will decline it [the request]. I already got a fine, and that's a loss of money…" D1F2*

b) Distance and time to the pick-up point: The distance and travel time between the driver's location and the pick-up point appear to be an influential factor. Given that drivers are not able to see the ride destination, a few drivers said they did not tend to accept the requests in which their pick-up points were located far from their current location. This is because there is a risk of ending up with a short-distance ride after driving to the faraway pick-up point.

> *"You just shouldn't accept some rides. I mean, you know how much time it may take you to get to the customer. For me, if it's more than 8 minutes I say: No, thank you!... The location is decisive. Rides on Dam Square or Damrak Street, I also refuse." D3F1*

> *"… If I have to drive a long way to pick up the client. Is it only a little, or a lot? If it's a lot then I will refuse. Because if the ride is only 2 kilometers, then I drove there for almost nothing." D3F2*

c) Rider's rating: Rider's rating is another factor that is always shown to drivers. In contrast to drivers who are not able to work for the platform when their rating is less than a certain threshold, riders can request rides regardless of their rating. Some drivers stated that they preferred not to accept the requests of the riders who have a low rating. The high risk of misbehaving as well as giving the driver a low rating was mentioned by some drivers as the main reason for declining those requests.

> *"If I see the client has a rating of 3.7, that means a lot of drivers gave a bad rating. If I see that, I refuse." D3F2*

d) Surge pricing: Amongst the additive information, surge pricing may indirectly lead to declining many requests. Both riders and drivers are informed if the price of a request has surged which means higher income for drivers. That is why drivers try to enter those areas and receive promoted requests. Some drivers reported that they did not accept the requests with standard pricing when they were close or on the way of surge pricing areas.

> *"When I drive somewhere that there's no surge, but I'm close to it, I'll reject other rides. I prefer to go to the surge area and take a ride there rather than taking a ride away from the surge area." D6P1*

> *"If there is surge pricing, and I will get a request without surge pricing, then I will refuse. I won't take it. Because I know a little bit further on, I can get a ride for 2-3 times of the normal price" D3F2*

One of the drivers who was working for both UberX and UberBlack stated neither the rider's rating nor surge pricing was decisive for him when working as an UberBlack driver. This is because there is usually no surge pricing for UberBlack since the price is already higher for

UberBlack. On the other hand, UberBlack riders are more desirable and generous in terms of leaving tip.

> *"... I also drive for UberBlack... You won't have difficult clients... There is almost no surge pricing because it's already higher...." D3F2*

e) Long-distance rides: Many drivers mentioned that they avoided short-distance trips since the trip fare was low. It could be worse if a short-distance trip is combined with traffic congestion given that drivers are paid based on kilometers travelled. Long-distance rides are appealing for drivers since they can drive longer without any stop, therefore, higher earning.

> *"... It's really bad to be in a traffic jam for a long time for a short ride. For example, it's 2 kilometers and you will be in a traffic jam for 20 minutes." D1F1*

> *"Your income is really low. Most of the time you get short rides" D1P3*

Many drivers said they are more likely to accept requests indicated by 30+ in the application, indicating that the ride takes more than 30 minutes. Long-distance rides which are complemented by surge pricing were appreciated by all drivers as the best rides.

> *"I prefer 30+ next to a ride if it's longer than 30 minutes. So, you immediately know it's a long ride." D4F1*

> *"Long journeys are equivalent to good rides, so that's great. And it's even better if you also get a dynamic rate" D6P1*

f) Destination prediction: It appears that drivers can predict some characteristics of the ride in order to make a decision about the request. The plausible destination, for example, was mentioned by some drivers as one of the criteria. The most experienced drivers said that they predicted the final destination of the requests based on the rider origin and the request arrival time, so the requests which seemed to be short rides were declined.

> *"If it's [pick-up point] a hotel and also time of the day. Very early in the morning you just know for sure it [the ride] will be to Schiphol. But when it's 8 am, your chances go down to 50/50. Because a lot of people also go to their office then... based on that I decide if I want to reject or accept." D2F3*

g) Experience: Based on the discussion in the focus group meetings, we can conclude that the experienced drivers were more selective in choosing whether to accept requests. They do not usually accept all requests: since they are familiar with the areas and the characteristics of the requests, they are able to assess if a request is worth being accepted. The most experienced driver (5 years) had an acceptance rate of 10% while new joiners (less than 6 months) had 90% on average.

> *"When I'm in the city I get a new request every 10 seconds or every minute. And in other busy areas around every 2 minutes. And I think I accept about 1 out of every 10" D2F3*

> *"I also accept almost everything" D5P3*

h) Cancellation criteria: The other choice made by drivers is to cancel a trip after accepting its request even though it is preferred not to cancel trips due to the possible consequences. Risky pick-up points, short-distance rides, and problematic riders were mentioned as the main reasons for the cancellations. Some inexperienced drivers stated that despite the fact that they are shown the pick-up address before accepting the request, they could not recognize if it has a risk of getting fined. That is why they accepted the ride, approached the address to assess the pick-up point. If they found it risky to stop, they cancelled the ride.

> *"You will have to cancel because you cannot stop there [risky pick-up points]" D1F2*

2.3.2.2 Relocation strategies

When the rider is dropped off, the ride is finished. Drivers, therefore, have three so-called relocation strategies options if they tend to continue their shift. They can either wait at certain places or cruise to some random places or drive to some target areas where more demand is expected. Although drivers pursue the same objective which is maximizing the occupancy rate, therefore, profit, their relocation strategies differ depending on several factors such as their attitudes and experience.

a) Experience: Most beginning drivers preferred not to wait because they enjoyed moving and also, they want to avoid having to pay for parking; Otherwise, they might get fined. Therefore, they drive around or drive somewhere until a request appears. This behaviour can increase the empty rides and cause some environmental issues due to the risk of increasing vehicle kilometers travelled.

> *"...me neither [I never park]. I'm on the side with my car lights on… and then you just hope that your customer comes quickly... I never stand still whenever I have to wait for a ride. I just drive around." D6P1*

> *"I like to keep on moving actually. I just follow certain routes. For instance, when I'm in the West… I just go in the direction of Schiphol. And if I get a ride along the way I take it…" D6P3*

In contrast, experienced drivers tended to wait in order to decrease their empty trips. They know the safe places to park without paying for it and getting fined.

> *"I've stopped driving around for a year. Whenever I drop off someone at the Prinsengracht [a neighbourhood in Amsterdam], I just know where I can stay and I stay there until a new ride comes in…" D2F3*

b) Surge pricing area: Given that drivers are able to see the surge pricing areas on the map, some beginning drivers said that they tracked them. While more experienced drivers stated that they did not follow those areas since many drivers competed to reach there and got the potential promoted requests which led to oversupply and consequently no ride. Furthermore, they believed that the application deliberately does not show the surge area in real-time in order to gather drivers in a certain area. The reason might be for improving the level of service for passengers (shorter waiting times).

> *"You see surge pricing on the map. Then, you drive where there are red spots. You will see 1.6 in this area, so you know if you get a ride there, the price will be times 1.6. If you get a request, you will also see 1.6 on the bottom right of the screen. And if you don't see this, but you know it's there, then it's not smart to take it... It could be that you are two streets outside of this area." D1F2*

> *"I never drive to the surge." D3F1*

These statements confirm the findings of Jiao (2018). He concluded that the ambiguity and unforeseeability of the surge pricing mechanism pose significant challenges for the system stakeholders.
c) High-demand area: There is an icon like a flashlight in the app that shows the areas in which the demand is higher, but it is not surge pricing. A few drivers said that they did take it into consideration for repositioning while some drivers believed that there is no point to follow it.

> *"There's also an icon that means that if you go to a certain place there's a higher chance of getting a ride. It's a blue icon." D2P2*

> *"I don't look at it [high demand icon] normally. It isn't an important factor for me." D4P2*

d) Rider's application: After finishing a trip, some drivers turn on the rider's application in order to check the number of drivers in the area. Then, if there is intense competition, they tend to relocate to places where the chance of getting a ride is higher.

> *"I drive around the corner, stop there for a bit and launch the Uber app. The one for passengers, which allows me to see how many Uber drivers are there and if there are many in the area, I'll drive somewhere else. But if there's not much competition, I stay there for a little bit. So, I actually look through the app of the customer." D3F1*

e) Spatial position: The distance from the center is another influential factor. A few drivers said that if they end up with a location where is further away from the center, they can wait more in order to reduce empty trips.

> *"...If you have to go somewhere outside of Amsterdam. Then I wait there for a bit, and I don't drive back immediately." D4P2.*

f) Temporal status: It appears that relocation strategies are time-dependent and have strong temporal patterns. A driver said that at night, he did not wait after finishing a trip in a residential area and immediately drove back to busier areas while in the afternoon/evening, he preferred to wait for a few minutes at the location of the previous ride to find the next passenger. The reason is that the probability of getting a ride in a place out of the center is lower at night.

> *"During night time you don't have to wait in a residential area, you would just drive back. But at 7 pm or 3 pm, chances are higher." D6P1*

2.3.2.3 Working shift and area

The most important advantage of the platform mentioned by all Uber drivers is the flexibility to select the working schedule and service area. This was the key reason for many drivers to join Uber to start with. The decision regarding the working shift is heavily dependent on the drivers' employment status (whether a full-time or part-time Uber driver) and preferences/aversions.
a) Preferences/aversions: Some drivers said that they preferred to work in the evening because they were not morning persons. While some stated they tended to work in the morning to avoid drunk/misbehaving riders given that the probability of having those riders is much higher in the evening/night. A few drivers added that they did not like spending the whole evening working

instead of having some social activities, so the morning shift was their preference. It appears that the drivers gave priority to their aversions to decide about their working shift.

> *"I work from 3 pm to 10 pm. Almost always. I really hate the alarm clock in the morning. I like to stay in bed late. So, in the mornings, I just do my things, and when it gets a little later in the afternoon, I think… let's get going…" D3F1*

> *"...nights are not for me. All those drunk people..." P2M3*

b) Demand activity pattern: Working hours in mid-week days may differ from weekends. This is because commuting trips are performed in the morning during a week while leisure rides, as the main trips on weekends, are more requested in the evening. Thus, demand activity pattern would be an influential factor for choosing the working schedule.

> *"...on weekdays, I work during the daytime more, while on the weekends I work more in the evenings." P4F1*

c) Demand prediction: Most of the drivers believed that the city center is one of the main spots where the chance of receiving ride requests is higher. This is because many rides are requested by tourists at hotels located in the city center and also commuters who enter and exit the area.

> *"Mostly I go to the city center. There are the biggest chances of getting a ride… I live in Amsterdam, but not in the center. So, most of the times I will go to the city center... mostly in the mornings. Most hotels are in the center. But it's not only tourists who take Uber… Also working people. People who live and work there." D2P2*

Some drivers do not prefer requests from the city center because they think that most of them are short rides which are not desirable for drivers. Long trips are mentioned by all drivers as the most attractive rides, especially when combined with surge pricing.

> *"I'll move around the edges of the center. Because in the center itself, people just stay there [short rides]. But in IJburg or Zuid [neighbourhoods outside of the city center], you know for sure that people will go towards the center. Those are longer rides." D4P3*

Weather condition, as well as the operation of public transportation and flights, can also influence the drivers' decisions on their spatial-temporal coverage. Many drivers reported that demand is higher on rainy, snowy, and cold days and also in case of a disruption in public transport or flights. An underlying distinction can be drawn between part-time and full-time drivers in this case. As the part-time drivers were less flexible than full-time drivers due to other activities/commitments, they did not tend to change their schedule and service area because of the external factors. While many full-time drivers followed the weather condition and public transport operations through either Uber application or weather forecast/planner applications or their community in order to decide when and where to work.

> *"Disruptions in public transport are also really important. During those moments you'll get a lot of clients." D5F1*

> *"Those kinds of things [disruptions in Schiphol or PT] don't happen a lot... I don't change my whole schedule just because something is happening" D4P2*

d) Moreover, events such as concerts and festivals can potentially impact the drivers' working schedule and area. Drivers are informed about planned events on a weekly basis through a newsletter sent by Uber every Monday morning. Therefore, they can make an informed decision about their working plan.

> *"If there's a party or festival somewhere. Most of the time I'll make sure to be there." D5P3*

e) Surge pricing: Although many experienced drivers believed that surge pricing area is not reliable, some beginning drivers said they checked the application and if surge pricing appeared, they go online. A few drivers reported that the information shown in the offline and online status is different. Sometimes, the offline application overestimates the demand in order to encourage drivers to join the system resulting in larger fleet sizes for the platform.

> *"You also have dynamic prices. You'll see that on your screen. You can also decide what hours you work based on those prices. They try to manipulate it sometimes." P1M1*

f) Experience: Drivers gradually learn when and where to work for earning more money based on their experiences. Thus, experienced drivers could find the places where the probability of getting their favourite trips (e.g., long-distance rides) is higher.

> *"It's just experience. I've driven for Uber for so long and I've driven as a street taxi, so I know everything. You have so many hotels around there. 90 percent of my rides go to Schiphol. You just have to know where to stand. And don't accept everything... I know all the addresses of hotels..." D2F3*

2.3.3 Drivers' Expectations

The interaction of drivers with the platform is based on their knowledge about the system environment and their experience as a professional driver. The more drivers are familiar with the business context, the more informed decisions they can make, so their expectations appear to be more well-grounded. In this section, the expectations and preferences of the drivers are described in four categories including requests, shared rides, income, and low-demand areas.

2.3.3.1 Requests

a) Ride destination: Many drivers believed that they should have been able to see the ride destination before accepting the request so that they could consciously incorporate this information into their decision making. Despite the fact that it is desirable for drivers to have as much information as possible, a few drivers argued that it is not reasonable (given the platform's objectives) to expect to see the destination in advance since most of the short rides might be declined.

> *"What's important for me is that you could see the destination before you accept. Because now, you only see that afterwards." D1F1*

> *"...Then all short rides would be refused. So, they'll never do that" D3F1*

b) Additional information: Some drivers would like to have more detailed information to enable making a more informed decision on accepting/declining requests and finding a suitable spot to pick-up passenger(s). For instance, the luggage characteristics including size and weight, number of passengers, if the rider has a pet or baby, and so on.

> *"Luggage is very important. Sometimes, they have so many bags that don't even fit... An icon on your app for dogs and babies..." D2F3*

"How many people you will pick up, I'd like to know that... I'd like to know if they have children. But I would still pick them up. I have a kid myself; I'd like to do that. [if you know there is a baby] you know that you have to find a good spot to stop." D3P3

c) Rider's photo: Riders are able to see the driver's photo when they request a ride, while drivers do not have access to the rider's photo. Some drivers stated they should have been able to see riders' photo to recognize them and pick them up more conveniently. Otherwise, they argued, riders should not be able to see drivers' photo because if it is about privacy, it has to be a mutual protocol to avoid discrimination.

"I think the profile picture needs to be private. We also don't see the picture of the client. They can make a screenshot for example... why only us and not them?" D1F2

Some studies argue that using the name and photos in the profile is a double-edged sword. On the one hand, it can build trust between two sides, but on the other hand, it may lead to gender and racial discrimination (Fistman and Luca, 2016; Ge et al., 2016)
d) Rider's live location: A few drivers believed that it would be really helpful if they could see the live location of riders. Then, they would manage to pick up the rider more efficiently given that the expected pick-up location is sometimes different from the actual pick-up point.

"The client could be able to choose to share a live location. It would be nice to always see the live location. Sometimes it's a tourist, and then it could be difficult to explain where he could stand, especially when he doesn't speak English very well…" D2P2

e) Pre-booked rides: At this moment, drivers are allowed to see if the received request is pre-booked. One of the drivers suggested that it could be helpful if when she dropped off a passenger, she would be able to see all pre-book trips in that area in advance. It could enable drivers to decide whether to wait there or move to another location.

"They [drivers] would use pre-booking. Then, they would know which rides will come... It would help you decide whether you'll wait or not." D5F1

f) Relocating riders: One of the main concerns of drivers is risky pick-up points. Relocating riders could be a solution to convince drivers to accept requests which appear to have risky pick-up spots. A few drivers suggested that Uber should relocate riders and ask them to find a safer place for being picked up.

"You're not allowed to stop there [Dam square – a risky pick-up point]. They should send the clients somewhere you are allowed to stop. And then we can pick them up there." D5F1

2.3.3.2 Shared rides

Uber does not offer yet its pooled trips product (i.e. Uber Pool) in the Netherlands. Notwithstanding, many drivers disliked the idea of shared rides and the associated matching and pricing mechanisms. Some drivers were familiar with the concept of pooled rides through another ride-sourcing company namely "ViaVan" which exclusively provides on-demand shared transit services in Amsterdam.
a) Pricing: Based on the drivers' understanding of the ViaVan pricing strategy, drivers are paid based on the kilometers travelled, regardless of the number of passengers. Therefore, additional passengers do not necessarily lead to higher earning. Most drivers said shared rides would be

appealing if passengers would have paid separately. One driver said extra pick-up travel time and embarking fee should be considered in the trip fare for each passenger.

> *"...you really have to get both the embarking fee as well as the extra time. So, you can really see it as a separate customer" D6P1*

b) More frequent stops: It is not desirable for drivers to stop because every stop can increase the operational costs as well as the risk of getting fined. A few drivers asserted that they preferred to stop as little as possible and were concerned that shared trips would increase the number of stops.

> *"It's more about that you would have to stop more often, which is already difficult because you are not allowed to stop in many places. The best is to stop the least possible and being able to drive on." D3F2*

c) Conflicts between riders: Some drivers pointed to the possible conflicts which may arise among riders and between riders and the driver especially when one of the riders is in a rush. Despite the fact that the riders requesting shared ride are aware of some possible delays and deviations, there is still, for example, a chance of conflict between riders especially when a rider is in rush and the driver needs to pick up another passenger who has requested a ride, but he/she is not at the pick-up point. A few drivers believed the rider who is in a hurry may put some pressure on the driver which could be stressful for the driver and affect the driver's rating given by the riders.

> *"You are with a client in the car, and you need to pick up the other one. And this person is not at the location, and the other client is in a rush... That's a hassle." D2P2*

> *"... you'll get some pressure from the person that's going to be late... Yeah, you make one mistake and everyone's day is ruined. Take the wrong exit and someone is late and the other as well. It will only get worse…" D5P3*

2.3.3.3 Income

a) Low income: Most drivers complained about their low income due to the platform's high commission fee (25% of each trip) and strong competition between drivers. They suggested that the commission fee should be lowered and the competition between drivers needs to be controlled by imposing a constraint on the maximum number of active drivers in the region.

> *"I [as Uber CEO] would set a maximum of drivers in all big cities. So, a max in Amsterdam and Utrecht. There shouldn't be too many drivers." D2P1*

This is in line with the For-Hire Vehicles (FHV) regulations which have recently been introduced in New York City. In order to comply with the new regulations that aim to increase driver's income and relieve congestion in Manhattan, ride-sourcing platforms have limited the access of drivers to the application in some areas.
b) Minimum age: The other measure proposed by some drivers for decreasing the competition and operational costs was to set a minimum age for Uber drivers. After this suggestion, a discussion was initiated about the consequences faced by experienced drivers because of irresponsibility and the lack of experience of young drivers. The logic behind it is that young drivers cause a lot of accidents which can have ramifications like damaging Uber's reputation

and increasing the insurance fees. Surprisingly, one of the youngest drivers accepted the criticism during the discussion.

> *"...there are so many drivers of 18 to 21…. They're still in school. And during the summer they start working for Uber and then they hit bikers or even kill people. And we have to deal with the consequences for the rest of the year, while they just go back to school." D4F1*

> *"One of the reasons that insurances are so expensive now, is that because so many inexperienced drivers are now on the road. Me as well... therefore more experienced drivers like this gentleman, or that lady have to pay a lot for the insurance, so they are really a victim of that." D1F1*

c) Minimum wage: Many drivers stated that they were promised to earn 1000 euros per week, while it was not realistic. They believed that this misleading and incorrect information is spread by the platform in order to attract more drivers and oversaturate the market at drivers' expense.

> *"I just want to get what they promised, which is about 1000 euros per week" D1P3*

Some of them believed that a minimum wage per hour should be set and if they reach that point, the shift can end. It appears to be a feasible regulatory measure given that ride-sourcing drivers working in NYC benefit from a minimum income of $17.22 per hour (after expenses) following the recent introduction of the FHV regulations in NYC.

2.3.3.4 Low demand areas

a) Spatial bonus: Making a ride to a low-demand area could potentially decrease the utilization rate of drivers given that the probability of receiving a ride is lower there. This is why the spatial bonus is needed to balance between demand and supply and hence reduce spatial disparities by supporting trips to low-demand areas. Some drivers pointed out that this risk needs to be compensated in order to persuade them to accept those rides. For example, a bonus should be set for a certain number of trips to low-demand areas or the commission fee could be lower in some areas (dynamic commission fee).

> *"If you have done 10 rides from a certain place, you'll get a 100 euros bonus. For once, or every 10 rides. I mean, if it's a place where nobody else comes… I think that for certain cities, they should have no commission. If you pick someone up there, you don't have to pay the 25 percent." D2F3*

b) Guaranteed hourly income: Another driver argued that since he could not trust Uber to give him a bonus for 10 rides, he preferred to have a guaranteed hourly income to offer a service in low-demand areas. This comment can also stress the necessity of dealing with the persistent strong mistrust.

> *"If they want me to go to Lemsterhoek [a low demand area in Rotterdam], I just want a guaranteed hourly rate. Not 10 rides. Then I do only 9 and the system might reject me after that. I don't trust that." D3P3*

2.4 Discussion

While we make no claim as to the generalisability of the qualitative results, we propose, as a mean to synthesize our findings, a conceptual model that can be used as further reference for future research. It provides a framework by which it is possible to characterize the main components of the behaviour of these important agents in the ride-sourcing environment. Based on the identified themes in the focus group sessions, Figure 2-2 illustrates the relationship between the tactical and operational decisions of drivers and the factors affecting them.

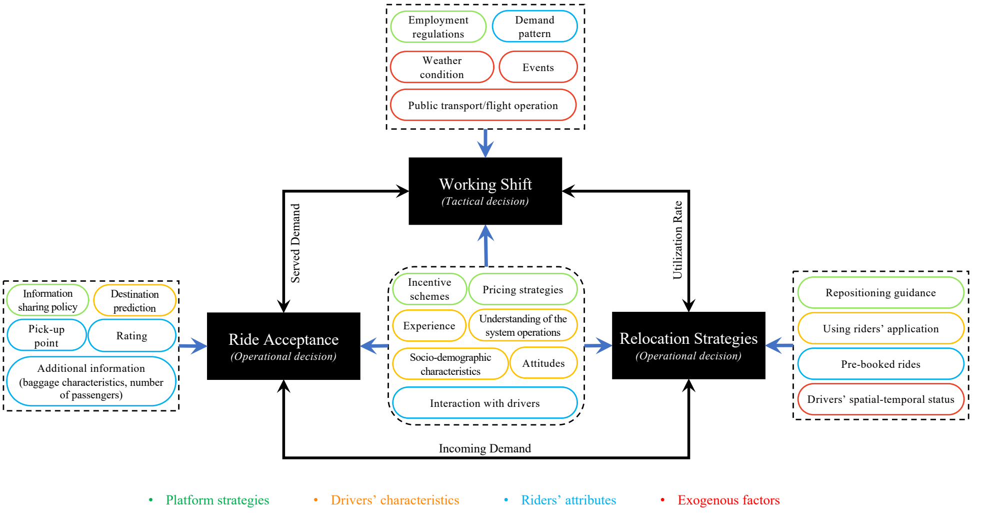


Figure 2-2: Conceptual model of tactical and operational decisions of ride-sourcing drivers

The decisions of ride-sourcing drivers are divided into working shift, relocation strategies, and ride acceptance. These can be influenced by a set of factors categorized into platform strategies, drivers' characteristics, riders' attributes, and exogenous factors (this is depicted by using different colours). The items are also grouped based on the associated decision(s) that they affect. The middle-dotted box represents the factors that affect all the three types of decisions. Platform's incentive schemes and pricing strategies, drivers' experience, understanding of the system operations, socio-demographic characteristics, attitudes, and rider's interaction with drivers impact the working shift, relocation strategies, and ride acceptance behaviour of drivers. Moreover, the platform information sharing policy, destination prediction by drivers, rider's pick-up point, rating, and willingness to share additional information such as luggage characteristics and the number of passengers are likely to play a crucial role in the ride acceptance behaviour. Relocation strategies might be influenced by the platform repositioning guidance, pre-booked rides, drivers' spatial-temporal status after finishing a trip, and the level of competition between drivers which can be checked by the rider's application. At the upper-level, platform employment regulations (e.g., maximum working hours), demand pattern, weather condition, scheduled events such as concerts, the level of service and operations of public transport as well as flights are, in addition to those factors that apply to all decision dimensions, relevant for the drivers to decide on their working shift.

Both tactical and operational decisions are reciprocally connected. Taking into account that the choice of a relocation strategy is time-dependent and that drivers tend to reduce the idle time within their working hours, the relationship between working shift and relocation strategies can be governed by the utilization rate which is the ratio between the occupied time and the working shift. Moreover, working shift and ride acceptance might be linked by the served demand so that drivers assess the shift profitability based on the earned income which is dependent on the characteristics of the accepted rides during the selected working schedule. The operational decisions could also be related based on the incoming demand given that drivers choose a repositioning tactic to find ride requests whereas if they do not receive desirable requests, they may adapt their relocation strategies.

The relative importance of the identified determinants, as well as the inter-dependency between the different driver decision dimensions, should be subject to future research. On the other hand, more items and links can be added to this framework given that some topics have not been covered in the focus group sessions; for instance, refuelling strategies, multi-homing issues (i.e., drivers are connected with more than one ride-sourcing platform at the same time), drivers' car ownership (owning or leasing the car?) and their implications. We believe that the findings from this qualitative research provide input into setting a research agenda focusing on the supply-side dynamics of the ride-sourcing double-sided platform.

2.5 Conclusions

Ride-sourcing platforms have been rapidly introduced in recent years in cities around the globe. As a two-sided platform with gig economy business models, ride-sourcing companies match drivers with passengers' requests. While the interactions between individual drivers and the platform determine the supply-side dynamics, drivers also directly interact with passengers. As such, drivers are in the heart of the ride-sourcing system, yet very limited research attention has been devoted to understanding their motives and perceptions. This is of particular relevance given the existing tension between drivers and the platforms in several countries where these companies operate. To this end, we have conducted a series of focus groups with Uber drivers working in the Netherlands in order to gain deep insights into drivers' perceptions of the system operations and their interactions with the platform.

We found that while all drivers strive to maximize their revenue their strategies can be significantly different amongst each other. The focus group insights indicate that the behaviour of ride-sourcing drivers can be affected by many exogenous and endogenous elements depending on platform strategies, drivers' characteristics, riders' attributes, and exogenous factors.

Ride-sourcing drivers have several main decisions during the course of their work: ride acceptance, relocation strategies, working shift and geographical area. Drivers need to decide whether to accept/decline a ride request based on the limited information provisioned. Although some beginning drivers found it extremely challenging to make an informed decision on requests, most of the experienced drivers believed that many requests should be declined based on some criteria such as pick-up point location, distance to the rider or rider's rating. However, having access to more detailed information about the request's characteristics such as the final destination, trip fare, the number of passengers, and luggage specifications was considered desirable but not available yet in the platform

The level of experience was also found to be an influential factor in drivers' relocation strategies in which many beginning drivers followed the platform repositioning guidance whereas more experienced drivers did not trust the application recommendations such as surge pricing areas and high-demand spots.

The flexibility in choosing a working shift and area in which to operate was appreciated by all drivers as the key reason for joining the system. This freedom enables drivers to plan their working schedule based on their preferences. Given that part-time drivers had less flexibility due to their other commitments and activities, a sharp distinction between part-time and full-time drivers in their decisions on working shift and their will and ability to respond to prevailing conditions was identified.

Given that ride-sourcing platforms constantly introduce new features such as Rematch and maximum working hours, it appears to be crucial to ensure that drivers are adequately briefed on new functionalities. Otherwise, there might be a high risk of misunderstanding of the system

operation which leads to unexpected and seemingly irrational behaviour of drivers. Moreover, we observed a strong mistrust of the drivers in the platform due to what was perceived by the focus groups as an unfair reputation system, unreliable navigation algorithm, high competition between drivers, a passenger-oriented platform, high commission fees and misleading tactics.
Following the insights gained in this study, future research should examine the determinants of drivers' operational and tactical decisions by means of either stated preferences choice experiments or field observations of revealed preferences for ride-sourcing drivers. Estimating choice models for explaining driver's decisions (e.g. joining the platform, working shift, rebalancing, ride acceptance) will facilitate the assessment of the impacts of different policies and system conditions on supply-side dynamics and system performance. This study was conducted in the Netherlands where there is a single ride-sourcing platform (Uber) that dominates the market. An important research direction would be to replicate such a study in a more competitive environment in which several ride-sourcing companies are trying to attract both users and drivers. It should be noted that the data collection was conducted prior to the COVID-19 pandemic. Further insight is required to understand the possible changes to drivers' behaviour due to the new demand patterns, changes in users' travel behaviour, and public health risks. It is also recommended to look at this system through the lens of other stakeholders including platform providers, policymakers, and users to explore their attitudes, preferences, concerns, and limitations. Then, a comprehensive conceptual model may be developed to explain the dynamics between all the agents. Last but not least, the approach used in this research can be applied to study the ecosystem of other gig economy businesses such as delivery and freelancer services.

Chapter 3: Ride Acceptance Behaviour

In Chapter 2, the behaviour of ride-sourcing drivers was qualitatively investigated, and a conceptual framework was proposed to describe the relationship between the operational and tactical decisions of drivers. In this chapter, the identified framework is used to delve into one of the most crucial operational decisions, ride acceptance behaviour.

Ride-sourcing drivers have the choice of either accepting or rejecting ride requests. This decision has direct consequences for all the parties: In the case of declining, both the driver and the corresponding passenger wait for the next possible match and leaves the system if no match is found within their expected time window. Either case is disadvantageous for the platform, given a lower matching rate leading to lower income/market share for the platform and a lower satisfaction of both sides due to experiencing a higher wait/idle time. To this end, ride acceptance behaviour may significantly influence system operations

Although most previous studies have assumed that the drivers are fully compliant (i.e., all the requests are accepted) or the fleet is automated, this chapter aims to unravel drivers' decisions on ride requests and identify their influential factors. First, Section 3.1 elaborates on the implications of the ride acceptance decision, reviews the limited literature, and identifies the research gaps. Then, the research methodology is explained in Section 3.2, followed by Section 3.3, which presents the survey design as well as the data collection process. The results are provided in Section 3.4. The chapter is concluded in Section 3.5.

This chapter is based on the following papers:

- Ashkrof, P., de Almeida Correia, G. H., Cats, O., & van Arem, B. (2022). Ride acceptance behaviour of ride-sourcing drivers in the era of COVID-19. *Presented at the Thredbo 2022 conference in September 2022 in Sydney, Australia.*
- Ashkrof, P., de Almeida Correia, G. H., Cats, O., & van Arem, B. (2022). Ride acceptance behaviour of ride-sourcing drivers. *Transportation Research Part C: Emerging Technologies*, *142*, 103783.

3.1 Introduction

Recent technological innovations in the mobility sector have facilitated the emergence of new modes of transport with ride-sourcing. Offering door-to-door transport services, these two-sided ride-sourcing platforms match passengers requesting rides through a mobile app with semi-independent drivers who do not only serve as chauffeurs but also act as private fleet providers. Ride-sourcing drivers mention benefiting from a considerable degree of flexibility, freedom, and independence as the most indispensable determinants for them choosing to join the platform, in one of the most prevalent examples of the gig economy (Hall and Krueger, 2018; Ashkrof et al., 2020). Drivers can freely decide where and when to drive for the platform. These choice dimensions dynamically impact the supply-demand intensity and limit the control of the central platform over drivers. Moreover, once ride-sourcing drivers decide to drive and select their working shift and area, they receive ride requests and can choose whether to accept or decline them. Drivers' choice making has far-reaching consequences for the system performance. For instance, a delayed response due to the low acceptance rate of drivers increases the waiting time of a rider and thus yielding a lower level of service. No response to a ride request decreases rider satisfaction and may affect customer retention. In both cases, this can have a direct and indirect negative impact on drivers' earnings and the platform profit. Xu et al. (2018) report that approximately 40% of the ride-hailing requests of the Didi Chuxing platform (a ride-sourcing platform in China) were aborted and received no response from drivers on 23 January 2017 in Shanghai. According to the data published by Didi Chuxing in 2017, they report that the platform also faced a low acceptance rate in the other big cities in China, even during non-peak hours, which carried considerable implications for the system performance (e.g., higher waiting time for riders).

A successful match between demand and supply is the key objective in ride-sourcing operations to safeguard the mutual interests of the actors. The rider is transported from the specified pickup point to the desired location while drivers providing the service earn money, and the platform making the matching obtains a profit. Notwithstanding, while passengers aim to minimize the trip costs, waiting and travel time, drivers' objective is to maximize their earnings and minimize idle time. The platform itself strives mostly for profit maximization and satisfying its paying customers. Hence, the matching process is non-trivial due to the need to satisfy contradictory objectives and choices of the stakeholders. That is why various policies and matching strategies are adopted to keep the balance between agents' interests. In such a novel economy, special attention should be devoted to drivers as service suppliers who make the final decision on ride requests impacting the rider satisfaction as well as the platform reputation and revenue. Nonetheless, since the entry of the ride-sourcing business into the market, the relationship between platforms and drivers has been fragile. Judging by the worldwide strikes and lawsuits filed around the world, an increasing tension has recently been observed due to the dissatisfaction of drivers with their working conditions (Hamilton and Hernbroth, 2019). Such dissatisfaction may cause distrust (Rosenblat and Stark, 2015; Wentrup et al., 2019) that can influence drivers' choices, particularly ride acceptance behaviour. Therefore, a win-win efficient matching strategy considers the utilities and limitations of all the parties through the purposeful assignment of ride requests with the nearby drivers with the highest acceptance probability. To assess this probability, it is crucial to gain a better understanding of the supply-side behavioural dynamics under different circumstances.

Research devoted to the supply side has hitherto been primarily focused on operational dimensions such as pricing strategies (Nourinejad and Ramezani, 2019; Xue et al., 2021), relocation guidance (Zha et al., 2018b), matching strategies (Chen et al., 2021; Ke et al., 2021), and estimated travel time (Z. Wang et al., 2018). In most cases, it is assumed that the fleet is operated by either fully automated vehicles which are not currently and may not be soon in operation (SAE International, 2018) or perfectly compliant rational drivers, whereas the evidence suggests that drivers' multidimensional and autonomous decisions can significantly influence the system performance.

A growing body of literature in both journalistic and academic formats has attempted to qualitatively and quantitatively investigate the labour properties of digital on-demand mobility services. Analysing a sample of around 18,400 taxi drivers working in the United States, Wang and Smart (2020) argued that the hourly income of taxi drivers has declined since the introduction of Uber. Leng et al. (2016) concluded that monetary promotion increases drivers' acceptance rate and reduces their idle time using the 40-day trip data of 9000 ride-sourcing services collected in Beijing. Zuniga-Garcia et al. (2020) proposed a framework to measure ride-sourcing driver productivity (i.e., drivers' hourly earnings across two consecutive trips ahead) based on the spatial and temporal variation. They found out that the principal element in ride-sourcing driver productivity is trip distance. Based on the findings, short trips result in lower productivity even in high-demand areas. Through a nine-month qualitative study into the Uber driver working experiences, Rosenblat and Stark (2015) reported that Uber manages the labour force and gains a soft control over drivers using algorithmic labour logistics such as pricing and information dissemination strategies, which constantly interact with drivers and shape their behaviour.

Ride-sourcing platforms collect and utilize historical and real-time information of the demand and supply sides to match ride requests with available drivers. This information is processed and selectively shared with the platform drivers to keep the balance between match quality (the attractiveness of a match – for both riders and drivers) and match rate (the number of matches within a specific time interval) which can conflict (Romanyuk, 2016). Aiming for a high match rate compels drivers to accept less attractive requests which leads to low match quality. On the other hand, a low match rate increases the waiting time for passengers and thereby lowering their satisfaction and loyalty. Moreover, it reduces the occupation rate of drivers, which is affecting negatively drivers' income and may contribute to traffic congestion (Beojone and Geroliminis, 2021), as well as decreases the platform revenue and its control over the workforce. Therefore, maintaining this balance improves system efficiency and the two-sided user experience.

To find such a balance, an in-depth understanding of the behaviour of individual agents is needed. Despite the extensive literature on various aspects of the demand side, the supply-side behaviour remains so far largely unknown. Conducting a focus group study with ride-sourcing drivers working in the Netherlands, Ashkrof et al. (2020) proposed a conceptual framework that characterises the relationship between tactical (working shift selection) and operational decisions (ride acceptance and relocations strategies) of drivers and the potentially related factors. They reported the distinctive behaviour between part-time and full-time drivers, as well as beginning and experienced drivers. In a closely related paper, Xu et al. (2018), found that ride requests with economic incentives such as surge pricing are more likely to be accepted by drivers. To the best of our knowledge, our research is the first study that attempts to comprehensively investigate the quantitative effects of various determinants on drivers' ride acceptance behaviour through undertaking a cross-sectional stated preference (SP) survey. The experimental design includes a wide range of attributes from the existing features that are currently known to drivers such as pickup time, surge pricing, rider rating, idle time and so forth to several hypothetical ones including traffic congestion, trip fare, and guaranteed tip. The findings can provide new insights for algorithm developers, platform providers, policymakers, and researchers working in this field. The focus of this original empirical study is on the unique data collected from Uber and Lyft drivers working in the US where the ride-sourcing platforms have emerged and thrived. Moreover, the target group is extended also to drivers working for Uber and ViaVan (a European shared on-demand transit service) in the Netherlands to tentatively examine the transferability of the results to the European context. Since the survey has been conducted during the pandemic crisis, we also examine the effects of related views and attitudes on drivers' ride acceptance choices.

The remainder of this paper is organised as follows: Section 2 explains the methodologies applied for the data collection and the data analysis processes. Section 3 focuses on the study results including the descriptive analysis, the exploratory factor analysis, and the choice modelling estimation. Lastly, the findings are discussed and the paper is concluded in Section 4.

3.2 Methodology

Due to the binary decision of accepting or declining a request, the choice modelling approach is applied to analyse the data at the disaggregated level and estimate the effects of the identified attributes. This method is based on the probabilistic choice theory that assumes that the decision-making process has a probabilistic nature (McFadden, 1974; Hensher et al., 2005; Bierlaire and Lurkin, 2020). Although humans are presumed to be deterministic utility maximizers, the full specifications of the utilities are unknown to the analyst. This causes stochasticity that is addressed by the so-called Random Utility Maximisation (RUM) approach capturing the unexplained variation using random variables. The utility function of alternative j is mathematically formulated as follows:

$$U_j = V_j + \varepsilon_j \tag{1}$$

Where V_j and ε_j, which are typically assumed to be two independent and additive contributors of the utility function, represent the systematic (deterministic) part and the error term (random parameter), respectively. The error component captures the unobserved effects and randomness in choices. This component is constructed based on distributional assumptions on the joint distribution of the error term vector. It is typically assumed that the random variables are independently and identically distributed (IID) under an EV1 (Extreme Value Type 1) distribution.

In this study, ride rejection is considered as the reference alternative. Thus, all the attributes are incorporated into the systematic utility of the ride acceptance alternative, denoted by V_a which is assumed to be a linear association of the observed variables presented in Eq. (2):

$$V_a = \sum_{k=1}^{K} \beta_k . x_k + \sum_{m=1}^{M} \beta_m . x_m \tag{2}$$

The first term includes the variables x_k that are included in the SP choice sets such as drivers' spatiotemporal status, passenger characteristics, and ride attributes. The second component is associated with the individual-specific attributes x_m such as socio-demographic characteristics of the drivers. β_k and β_m represent the marginal impacts of the choice set attributes and individual-specific factors, respectively.

Given that the attitudes of individuals cannot be directly observed, a set of measurable variables is defined to identify the attitudinal factors associated with the COVID-19 pandemic and include them in the utility function. The latent components are initially identified by conducting an Exploratory Factor Analysis (EFA). Next, the so-called Integrated Choice and Latent Variable (ICLV) model is used to integrate the fitted latent and explanatory variables (Ben-Akiva et al., 2002). The ICLV model consists of two modules including a choice model and a latent variable model. The latent variables are identified using the measurement equations in the latent variable model. In the choice model, utility is also a latent component that is obtained from respondents' choices. Moreover, the structural equations represent the cause and effect relationships and link the observed/latent variables to the latent variables. The structural and measurement models are formulated as follows:

Structural Model

$$X_l^* = \Upsilon_{0l} + \sum_{r=1}^{R} \Upsilon_{lr} x_r + \eta_l , \qquad \eta \sim N(0, \Sigma_\eta) \tag{3}$$

$$U = \sum_{r=1}^{R} \beta_r x_r + \sum_{l=1}^{L} \beta_l x_l^* + \varepsilon, \quad \varepsilon \sim N(0,1) \tag{4}$$

Measurement Model

$$I_i = \alpha_{0i} + \sum_{l=1}^{L} \alpha_{il} x_l^* + \upsilon_i, \qquad \upsilon \sim N(0, \Sigma_\upsilon) \tag{5}$$

$$y = \begin{cases} 0 & if\ U \leq 0 \\ 1 & if\ U > 0 \end{cases} \tag{6}$$

Where index l refers to a latent variable, r to an explanatory variable, i to an indicator; x and x^* to a vector of explanatory and latent variables, respectively; γ, β, α to parameters to be estimated; $\eta, \varepsilon, \upsilon$ to respective error terms with mean 0 and variance Σ (1 for ε) ; and y to a vector of choice indicator. It should be noted that the measurement equations are originally associated with continuous indicators and can also be applied to discrete measures using additional parameters accounting for the discrete levels. A simultaneous maximum likelihood estimation was employed to consistently and efficiently integrate discrete choice and latent models. The ICLV modelling framework is presented in Section 4.3.
The software package PandasBiogeme (Bierlaire, 2020) was employed to estimate the choice models using the Maximum Likelihood Estimation (MLE) approach. The objective of MLE is to find parameter estimates by maximising the likelihood function which includes the choice probabilities related to the alternatives chosen in the data.

3.3 Survey Design and Data Collection

3.3.1 Choice Experiment Design

Central operators apply various information-sharing policies which yield a partial disclosure of information about ride requests and the characteristics of passengers and drivers. Such policies are adopted by ride-hailing platforms which leverage the inherent asymmetry in access to information, providing drivers with limited information when making work-related decisions. Specifically, ride acceptance behaviour is affected by such policies that restrain the thorough assessment of the ride quality (Ashkrof et al., 2020). In both the US and the Netherlands, the information provided to drivers is remarkably limited. Most notably, trip fare and final destination are not shown to drivers before ride acceptance. This so-called blind passenger acceptance is meant to avoid destination-based discrimination (Smart et al., 2015) but at the same time, it can decrease the income for drivers (Rosenblat and Stark, 2015). Despite such ambiguity, drivers can still evaluate the attractiveness of incoming requests based on the available information to maximize the utility of ride acceptance (Ashkrof et al., 2020).
In this study, two scenarios are defined based on the platform information-sharing policy: Baseline Information Provision (BIP) and Additional Information Provision (AIP). In both scenarios, drivers are requested to decide whether to accept or decline ride requests based on a finite set of information provisioned. The BIP scenario mimics the current system operations

where a driver needs to decide on the ride request based upon their current spatiotemporal status, ride attributes, and passenger characteristics. Then, in the AIP scenario, some additional - currently unavailable - information such as monetary features about the same request, is added to the previously shown information giving drivers a second chance to make a choice. This enables investigating which and to what extent factors impact the decision of drivers in the existing system setting, as well as examining drivers' response to the information that is not currently available for them. Moreover, some studies including Morshed et al. (2021) argue that the COVID-19 pandemic has influenced the demand side which can potentially affect how drivers make choices such as accepting more/fewer rides, changing working shift or relocation strategies. That is why the attitudes of drivers towards the pandemic are also investigated in this research. To this end, a cross-sectional SP survey has been designed to collect the required data for further analysis.

Figure 3-1 illustrates the information provision setup in the SP choice experiment. Drivers receive a ride request associated with certain characteristics and they then indicate their choice to accept or decline it. This is the BIP scenario that simulates what drivers presently experience and provides the following set of relevant information:

- Request time: The time when a ride request (ping) pops up.
- Type of request: Private or shared rides.
- Waiting/idle time: The duration between the last drop-off and the incoming ride.
- Pickup time: Travel time between driver's current location and rider's waiting location.
- Last request status: Whether the previous ride request has been declined or not.
- Rider rating: The average rating of the rider given by drivers.
- Surge pricing: A bonus for drivers offered by the platform when demand (locally) exceeds supply.
- Driver's location: The type of built environment where the driver is located.
- Long trip (30+ min): Whether the ride takes more than 30 minutes.

Once drivers make a decision, they are given more information, which is currently unavailable, about the same ride while the baseline information is still shown. The additional information in the AIP scenario includes:

- Trip fare: The gross amount of trip fare.
- Guaranteed tip: We hypothesize that passengers can indicate how much they are willing to tip when requesting a ride and this info can be shared with drivers when a ping pops up. As soon as the ride request is matched, the specified amount of tip is enforced in case the trip is successful.
- Traffic congestion: The estimated delay between the pickup point and the destination caused by traffic congestion.

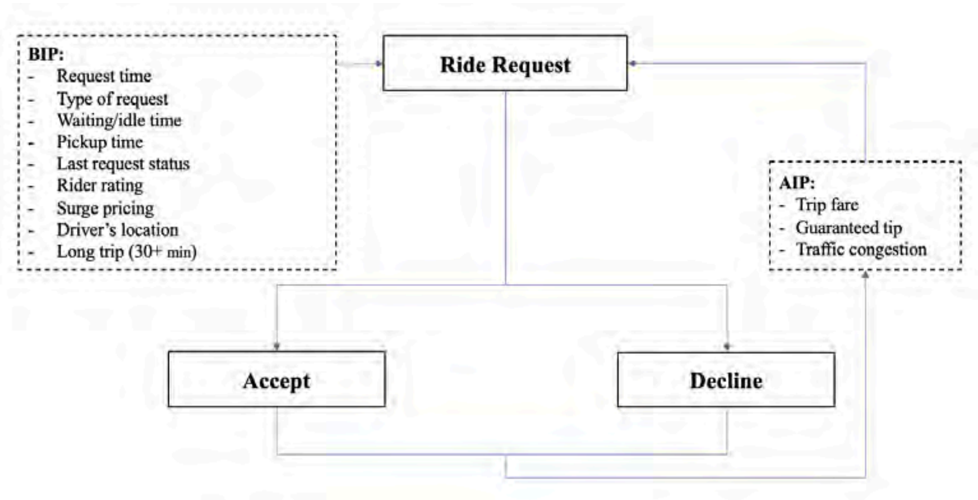


Figure 3-1: Information provision setup in the SP choice experiment

In order to generate the experimental design of the SP survey, we identify the alternatives, attributes, and attribute levels and thereafter the type of design, model specifications, and experiment size are determined. This process is replicated with the updated input to ensure all the elements are in line with the research objectives. In the context of the choice dimension taken into account, Accept and Decline is the binary decision of drivers on ride requests which are considered as the alternatives and the information shown in each scenario are the attributes. Table 3-1 shows the attributes, attribute levels and labels derived by the current system operations, literature, interview with drivers (Figure 2-2), and posts on drivers' forums and then adjusted through a soft launch of the survey.

Table 3-1: Attributes, attribute levels and labels

BIP	**Attributes**	**Attribute levels/labels**
	Request time	Pivoted around the working shift
	Type of request	Uber X, Uber Pool
	Waiting/idle time (min)	0, 5, 15
	Pickup time (min)	5, 10, 15, 20
	Last request status	Declined, Accepted
	Rider rating (stars)	3, 4, 5
	Surge price ($/€)	0, 1.5, 3
	Driver's location	City centre, Suburb
	Long trip (30+ min)	Yes, No
AIP	Estimated trip fare ($/€)	8, 16, 24
	Guaranteed tip ($/€)	0, 1.5, 3
	Delay due to traffic congestion (min)	0, 15, 30

Except for request time, the levels and labels of all the variables are specified in the table. UberX and Uber Pool refer to the private and shared-ride services, respectively. Waiting/idle time ranging from 0 to 20 minutes in this survey indicates the duration of the driver's idle status since the last drop-off. The previous request that has been declined is assumed to play a role in ride acceptance. The average rating of the riders is always shown to the drivers. Travel time between the location of driver and rider varies between 5 and 20 minutes in this experiment.

The location of the driver is presumed to be either in the city centre or suburb. Surge pricing is a value that is added to the trip fare when applicable. If a trip is estimated to be taking longer than 30 minutes, drivers are notified in advance. Estimated trip fare, guaranteed tip, and the delay due to traffic congestion that are not currently available in the app are shown in the AIP scenario.

Request time is assumed to be pivoted around the reported working shift of the respondents. This is because ride-sourcing drivers can freely select their working shift and area thanks to the flexible labour model. Given that demand and supply intensity significantly varies at different times of the day as well as days of the week, drivers may have various experiences depending on the selected working shift. The pivot design ensures that drivers can relate to the temporal characteristics of the experiment by closely resembling the experienced context to improve the response reliability. This also helps to compare the behaviour of individual drivers on different days of the week and various time slots such as peak or off-peak hours and the beginning or end of the shift.

To set up an individual-specific experiment, the segmentation procedure is applied. In this procedure, a set of designs is constructed to segment the population based upon multiple identified reference points (Rose et al., 2008). In this study, time of day is clustered into five categories: morning (5-11), midday (11-15), afternoon (15-19), evening (19-23), night (23-5) and also drivers are assumed to start their shift in one of these categories and work for either 4 hours a day (half a shift) or 8 hours a day (full shift). Therefore, the working shift in a day is divided into 10 groups as shown in Table 3-2. Each column indicates a separate working shift that corresponds to a group of drivers. Accordingly, a library of designs is generated for the request time that has three levels in each working shift. These levels represent the beginning, the middle, and the end of the shift, respectively. Ultimately, each respondent is systematically assigned to one of these pre-defined designs based on their reported working pattern. For example, a driver who starts his/her shift at 16:00 and works for 4 hours in a day is assigned to the Afternoon 4 hours column, hence, the request time levels for this driver will be 17:00, 19:00, and 21:00.

Table 3-2: Segmentation of the request time based on the working shift of drivers

	Morning (5-11)		**Midday (11-15)**		**Afternoon (15-19)**		**Evening (19-23)**		**Night (23-5)**	
	8h	**4h**	**8h**	**4h**	**8h**	**4h**	**8h**	**4h**	**8h**	**4h**
Request time	8	8	13	13	17	17	21	21	2	2
	12	10	17	15	21	19	1	23	6	4
	16	12	21	17	1	21	5	1	10	6

Even though a full factorial design takes into account all the possible combinations of the attribute levels resulting in a more reliable estimation of the parameters, it does so at the cost of imposing a significant cognitive burden on respondents due to generating numerous choice sets. Therefore, a fractional factorial design is used to construct the design matrix. This method may lead to a bias given the loss of some information. Hence, an appropriate strategy should be adopted to minimize such error. To this end, the efficient design method is used to generate an efficient combination of the attribute levels by minimizing the possible standard errors of the parameter estimates. To this end, the efficient design method is used to generate an efficient combination of the attribute levels by minimizing the possible standard errors of the parameter estimates. These standard errors are estimated by calculating the roots of the diagonal of the asymptotic variance-covariance (AVC) matrix. Next, the so-called D-error which is the determinant of the AVC matrix is used to set up the most efficient design with the adequately low $D - error$ (Bliemer and Rose, 2010). Since no prior information about the parameters was available, $D_z - error$ (priors equal to zero) was initially used to construct the choice sets. A pilot of 50 responses was conducted to obtain the priors. Then, $D_p - error$ was applied to minimize the standard error of the estimated parameters and reconstruct the experiment design accordingly. However, due to the small sample size, the estimated priors were statistically insignificant which might result in a less efficient design (Walker et al., 2018). The following equations present the mathematical formulation of the $D - errors$:

$$D_z - error = \det(\Omega_1\ (X, 0))^{\frac{1}{K}} \tag{7}$$

$$D_p - error = \det(\Omega_1\ (X, \beta))^{\frac{1}{K}} \tag{8}$$

Where Ω is the AVC matric, X refers to the choice set design, K denotes the number of parameters, and β is the best estimate of parameters derived from the soft launch.
Moreover, two scenarios need to be designed based on the identified framework. The BIP choice design comprises the existing attributes that are currently shown to drivers. In the AIP experimental design, both existing and hypothetical attributes are included in a way that the levels of the attributes shown in the BIP scenario remain unchanged enabling respondents to reassess the same ride request with more information. To implement this strategy, the model averaging method that allows multiple experiments to be evaluated at the same time is used. In this technique, the estimated AVC matrices are merged into one matrix that can be optimized for an efficiency measure such as $D - error$ (Rose and Bliemer, 2009). Therefore, both BIP and AIP models were designed simultaneously which led to a single design optimized for both models. Furthermore, a level constrained design is used to avoid unrealistic/unfeasible combinations of the attribute levels (e.g., a long ride with a fare of $8). Eventually, 24 choice sets in 4 blocks were constructed using the NGENE software package (ChoiceMetrics, 2018).

3.3.2 Questionnaire Structure

An online questionnaire instrument is used to transform the design matrix into meaningful choice sets that are randomly shown to respondents. Figure 3-2 displays a screenshot of the experiment interface which is carefully designed and checked through feedback from the pilot study to clearly simulate the ride request arrival process in both BIP (left) and AIP (right) scenarios.
Furthermore, a set of screening questions is embedded at the beginning of the survey to ensure respondents are eligible to take part in this survey. The criteria are being older than 18 years old, Uber/Lyft drivers in the US or Uber/ViaVan drivers in the Netherlands (For the sake of consistency, Lyft and ViaVan drivers require to have some experience with driving for Uber), and also working at least once a week. After meeting the requirements, respondents are asked about their working pattern as input for getting assigned to the relevant design. The next part of the questionnaire is the choice experiment followed by some questions about their working pattern, employment status, experience, attitudes towards the COVID-19 pandemic and their socio-economic characteristics.

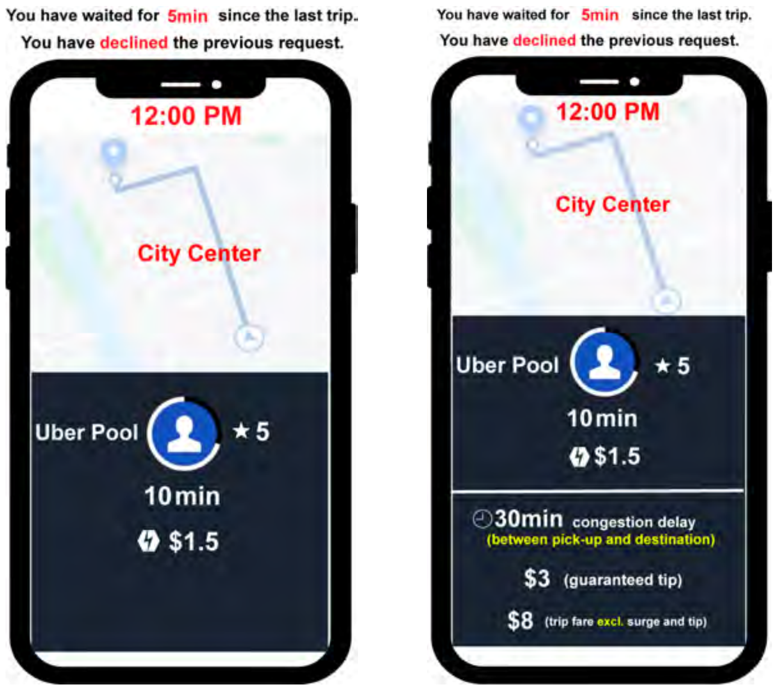


Figure 3-2: Experiment interface in the BIP (left) and AIP (right) scenarios

3.3.3 Data Collection

As a highly specific target population, recruiting ride-sourcing drivers was a laborious task. A panel provider was employed to reach out to Uber and Lyft drivers in the US as well as Uber and ViaVan drivers working in the Netherlands. The data collection process took about three months from November 2020 to February 2021. Respondents were offered $50 (€50 in the Netherlands) to take part in this study. In total, 4367 respondents in the US and 1045 ones in the Netherlands were contacted. The respondents who failed one of the screening questions were screened out. Eventually, a sample of 752 and 68 drivers was drawn in the US and the Netherlands, respectively with an average survey completion time of about 25 minutes. After conducting a thorough data quality analysis, 576 responses in the US and 58 cases in the Netherlands were approved and the other observations were excluded from further analysis due to either short response time or lack of sufficient attention. Despite all the efforts, a larger Dutch sample within the designated time frame was not attained due to the relatively smaller number of active ride-sourcing drivers in the Netherlands. Therefore, the focus of this study is on the US sample and the Dutch data is mainly used for a brief tentative comparative analysis.

3.4 Results

3.4.1 Descriptive Analysis

The working and sociodemographic characteristics of the respondents are reported in Table 3-3. Almost half of the drivers in the US exclusively drive for Uber while only 13% drive solely for Lyft. Multihoming strategy (i.e., working for several platforms simultaneously) is used by

41% of the respondents in the US. Uber is more dominant in the Dutch context where 77%, 2%, and 21% drive for Uber, ViaVan and both, respectively.

Table 3-3: Working and sociodemographic characteristics of the respondents

Item	Categories	Sample Composition (%)		Code in the model
		US	NL	
Platform	Uber	46.4	77.6	NA
	Lyft (US) / ViaVan (NL)	12.8	1.7	
	Both	40.8	20.7	
Experience	Less than 12 months [Beginners]	5.4	10.1	Dummy Variable 1= Beginners 0 = Other
	13-24 months	28.8	23.5	
	25-36 months	27.4	34.2	
	More than 36 months	38.4	32.2	
The most common working day	Monday	28.8	19.0	Dummy Variable 1= Weekend/Friday 0= Other
	Tuesday	12.2	8.6	
	Wednesday	9.0	3.4	
	Thursday	6.8	8.6	
	Friday	21.9	24.1	
	Saturday	16.5	34.5	
	Sunday	4.9	1.7	
Working Shift Start Time	Morning	73.1	67.2	NA
	Midday	14.6	17.2	
	Afternoon	7.5	8.6	
	Evening	3.6	6.8	
	Night	1.2	0.0	
Satisfaction level	Rating the system operations with 4.5/5 out of 5 stars [Fully satisfied]	49.8	17.2	Dummy Variable 1= Fully satisfied 0= Other
	Other	50.2	82.8	
Gender	Male	73.8	72.4	Dummy Variable 1= Male 0= Female
	Female	26.2	27.6	
Age	18-30	16.8	60.3	Continuous Variable
	31-40	66.5	20.7	
	Older than 40	16.7	19.0	
Employment status	Part-time	60.9	62.1	Dummy Variable 1= Part-time 0= Full-time
	Full-time	39.1	37.9	
Education level	Having a college degree or higher [Educated]	66.7	22.3	Dummy Variable 1= Educated 0= Other
	Other	33.3	77.7	

In both countries, the majority of drivers have working experience of 13-36 months as ride-sourcing drivers. Regarding the working days, Monday in the US and Saturday in the Netherlands are the most popular days to work in our sample. About 70% of the respondents start their shift in the morning and work for either 8 or 4 hours. The drivers in the US sample are more satisfied than the Dutch counterparts with around half of them rating the system operations with 4.5/5 out of 5 stars.

Male drivers compose more than 70% of the sample. The average age of the drivers is 36 and 31 years old in the US and the Netherlands, respectively. Around 60% of the sample consists of the drivers who have other work-related sources of income, from here on labelled as part-time drivers. The data also demonstrates that the part-time drivers on average work fewer hours per week than full-time ones do. In our sample, the US drivers are more educated given that more than 65% of the drivers in the US have a college degree or higher, hereafter “educated”, as opposed to the Dutch sample with roughly 20% educated drivers.

The experience, views and attitudes of drivers towards the COVID-19 pandemic are measured by a set of statements presented in Table 3-4. A 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree) was used to capture the opinions of the respondents. The mode (the most chosen response) for each indicator is calculated to measure the central tendency of the sample in each country. Most of the drivers stated that they were concerned about the pandemic and getting infected by passengers and that they also took preventive measures to protect themselves and their clients. Furthermore, they believed that their job had been negatively affected by the pandemic. In some cases, the majority of drivers in the US and the Netherlands had different points of view. Most of the drivers working in the Netherlands neither agreed nor disagreed with changes in working shift and not driving to the busy areas while the US counterparts indicated their agreement with these statements. A contrasting viewpoint is observed between two groups of drivers about the number of incoming requests since the pandemic. The majority of the US drivers stated that they receive more requests compared to before the pandemic whereas the Dutch sampled drivers disagreed with that. Moreover, most of the drivers in the Netherlands believed that the pandemic has changed the way that they work as ride-sourcing drivers while the drivers working in the US had the opposite perception.

Table 3-4: The indicators measuring the attitudes of drivers towards the COVID-19 pandemic

No.	**Statements**	**US**	**NL**
		Mode	Mode
1	I believe that the COVID-19 pandemic has negatively impacted my job as a driver.	5	5
2	I accept more rides than before the pandemic.	4	4
3	To comply with social distancing measures, I don’t like to have more than one passenger in my car.	4	3
4	I don’t care about the COVID-19.	1	1
5	I have completely changed my working shift due to the pandemic.	4	3
6	If I end up in a busy area, I don’t wait there because of the risk of getting infected.	4	3
7	I’m afraid of getting infected by my passengers.	4	4
8	I don’t drive to surge or high demand areas because those areas are more crowded and the risk of virus transmission is higher.	4	3
9	There is no change in what I had been doing as a driver before the pandemic.	4	2
10	I take preventive measures such as wearing a face mask, disinfecting my car, etc. to protect myself and my passengers.	5	5
11	I receive many more rides than before the pandemic.	4	2

3.4.2 Choice Model Estimation and Results

In total, six different models for both BIP and AIP scenarios are estimated for the US data. In each scenario, three types of models are estimated: Primary, Full, and Panel models. The primary model includes only the alternative-specific variables that are provided in the choice experiment. Driver's sociodemographic characteristics and working pattern are added to the ride-related attributes in the full model. This categorisation gives insights into the effects of various sets of variables depending on the application of interest. For instance, the primary model can be applied when no information about the drivers' characteristics and attitudes is available. Given that each driver completed six choice tasks in each experiment, the panel models are estimated using 10000 random draws to account for the correlation between choices made by the same individual (panel effects). The random component (Sigma_ASC_ACCEPT) is highly significant which shows a strong consistency in an individual's choice of whether to accept rides when performing repeated. The values of the estimated parameters are larger in the panel models due to the relaxation of the IID error. Furthermore, the distinction between the AIP and BIP experiments is associated with the additional information shared with the drivers. It should be noted that a bottom-up modelling approach was applied to estimate various models with main and interaction effects. We present and discuss the results of the final models with the highest model fit. In addition, the primary model estimation with main-effects-only in both scenarios is reported in Appendix A.

Table 3-5 summarises the results of the BIP model estimation including the parameter estimates, their significance value, and the model fitness. ASC_Accept represents the alternative specific constant incorporated in the utility function of the ride acceptance alternative. The positive significant parameter suggests an unobserved tendency towards ride acceptance. This implies the overall effects of the factors that have not been included in the experiment are in favour of the ride acceptance alternative.

As expected, Pickup time which refers to the drive time from the driver's current location to the pickup point has a negative effect on ride acceptance. This is due to the fact that the pickup time increases ride disutility since drivers are not paid while driving without a passenger. Moreover, given that no information about the trip fare and the ride destination is available in this scenario, it is not guaranteed that the incurred cost is compensated by the ride. In the full model, an interaction between the pickup time and the employment status of drivers is found significant. Part-time drivers who have other sources of income are noticeably more sensitive (almost three times) to the pickup time than full-time drivers who are entirely financially reliant on the job. This observed reluctance to take a risk may presumably stem from the more constrained working shift which makes them more conscious of time. Moreover, part-time drivers may pick up passengers on their way to/from work which can explain their time sensitivity.

Another temporal component is idle time which has a marginal negative effect on ride acceptance. Drivers' expectations may rise in relation to the time between the last drop-off and the incoming request. This is because waiting for a request leads to being idle which decreases the occupation rate and increases drivers' costs that need to be compensated. Consequently, this result suggests that drivers might prefer cherry-picking with increased elapsed waiting time.

The drivers mostly working during the evening peak hours (16:00-00:00), weekends and Fridays, when demand is relatively higher, are more prone to decline ride requests, everything else being equal. When the frequency of incoming requests rises, drivers become more selective given that a strategical wait may lead to receiving a more profitable ride. Similarly, there is a tendency towards ride rejection at the beginning of the shift and in the city centre. These effects may be due to the expectation of having more opportunities during the remainder of the shift.

The estimated parameter of UberX*Long ride*Rating*Declined ride suggest that there exists an interaction between request type (Uber X/Pool), long-distance trips (+30 min), rider rating, and the previously declined ride. The positive sign implies that the chance of ride acceptance is higher when a private ride (e.g. Uber X) taking more than 30 minutes is requested by a high-rated passenger while the previous request has been declined. The combination of these components indicates a favourable ride type, one that is perceived to be profitable (long ride), less complicated (private ride), trustworthy (high-rated rider), and pressure reliever (offered after a declined ride).

Table 3-5: The results of the BIP models

Parameters	**BIP**					
	Primary	**P-value**	**Full**	**P-value**	**Panel**	**P-value**
ASC_Accept	1.810	0.000	0.417	0.028	0.831	0.000
Pickup time [min]	-0.050	0.000	-	-	-	-
Pickup time * Full-time drivers [min]	-	-	-0.027	0.011	-0.033	0.009
Pickup time * Part-time drivers [min]	-	-	-0.072	0.000	-0.093	0.000
Idle time [min]	-0.017	0.007	-0.018	0.005	-0.023	0.003
Working time [1=Peak hours]	-0.560	0.000	-0.368	0.001	-0.497	0.004
Working day [1=Weekend/Friday]	-0.443	0.000	-0.334	0.000	-0.664	0.000
Driver's location * Shift segment [1= City centre and Beginning of the shift]	-0.303	0.003	-0.284	0.007	-0.384	0.002
UberX*Long ride*Rating*Declined ride	0.091	0.001	0.102	0.000	0.120	0.000
Surge pricing [USD]	0.101	0.002	0.110	0.001	0.139	0.001
Employment status [1=Part-time drivers]	-	-	1.110	0.000	1.420	0.000
Experience [1=Beginners]	-	-	0.353	0.001	0.473	0.041
Gender [1=Male]	-	-	0.421	0.000	0.765	0.000
Satisfaction level [1=Fully satisfied]	-	-	0.607	0.000	0.851	0.000
Education [1=Educated]	-	-	0.080	0.332	0.176	0.272
Sigma_ASC_Accept	-	-	-	-	1.43	0.000
Initial Log-Likelihood	-2395.517		-2395.517		-2395.517	
Final Log-Likelihood	-2031.504		-1959.983		-1823.965	
Rho-square	0.152		0.182		0.240	
AIC	4079.008		3947.966		3677.930	
BIC	4128.191		4034.036		3743.272	

As expected, surge pricing - a spatial-temporal pricing strategy that aims at managing supply-demand intensity - increases the probability of ride acceptance.

When a request is subject to surge pricing, drivers can earn more money which incentivises them to accept it. Surge pricing which is the only monetary variable in the BIP experiment can be used to calculate the value of pickup time by computing the ratio between Pickup time and Surge pricing. Based on the results of the primary model, the value of pickup time is 0.50 USD/min. This implies that a minute increase in the pickup time can be offset by an increase of 0.50 USD in the value of surge pricing. According to the full model, this value for the full-time drivers and part-time drivers is 0.25 USD/min and 0.65 USD/min, respectively.

Among the socioeconomic factors, employment status, satisfaction degree, gender, and experience level have the highest impact on the ride acceptance behaviour, in descending order. Part-time drivers are more likely than full-time drivers to accept ride requests. This may be because they consider this job as an extra income and also their available time is limited. The level of experience also plays an important role in accepting/declining ride requests. Beginners – drivers with one year or less experience – accept rides more often. As drivers learn about the system operational strategies over time, they are better positioned to make more informed decisions. Male drivers as well as highly satisfied drivers – drivers who rated the system operations with 4.5/5 stars - have a preference for accepting rides when limited information is provided. In such a blind decision-making scenario, they may have a higher tendency to trust the platform matching algorithm.

Table 3-6 presents the results of the AIP scenario in which more information is provided to drivers. The results show that some alternative-specific factors such as idle time and driver's location, as well as individual-specific attributes such as working time and gender are no longer significant. In contrast, several new alternative-specific factors including trip fare, guaranteed tip, and congestion level, as well as the individual-attribute education play an important role in explaining drivers' choices. Such changes possibly stem from the importance of monetary information related to all other attributes. As expected, trip fare and tip have a positive impact on ride acceptance whereas the level of congestion indicating the delay between the pickup point and the destination motivates drivers to decline ride requests.

Although the education level was not found to be an influential factor in the restricted information-sharing policy, the results of the AIP models indicate that drivers that attained higher levels of education (i.e. have a college or a higher degree) are more likely to accept rides. Similar to the BIP experiment, beginning and fully satisfied drivers tend to accept more rides. Beginning drivers may lack sufficient knowledge of the system operations to evaluate the ride quality and fully satisfied drivers have a higher trust in the system performance. As observed in the BIP models, pickup time increases the disutility of accepting a ride. It should be noted that the pickup time is more negatively valued compared to the delay associated with traffic congestion. This is arguably because drivers are paid based on trip distance and travel time, so traffic congestion is possibly taken into account although not a desired experience. Driver's employment status still has significant interaction with pickup time. Part-time drivers are more sensitive to pickup time due to more constrained working hours. Additionally, the probability of accepting a ride by a part-time driver is substantially higher than for a full-time driver. As in the BIP scenario, the interaction between request type, long ride, rider rating, and the previous declined ride is still present and leads to higher ride acceptance.

Table 3-6: The results of the AIP models

Parameters	AIP					
	Primary	P-value	Full	P-value	Panel	P-value
ASC_Accept	1.560	0.000	0.388	0.116	0.618	0.052
Pickup time [min]	-0.053	0.000	-	-	-	-
Pickup time * Full-time drivers [min]	-	-	-0.021	0.092	-0.027	0.047
Pickup time * Part-time drivers [min]	-	-	-0.076	0.000	-0.091	0.000
Idle time [min]	-0.005	0.522	-0.005	0.518	-0.008	0.374
Working time [1=Peak hours]	-0.057	0.629	0.027	0.825	-0.155	0.304
Working day [1=Weekend/Friday]	-0.507	0.000	-0.412	0.000	-0.532	0.000
Driver's location * Shift segment [1= City centre and Beginning of the shift]	-0.135	0.252	-0.137	0.253	-0.230	0.086
UberX*Long ride*Rating*Declined ride	0.086	0.011	0.087	0.011	0.105	0.003
Surge pricing [USD]	0.075	0.048	0.076	0.049	0.086	0.040
Trip fare [USD]	0.039	0.000	0.041	0.000	0.049	0.000
Guaranteed tip [USD]	0.090	0.014	-	-	-	-
Guaranteed tip * Full-time drivers [USD]	-	-	0.208	0.000	0.242	0.000
Guaranteed tip * Part-time drivers [USD]	-	-	0.021	0.647	0.012	0.694
Traffic congestion [min]	-0.011	0.002	-0.011	0.002	-0.015	0.001
Employment status [1=Part-time drivers]	-	-	0.981	0.000	1.170	0.000
Experience [1=Beginners]	-	-	0.271	0.023	0.284	0.14
Gender [1=Male]	-	-	0.113	0.259	0.133	0.400
Satisfaction level [1=Fully satisfied]	-	-	0.190	0.029	0.218	0.126
Education [1=Educated]	-	-	0.461	0.000	0.607	0.000
Sigma_ASC_Accept	-	-	-	-	1.140	0.000
Initial Log-Likelihood	-2395.517		-2395.517		-2395.517	
Final Log-Likelihood	-1752.026		-1722.981		-1654.379	
Rho-square	0.269		0.281		0.310	
AIC	3526.053		3481.963		3346.757	
BIC	3593.679		3592.624		3429.523	

Drivers' ride acceptance behaviour can be greatly affected if ride-sourcing platforms ask riders in advance about their minimum willingness to tip and then share this information with drivers when the request appears. Once the request is accepted by the driver, the specified amount of tip is automatically secured if the driver successfully picks up the rider. The results of the primary model suggest that drivers are roughly two times more sensitive to tip and surge price than to trip fare per monetary unit. In other words, one monetary unit of tip and surge is worth at least two monetary units of trip fare. This effect stems from tip and surge being considered as an add-on to drivers' income. Moreover, no platform service fee is deducted from the tip while trip fare and surge pricing are subject to the commission fee (which can be about 25%). It also turns out that there is a statistically significant effect for the interaction between the guaranteed tip and the employment status of drivers. Full-time drivers are more responsive to tip than their part-time counterparts.

In this experiment, the sensitivity to the pickup time and traffic congestion can be benchmarked against the three monetary variables. The values of pickup time based on the trip fare, surge pricing, and the guaranteed tip are 1.36 USD/min, 0.71 USD/min, and 0.59 USD/min, respectively. The trade-offs for the delay time due to traffic congestion are 0.28 USD/min, 0.15 USD/min, 0.12 USD/min respectively. This suggests that monetary promotions are relatively cheaper pricing strategies than the trip fare to compensate for the pickup time as well as the delay caused by a traffic jam.

To discover the relative importance of the attributes included in the choice experiments, a part-worth analysis is conducted. This decompositional method determines the utilities that each attribute and their levels add to the overall utility by calculating the part-worth utilities of each attribute level (i.e., the product between the attribute level and the estimated parameter). The relative attribute importance is obtained by calculating the ratio between the range of part-worth utilities of that attribute and the sum of ranges across all attributes. Table 3-7 reports the relative attribute importance based on the estimated parameters of the Primary model.

Table 3-7: Relative attribute importance based on the Primary model

Attributes	**Relative importance**	
	BIP	**AIP**
Pickup Time	27.7%	28.0%
Idle time	9.4%	-
Working time	20.7%	-
Working day	16.4%	17.9%
Driver's location * Shift segment	11.2%	-
UberX*Long ride*Rating*Declined ride	3.4%	3.0%
Surge pricing	11.2%	7.9%
Trip Fare	-	22.0%
Guaranteed tip	-	9.5%
Traffic Congestion	-	11.6%

The results show that pickup time is the most important determinant in both experiments. In the AIP scenario where drivers are provided with additional (monetary) information, trip fare is the second dominant attribute. This is a plausible outcome given that this attribute determines the major portion of drivers' income. However, as stated before, drivers are more sensitive to guaranteed tip or surge pricing than trip fare per monetary unit. In other words, after pickup time, trip fare is the most crucial determinant for drivers to accept or decline a ride, but when it comes to the comparison between the monetary components, one monetary unit of guaranteed tip or surge is valued over one monetary unit in trip fare. To illustrate, a ride with a fare of, for

instance, \$20 and a guaranteed tip of \$2 is preferred over a ride with a fare of \$22 and no guaranteed tip, everything else being equal.
Due to the relatively small dataset collected in the Netherlands, we could not estimate a statistically sound separate model for the Dutch sample. Alternatively, the data from both countries were merged after unifying the attribute units, allowing the analysis of the combined sample and identifying the possible differences in drivers' behaviour by specifying dummy variables. Among the estimated models, the following differences between the two groups of drivers in the AIP-Primary model were found. Sensitivity to traffic congestion was much higher among the drivers working in the Netherlands, possibly because the level of congestion is lower in the Netherlands, according to the traffic index (Traffic Index by Country, 2021). Furthermore, the trip fare was regarded as nearly two times more important in the Netherlands than in the US. There may exist multiple underlying reasons including the currency, tipping culture (which is less customary in the Netherlands than in the US), income level, and other economic indices. However, these observations need to be further investigated with a larger sample size in the Netherlands in order to draw more conclusive results. The results of the integrated model have been reported in Appendix B.

3.4.3 The COVID-19 Pandemic Implications

To investigate the effect of the COVID-19 pandemic on ride acceptance behaviour, first an Exploratory Factor Analysis (EFA) was carried out to reduce the number of variables through merging the highly correlated observed measures (Henson and Roberts, 2006; Spearman, 1904). In order to ensure that the EFA is applicable, the Kaiser-Meyer-Olkin (KMO) and Bartlett's tests were performed (Kaiser, 1974). To keep a balance between parsimony and comprehensiveness, the Principal Component Analysis (PCA) model was applied (Norris and Lecavalier, 2010) and then several tests and techniques including the eigenvalues greater than 1, scree plot, and parallel analysis were deployed to ascertain the minimum number of components. Due to the superiority of the oblique rotation which takes into account the component interconnections (Flora et al., 2012; Gaskin and Happell, 2014; Price, 2017), the direct oblimin method was used to independently rotate the factor axes and situate them near the observed variables. Consequently, two components summarising the variation of the measures with the factor loading greater than 0.5 were identified using the SPSS software package (Table 3-8).

Table 3-8: Results of the exploratory factor analysis

Indicators	**Components**	
	1	**2**
I believe that the COVID-19 pandemic has negatively impacted my job as a driver.		0.659
I accept more rides than before the pandemic.	0.748	
There is no change in what I had been doing as a driver before the pandemic.	0.825	
I take preventive measures such as wearing a face mask, disinfecting my car, etc. to protect myself and my passengers.		0.720
I don't care about the COVID-19. [recoded]		0.696
I receive many more rides than before the pandemic.	0.848	

Extraction Method: Principal Component Analysis.
Rotation Method: Oblimin with Kaiser Normalization.
Total Variance: 58.02%

The first factor labelled as ride-related COVID-19 attitudes is mainly concerned with the perception of drivers on the impact of the COVID-19 outbreak on ride requests and their operations. The second component is primarily related to the drivers' attitudes towards general effects of the pandemic and is thus labelled as general COVID-19 attitudes. Following the identification of the fitted latent variables and the relevant indicators, an ICLV modelling framework is proposed for integrating the latent variables into the choice model (Figure 3-3).

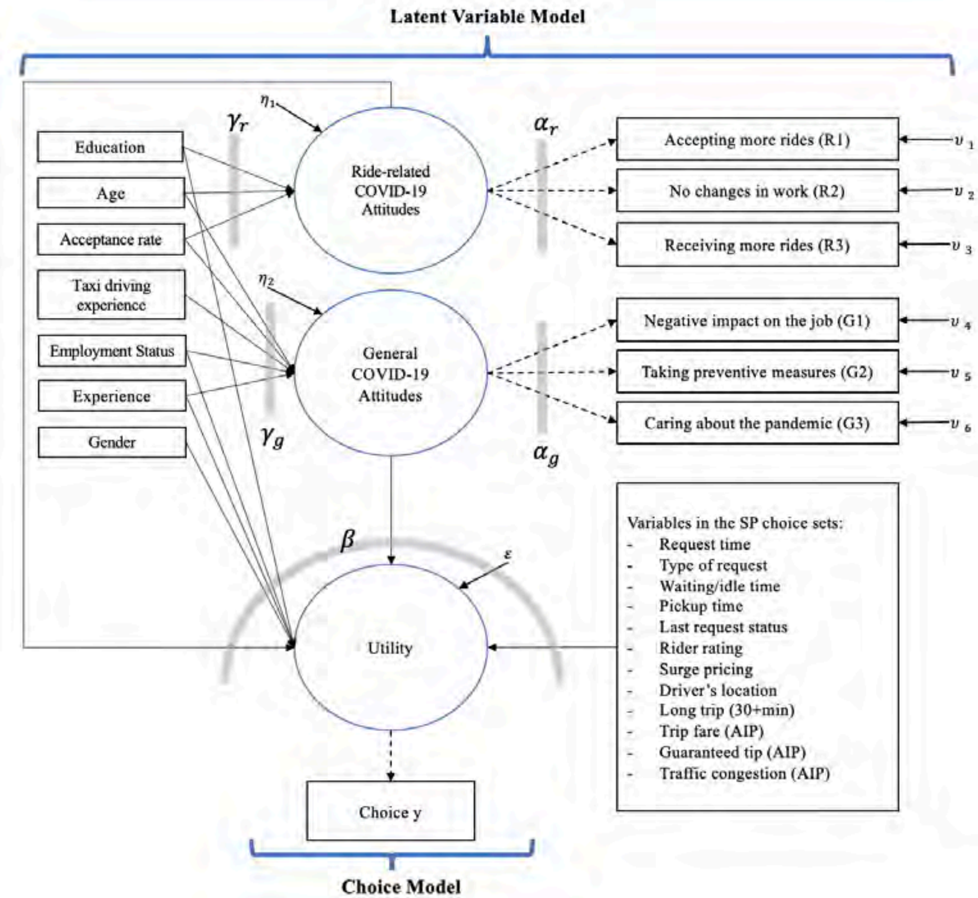


Figure 3-3: Framework of the Integrated Choice and Latent Variables model

As shown in Figure 3-3, the dashed arrows represent the relationship between the latent variables and the associated measures characterised by the measurement equations. The structural equations depicted by solid arrows represent the cause and effect relationships and connect the variables to the latent constructs. For each latent variable, one of the indicators is normalized for identification purposes (R3 and G3)[3]. To account for the panel structure, a random error component is included in the model specifications and the Monte Carlo simulation method with 10000 draws is employed to estimate the joint model. Table 3-9 reports the most relevant results of the model estimation. The full model estimation is included in Appendix C.

[3] The factor loadings as well as the error term scales are normalized to 1 and the constants are set to 0.

The results of the ICLV model show that the COVID-19 outbreak has negative effects on ride acceptance in both scenarios. The estimated parameter of ride-related COVID-19 attitudes is negative. This component is obtained from three attitudinal statements about accepting more rides that can be offset with receiving many more ride requests than before the pandemic and having the perception of no changes in work before and during the pandemic. These drivers have the impression of receiving notably more requests. While the evidence shows that the total number of requests has declined during the pandemic (Du and Rakha, 2021). However, some drivers have stopped working due to the more dramatic plunge in demand at the beginning of the pandemic, the high risk of getting infected, and the possibility of receiving unemployment benefits. This may have changed the ratio between supply and demand in the ride-hailing market so that competition between some groups of drivers has decreased and thus increasing their chance of receiving ride requests. Therefore, receiving more requests or at least having such an impression makes drivers more selective and causes more rejection. Moreover, the negative value of general COVID-19 attitudes suggests that the drivers who are prepared and protect their health by adopting preventive measures have a tendency to decline rides. This might be because of their concerns about the pandemic and the possible risks which echoes their impression of its negative impact on their job.

Table 3-9: Relevant results of the ICLV model

Name	**BIP**		**AIP**	
	Value	**P-value**	**Value**	**P-value**
$\boldsymbol{\beta}$_Ride-related COVID-19 attitudes	-0.579	0.000	-0.529	0.000
$\boldsymbol{\beta}$ _General COVID-19 attitudes	-0.418	0.000	-0.472	0.000
$\boldsymbol{\gamma_r}$_Education [1=Educated]	-0.510	0.000	-0.512	0.000
$\boldsymbol{\gamma_r}$_Age	0.036	0.000	0.035	0.000
$\boldsymbol{\gamma_r}$_Acceptance rate	0.639	0.000	0.625	0.000
$\boldsymbol{\gamma_g}$_Age	-0.063	0.000	-0.062	0.000
$\boldsymbol{\gamma_g}$_Acceptance rate	-1.100	0.000	-1.100	0.000
$\boldsymbol{\gamma_g}$_Taxi driving experience [1=Taxi driver]	-0.759	0.000	-0.697	0.000
$\boldsymbol{\gamma_g}$_Employment status [1=Part-time drivers]	0.336	0.000	0.331	0.000
$\boldsymbol{\gamma_g}$_Experience [1=Beginners]	-0.702	0.000	-0.695	0.000

In the measurement model, all the indicators are significant and their signs are plausible. Based on the results of the structural model, ride acceptance rate and age are the socio-demographic variables that are relevant for both ride-related and general COVID-19 attitudes. Drivers with an acceptance rate of over 70% as well as older drivers are less concerned about the general effects of the COVID-19 pandemic but are positively linked to the ride-related COVID-19 attitudes. Moreover, educated drivers have negative ride-related COVID-19 attitudes. This attitude indirectly leads to a higher acceptance rate which reinforces the direct effect of education level on ride acceptance. Moreover, beginners and drivers with taxi driving experience are more likely to be less cautious about the pandemic and its negative effects. By definition, beginning drivers started their job during the outbreak. Thus, they are likely to be those less concerned about the pandemic amongst the pool of potential drivers with those more concerned less likely to have opted to start working as drivers during the pandemic. Conversely, part-time drivers are more sensitive to the general COVID-19 effects. This is also an intuitive result given that part-time drivers have another job that needs to be taken care of. The signs and interpretations of the other parameters estimated in the choice model are similar to those obtained in the full model.

As recommended by Vij and Walker (2016), the potential benefits of the ICLV model over the reduced choice model (i.e., a choice model without the latent components while all the observable variables are directly included in the model specifications) are discussed. We find out that the log-likelihood of the choice sub-model of the ICLV model calculated as a function of solely the observable variables (Vij and Walker, 2016), is marginally smaller than the loglikelihood of the reduced form mixed logit model in both scenarios (10 and 5 points difference in the BIP and the AIP scenarios, respectively). This implies that the ICLV model does not result in an improvement in goodness-of-fit compared to the reduced form mixed logit model. Nevertheless, some variables (e.g., Age and Acceptance rate) that are significant in the ICLV model are found to be insignificant in the choice model without latent variables. These variables are however incorporated into the structural component of the ICLV model where they are linked with the latent variables. For instance, Age and Acceptance rate that are connected to both latent variables have inverse relationships with the ride-related COVID-19 attitudes and the negative effect on general COVID-19 attitudes. Therefore, the ICLV model does help identify these links and decompose the indirect effects of these variables on ride acceptance behaviour in the context of the COVID-19 pandemic.

3.5 Discussion and Conclusions

This research unravels the ride acceptance behaviour of ride-sourcing drivers through a stated preference experiment performed in the United States and the Netherlands. To the best of our knowledge, this is the first study attempting to comprehensively estimate the determinants of ride-sourcing drivers' ride acceptance behaviour. To this end, a set of potential attributes are identified based on the current system operations, driver-side app, existing literature, interview with drivers, and posts on drivers' forums. Then, two information-sharing policies are defined: Baseline Information Provision (BIP) and Additional Information Provision (AIP). The former scenario solely includes the variables currently shown to drivers in the most commonly used system setting, while additional information is provided in the subsequent phase of the experiment. In total, 576 and 56 qualified responses were collected in the US and the Netherlands, respectively. Subsequently, a choice modelling approach is applied to analyse the data. The focus of this study is on the US data due to the relatively small sample size in the Netherlands.

The monetary variables included in this study are surge pricing, trip fare, and guaranteed tip (i.e., the minimum amount of tip that is indicated upfront by the prospective rider). Surge pricing included in the BIP experiment is the only monetary attribute that is shared with drivers in the current system setting of the ride-sourcing platforms operating in the target area whereas trip fare and guaranteed tip are incorporated in the AIP scenario. Results reveal that guaranteed tip is the most highly valued monetary factor, especially for full-time drivers who are more financially dependent on the ride-sourcing platforms, followed closely by surge pricing. From the drivers' perspective, one monetary unit of tip or surge pricing as added income is considered about two times worthier than one monetary unit of trip fare.

In general, tipping is a pro-social consumer behaviour that is considered as an economically irrational action of customers and typically targets the low-income service providers (Azar, 2003; Elliott et al., 2018). Such a social norm has a profound economic impact on the US service industry (Shierholdz et al., 2017). In the US taxi industry in 2012, tipping comprised around 18% of the annual taxi revenue which is equal to $445 million (Bloomberg and Yassky, 2014).

Currently, Uber riders can tip after they are dropped off. Analysing 40 million observations of Uber tipping behaviour in 2017, Chandar et al. (2019) concluded that more than 15% of the trips are tipped although tips are given privately (no consequences for rider rating) and the chance of having a match with the same driver is fairly low. They also found out that the average amount of tip is approximately $0.5 per trip and for those rides that have been tipped, more than $3 is tipped which is about 26% of the trip fare. In this study, we have introduced a new form of tipping that is determined in advance. When the ride is matched, the specified amount of tip must be paid and naturally, the passenger can tip more to reward the service if satisfying.
This feature can be used when a rider highly disvalues waiting time (e.g., being in a hurry) and intends to persuade nearby drivers to quickly accept the ride. It is effectively a self-determined discriminatory pricing scheme that allows riders to signal their willingness to pay and thereby potentially influence the level of service received. This is in line with the study conducted by Flath (2012) which suggests that passengers with a strong aversion to waiting would tip taxi drivers to reduce the time needed to find a taxi. As opposed to trip fare and surge pricing, tipping is not directly imposed on riders by the platform which makes it less unfavourable from the rider's perspective. The results of this study suggest that such a feature can significantly impact drivers' ride acceptance behaviour. This can also be part of the platform pricing strategy through developing an algorithm that optimally calculates the trip fare and surge pricing based on the guaranteed tip determined by riders. This may lead to a higher acceptance rate and level of service which is beneficial for riders, drivers, and the platform.
Surge pricing is a spatial-temporal pricing strategy that is introduced to address an imbalanced supply-demand relation. However, surge pricing is one of the most controversial topics in the ride-sourcing literature given its enormous implications for all stakeholders involved. On one hand, it is argued that surge pricing is a near-optimal solution that decreases match failure as well as system inefficiency through suppressing the excessive demand and also increases the platform profit (G.P. Cachon et al., 2017; Nourinejad and Ramezani, 2019). Using machine learning techniques, Battifarano et al. (2019) propose that surge pricing can generate more profit if the value is predicted and disseminated to both riders and drivers in advance. On the other hand, surge pricing may lead to strategic waiting for both riders who seek normal price and drivers looking for higher prices which results in inefficient performance due to forward-looking behaviour (Ashkrof et al., 2020; Chen and Hu, 2020; Zhong et al., 2020). The results of this study indicate that surge pricing is an important determinant of ride acceptance behaviour by ride-sourcing drivers. This is in line with the findings of Chen et al. (2015). They found that drivers work longer and flexibly adjust their working shift when surge pricing is present even if they have already hit their daily target. Based on the findings of this research, surge pricing is the second most important monetary attribute that can strongly incentivise drivers to accept rides. The value of pickup time for surge pricing is estimated to be 0.5-0.71 USD/min. This has important consequences for determining the expected response of drivers to the introduction of surge pricing as a function of their travel time from the surge location and the surge price level. Unlike the guaranteed tip, no difference in perspectives of part-time and full-time drivers concerning surge pricing is found.
Nevertheless, employment status is a crucial attribute influencing the choice of drivers. Part-time drivers, who have other sources of income, show a strong preference for accepting ride offers compared to their full-time counterparts. This might be because part-time drivers supplement their revenue from other jobs and also have limited available time restricting their degrees of freedom. Hence, the opportunity costs of part-time drivers are potentially higher which leads to a higher acceptance rate (Baron, 2018).

Furthermore, the experience level of drivers with the ride-sourcing platforms and their operational strategies has been identified as a determinant that influences their choices in various aspects (Miranda et al., 2008; Rosenblat and Stark, 2015; Chu et al., 2018; Noulas et al., 2019; Wang and Yang, 2019). Based on the findings of this study, beginning drivers who have one year or less of experience with ride-hailing tend to accept more rides. Lack of sufficient experience and knowledge to evaluate the characteristics of ride requests and having higher trust in the system performance might be the underlying reasons for this tendency (Ashkrof et al., 2020). In both BIP and AIP experiments, pickup time, especially for part-time drivers, has a negative impact on ride acceptance due to the disutility of driving without a passenger, i.e. unpaid time. Therefore, in order to have a higher acceptance rate, a new matching algorithm can be developed that can calculate the response likelihood of nearby drivers and then offer the request to the driver with the highest probability of acceptance. For instance, less attractive requests can be matched with part-time beginning drivers. The introduction of such measures should consider their potential acceptance amongst drivers.

The COVID-19 crisis has hit many sectors including transportation and specifically ride-sourcing system as a form of shared mobility. Recent studies highlight the immediate and long-term effects of the pandemic on user's behaviour due to hygienic considerations and the financial consequences of the outbreak (Serafimova, 2020; Morshed et al., 2021). This may also apply to the supply side where drivers need to adopt hygienic and preventive measures such as using barriers between passengers and driver, equipping the car with disinfectant, and so forth. The findings of the ICLV model suggest that drivers with a higher sensitivity to the ride-related and the general COVID-19 effects tend to have a lower acceptance rate with the extent of which depending on their personal characteristics. For instance, beginners and full-time drivers are more likely to be less sensitive to the COVID-19 impacts on their job and particularly ride acceptance.

While the small sample collected in the Netherlands does not allow for estimating a full-fledged model, it has been observed that drivers working in the Netherlands are more sensitive to the trip fare as well as traffic congestion. These findings should be further investigated with a larger sample size from the Netherlands and possibly from other European countries. Another limitation of this research refers to the inherently typical bias of stated preference surveys in which respondents face a limited number of attribute levels and may not accurately grasp the choice experiments, especially the AIP scenario that includes several hypothetical new components. It can be insightful to validate the findings of this study through analysing a set of revealed preferences data concerning drivers' behaviour in ride-sourcing environments or field observation of drivers if possible. Moreover, the insights gained in this study can be integrated into ride-hailing analysis models (Kucharski and Cats, 2020) and used to assess the possible effects of driver's ride acceptance behaviour based on various information-sharing policies on the ride-sourcing system performance, including efficiency, level-of-service and profitability. Future research may investigate other aspects of ride-sourcing drivers' decisions such as registration to the platform at the strategic level, selecting working shift at the tactical level, and relocation strategies at the operational level.

Chapter 4: Relocation Strategies

In the previous chapter, ride acceptance behaviour was explored. In Chapter 4, the other operational decision of drivers (i.e., repositioning) is investigated. When the rider is dropped off, the ride is finished. Drivers, therefore, have three so-called relocation strategy options if they tend to continue their shift. They can either wait at certain places, cruise to random places, or drive to some target areas where more demand is expected. Platforms also highlight some areas on the map as high-demand or surge pricing areas. Many studies have assumed that drivers follow the platform repositioning guidance while drivers also have other choices.
This chapter identifies the determinants of drivers' choices on repositioning while being idle. Section 4.1 provides background information on repositioning options and their consequences. Then, the details regarding the survey specifications, data collection, and modelling procedure are provided in Sections 4.2, 4.3, and 4.4, respectively. The model estimation results are presented in Section 4.5. Finally, Section 4.6 provides the relevant discussions and conclusions.
This chapter is based on the following papers:

- Ashkrof, P., de Almeida Correia, G. H., Cats, O., & van Arem, B. (2022). On the Relocation Behaviour of Ride-sourcing drivers. *Presented at the hEART2022 conference in June 2022 in Leuven, Belgium.*
- Ashkrof, P., de Almeida Correia, G. H., Cats, O., & van Arem, B. (2023). On the Relocation Behaviour of Ride-sourcing drivers. *Transportation Letters.*

4.1 Introduction

Ride-sourcing companies - also known as Transport Network Companies (TNCs) – such as Uber and Lyft have been receiving a positive reception from the general public given their growing market share, especially among urban travellers (Conway et al., 2018), and have gained more than one-third of the international taxi market (Bryan and Gans, 2019). Ride-sourcing is a digital two-sided platform that matches ride requests submitted by riders via a mobile app with available drivers who supply a door-to-door transport service. In this setting, drivers are not only chauffeurs but also private fleet providers. Therefore, ride-sourcing drivers can make various choices at the strategic, tactical, and operational levels. At the operational level, drivers can independently decide on whether to wait around the drop-off location of the last rider, drive to the areas recommended by the platform, or cruise freely with the aim of finding a ride request. This freedom has fundamental implications for the system performance in general and the balance between supply and demand in particular. For instance, the unavailability of drivers in a certain region can increase the rider's waiting time and decrease the match rate, and consequently the system reliability. Furthermore, the so-called idle cruising - referring to moving while no passenger is in the car - can contribute to traffic congestion caused by ride-sourcing operations (Tengilimoglu and Wadud, 2021; Tirachini, 2020).

Ride-sourcing platforms are interested in steering individual suppliers so as to keep the balance between supply and demand. This is a complex task due to the unpredictable nature of the dynamic demand and the heterogeneity among service suppliers. Platforms adopt various dispatching algorithms, initiatives, and pricing strategies to efficiently reposition empty vehicles and possibly reduce the fleet size and total vehicle mileage. Using taxi trip data in New York, Vazifeh et al. (2018) propose a near-optimal repositioning framework that can decrease the fleet size by 30%. The mainstream of the literature is focused on the optimal algorithms for empty vehicle routing and repositioning to minimize the number of rebalancing vehicles (Braverman et al., 2019; Wen et al., 2018; Zhang and Pavone, 2016) and fleet size (Iglesias *et al.* 2019, Narayan *et al.* 2021), or maximize the profit of the platform and drivers (Gao et al., 2018; Godfrey and Powell, 2002). Another research direction is concerned with optimal surge pricing as a financial relocation incentive and its implications (Besbes et al., 2021; Chen et al., 2020; Lu et al., 2018). Despite the advanced algorithms that have been proposed in the literature and the variety of strategies tested in practice, related challenges such as a high number of idle vehicles, increasing empty mileage and traffic congestion persist (Henao and Marshall, 2019; Tengilimoglu and Wadud, 2021; Tirachini, 2020). Most of the studies assume that the drivers are fully compliant with the repositioning algorithms and policies of a centralized platform and ignore the behavioural aspects of individual drivers. While drivers' strikes worldwide and related court cases demonstrate a widespread dissatisfaction of drivers with the system operations that causes distrust. Such a distrust leads to drivers' dismissal of the platform suggestions and therefore influences the system efficiency and particularly idle repositioning (Özer et al., 2018). This calls for gaining a better understanding of drivers' behaviour and their response to various policies and strategies.

There is a growing body of literature aiming to explore the behaviour of ride-sourcing drivers in various aspects (Ashkrof et al., 2021; Fielbaum and Tirachini, 2020; He, 2021; Xu et al., 2020; Zuniga-Garcia et al., 2020). Ashkrof et al. (2020) carried out a qualitative analysis of system operations from the drivers' perspective and proposed a framework that maps the relationship between the tactical and operational decisions of drivers. They concluded that even though all drivers attempt to maximize their income, their approach differs considerably depending on the platform strategies, drivers' and riders' characteristics, as well as exogenous factors. Analysing 9000 ride-sourcing trips in Beijing, Leng et al. (2016) found out that the idle time of drivers is reduced when a set of financial incentives are offered by the platform. Zuniga-Garcia et al. (2020) demonstrated that the current relocation and pricing algorithms do not sufficiently take drivers' decisions into account. Using trajectory information of the DiDi drivers in China, Xu et al. (2020) reported clear customer search behavioural differences at various time of the day, especially between full-time and part-time drivers. Publicly available ride-sourcing data does not contain, however, information on drivers' positions when travelling without a passenger on-board and therefore cannot fully reveal drivers' repositioning behaviour and preferences. A tailored experiment is therefore needed to investigate the relocation decisions and preferences of drivers under various circumstances.

To the best of our knowledge, this is the first study that is specifically designed to empirically investigate drivers' relocation strategies and their reaction to the platform repositioning guidance. Furthermore, we also study drivers' responses to potential alternative policies and related information provisioned. To this end, a unique dataset of 576 ride-sourcing drivers working in the US is collected using an original carefully designed stated preference survey, and then a choice modelling approach is applied to analyse the data. The findings offer deep insights for platform providers, algorithm developers, policymakers, and other researchers in this field to facilitate the improvement of supply-side operations and planning. The next sections describe the survey design, data collection process, modelling, results, discussion, and conclusions.

4.2 Survey Design

Ride-sourcing drivers switch between three repositioning states during their work shift: wait/cruise to find a ride request, drive to pick up an assigned rider, and transport a rider to his/her destination. The first state is primarily dependent on the choices of the individual ride-sourcing driver while the others are mainly directed by the platform. These three states are highly interconnected; therefore, they can influence each other. To illustrate, successful matching, which is the main objective of ride-sourcing systems, is dependent on the availability of idle drivers in proximity to the clients which can be affected by their earlier decisions. Idle ride-sourcing drivers who intend to continue their shift and search for a new ride request have several relocation choices: (i) waiting in a place near the drop-off location of the last fulfilled trip; (ii) following the platform repositioning recommendation (e.g., driving to a surge area or a high-demand area), and; (iii) cruising to move away from the drop-off location neighbourhood based on the driver's experience, preferences, and intuition. Given the inherent difference between surge area, where surge pricing occurs due to a local high imbalance between supply and demand, and high-demand area - locations where the demand is expected to be high while the trip fare remains at the normal rate - driving to surge areas and driving to high-demand areas are considered in the following to constitute two distinctive options.

In this study, we consider the choice situation occurring when the driver has recently completed a ride and is searching for a new passenger while both surge and high-demand areas are available. Therefore, four relocation alternatives are defined:

- Staying as much as possible close to the current location (standstill or driving around)
- Driving to a surge area (shown by a coloured area ranging from light orange to dark red in the app)
- Driving to a high-demand area (marked by a blue flashlight icon in the app)
- Cruising freely into a different area based on the driver's experience, preferences, or intuition

We hypothesize this choice to be dependent on various factors including the spatial-temporal status of drivers, information display settings, driver's working pattern, and their socioeconomics characteristics. To investigate the relocation strategies of ride-sourcing drivers and the explanatory factors, a Stated Choice (SC) experiment is designed. Respondents (ride-sourcing drivers) are asked to choose whether to stay around their current location, follow the surge area, drive to the high-demand area, or cruise freely. The choice is first made based upon a set of existing attributes that drivers currently experience with existing ride-sourcing systems. Subsequently, some currently unavailable information and incentives are added to investigate their potential implications in the relocation choice. Figure 4-1 illustrates the experiment set-up employed in this study.

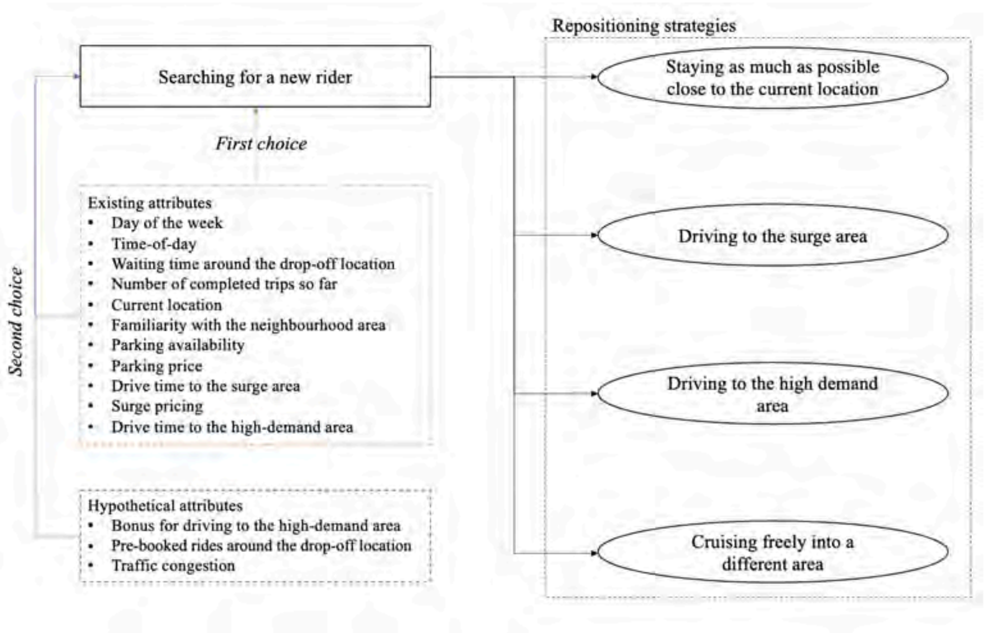


Figure 4-1: The stated choice experiment set-up

All of the existing and hypothetical attributes and their respective levels are identified based on the current system operations, driver-side app display, existing literature and the obtained from the findings of the focus group study presented in Chapter 2 (Figure 2-2), and posts made by drivers on drivers' online forums. Table 4-1 provides more details about the attributes as well as their respective levels and labels.

Day of the Week and Time of Day are pivoted around the driver's working pattern. At the beginning of the survey, drivers are requested to state their working days and hours. This information is dynamically used in the survey to create an individual-specific experiment and ensure that drivers can relate to the study context. The Day of the Week is obtained from the respective question and is directly imported to the choice set, while the segmentation technique is applied to determine the levels of Time of Day.

Using this pivot design approach, a library of designs is constructed and respondents are assigned to one of which based on the designated reference point(s). To this end, Time of Day is divided into ten segments based on the driver's shift starting time which can be one of the five time periods (i.e., morning, midday, afternoon, evening, and night) and working duration that can be either a full shift (8 hours) or a half shift (4 hours). Table 4-2 shows the segmented designs for Time of Day. To illustrate, if a driver starts his/her shift at 10:00 and works for approximately 8 hours, the displayed levels of Time of Day will be 8:00, 12:00, 16:00 for this driver.

Table 4-1: Attributes, attribute levels, and labels

Existing attributes	Attributes	Definition	Attribute levels/labels
	Day of the week	The most common working day	Revealed by the respondent
	Time of day	The time that the decision on repositioning is made	Pivoted around the working shift reported by the respondent
	Waiting time around the drop-off location [min]	The duration of standing still or driving around the last drop-off spot	5, 15, 25
	Number of completed trips so far	Number of fulfilled trips since the beginning of the shift	2, 6, 10, 14
	Current location	The type of operating area	City centre, Suburb
	Familiarity with the neighbourhood area	Whether the driver is familiar with the drop-off point area	Familiar, Unfamiliar
	Parking availability	Whether a parking spot is available in the vicinity	Available, Unavailable
	Parking price [$]	The parking fee in case there is an available parking space	0, 2, 4
	Surge pricing [$]	A bonus that is offered when the demand is notably higher than the supply	1, 2, 3
	Drive time to the surge area [min]	Travel time between driver's location and the surge area	5, 10, 15, 20
	Drive time to the high-demand area [min]	Travel time between driver's location and the high-demand area	5, 10, 15, 20
Hypothetical attributes (not currently used by the existing platforms)	Bonus for driving to the high-demand area [$]	A guaranteed bonus for repositioning to the high-demand area	1, 2, 3
	Pre-booked rides around the drop-off location [min]	A guaranteed ride if the driver is staying around for the indicated duration at the last drop-off location	5, 10, 15, 20
	Traffic Congestion	The level of congestion around the drop-off location	Highly congested, Free-flow

Table 4-2: The levels of Time of Day pivoted around the driver's working shift

Shift starting time	***Morning (5:00-11:00)***		***Midday (11:00-15:00)***		***Afternoon (15:00-19:00)***		***Evening (19:00-23:00)***		***Night (23:00-5:00)***	
Working Duration	**8h**	**4h**	**8h**	**4h**	**8h**	**4h**	**8h**	**4h**	**8h**	**4h**
Time of Day	8:00	8:00	13:00	13:00	17:00	17:00	21:00	21:00	2:00	2:00
	12:00	10:00	17:00	15:00	21:00	19:00	1:00	23:00	6:00	4:00
	16:00	12:00	21:00	17:00	1:00	21:00	5:00	1:00	10:00	6:00

To design the SC experiment with a statistically efficient combination of the attribute levels, a Bayesian efficient design is applied. First, the asymptotic variance-covariance (AVC) matrix is estimated by calculating the negative inverse of the expected second derivative of the loglikelihood function of the choice model. Subsequentially, the standard error of the parameter estimates is obtained from the roots of the diagonal of the AVC matrix and then is minimized to find an efficient design measured by an efficiency measure. The most widely used efficiency measure is the so-called D-error which is the determinant of the AVC matrix (Bliemer and

Rose, 2010). Given that no prior knowledge about the parameter estimates is available, the design was initially constructed using $D_z - error$ assuming the priors equal to zero (orthogonal):

$$D_z - error = \det(\Omega\ (X, 0))^{1/K} \tag{1}$$

Where Ω denotes the AVC matrix, X is the choice set design, and K refers to the number of parameters. Then, a pilot of 50 responses was conducted to estimate the priors and construct the AVC matrix. To achieve a more reliable design that is less dependent on the exact priors, the Bayesian design is used. In this method, the priors are assumed to be random variables expressing the uncertainty about the parameter value. To this end, the so-called $D_z - error$ expressed in Eq. (2) is used:

$$D_z - error = \int \det(\Omega_1\ (X, \tilde{\beta}))^{\frac{1}{K}}\ \emptyset(\tilde{\beta}|\theta)d\tilde{\beta} \tag{2}$$

Where $\tilde{\beta}$ is a random variable with a joint probability distribution function $\emptyset$ given parameter θ. In this study, $\tilde{\beta}$ is assumed to be uniformly distributed: $\tilde{\beta}(u, v)$ where u and v are the mean and standard deviation, respectively, obtained from the pilot phase. The software package NGENE (ChoiceMetrics, 2018) was used to construct 24 choice sets in 6 blocks that were randomly distributed between respondents.

The survey software platform Qualtrics is used to program an online questionnaire that enables the data collection process. To make sure that respondents comply with the survey requirements (i.e., being an active ride-sourcing driver working at least once a week), a series of screening questions is deployed at the beginning of the questionnaire. Eligible drivers are asked to provide details of their working pattern which then, as explained above, feed the segmented design. Next, the introduction to the choice experiment coupled with an example is shown and then respondents are requested to indicate their relocation choices based on the information provided. Figure 4-2 provides an illustration of the choice set displayed in each scenario. The last section in the survey collects respondent-specific information such as the driver's working as well as socio-demographic characteristics including work experience, employment status, job satisfaction level, gender, age, and education.

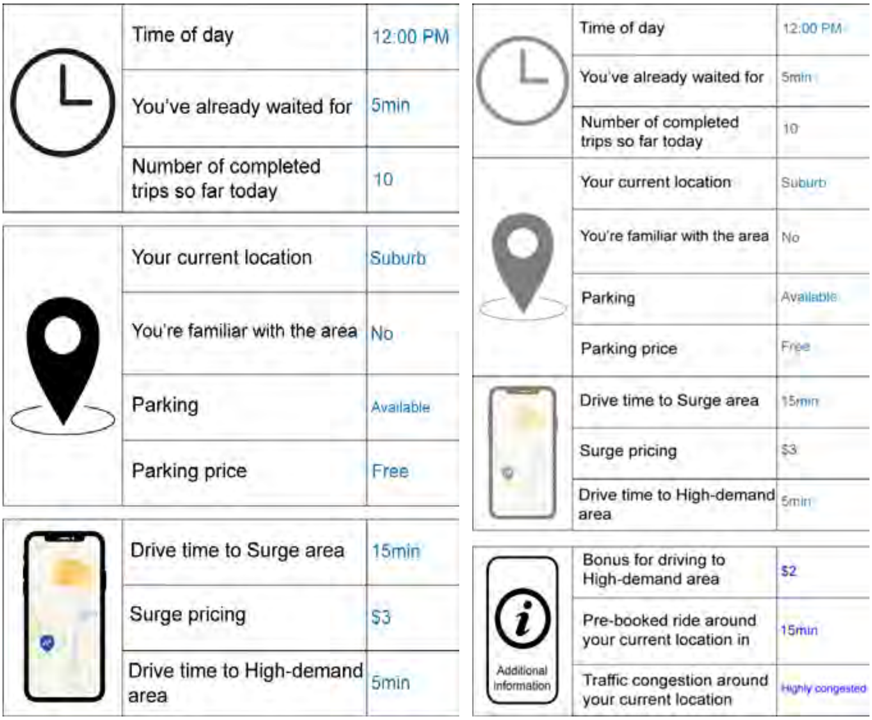


Figure 4-2: Choice set interface with the existing (left) and hypothetical (right) attributes

4.3 Survey Data

In this study, Uber and Lyft drivers working in the United States were selected to be part of the survey sample. A panel company was hired to recruit prospective respondents for this hard-to-reach target group. In total, 752 complete responses were collected between November 2020 and February 2021. A comprehensive data quality analysis was performed to filter out low-quality responses caused by short response time and the lack of sufficient attention. As a result, 576 responses were retained for the analysis.

The descriptive statistics of the data show that around 50% and 15% of the drivers solely drive for either Uber or Lyft, respectively; whereas the remaining of the drivers drive for both platforms (i.e., multihoming). Around 40% of the drivers are fully financially reliant on the ride-sourcing job, labelled as full-time drivers. These drivers also work on average more hours per week than part-time drivers - drivers who have other employment-related income. Regarding work experience, most of the drivers have been working as ride-sourcing drivers for the last 13-36 months. The most common workday is Monday. Furthermore, more than 70% of the drivers work in the morning shift for either 4 or 8 hours. About 70% of the sample consists of male drivers and more than 80% of the drivers are younger than 40 years old.

4.4 Discrete Choice Modelling

A discrete choice modelling approach is applied to unravel the relocation strategies of drivers and identify the influential existing and potential factors. Assuming that both surge and high-demand areas are available, we define four choice alternatives: waiting around, driving to a surge area, heading to a high-demand area, and cruising freely based on their experience and intuition. Then, the identified attributes are used to formulate the utility function of alternative j as follows:

$$U_j = \sum_{k=1}^{K} \beta_{jk} . x_{jk} + \sum_{m=1}^{M} \beta_{jm} . x_{jm} + \varepsilon_j \tag{3}$$

Where the first term refers to the alternative-specific attributes (x_{jk}) presented in the choice experiment, the second component includes the individual-specific factors such as driver's socio-economic characteristics (x_{jm}), and the last component is the error term (ε_j) that captures the unexplained variation under the assumption of being independently and identically distributed. β_{jk} and $\beta_m$are the coefficients vectors representing the marginal effects of the exploratory attributes and individual-specific factors respectively. The Random Utility Maximation (RUM) approach is used to estimate the choice models by the software package PandasBiogeme (Bierlaire, 2020).

To ensure a rigorous and reliable analysis, we use a variety of model specification techniques to identify the critical variables for inclusion in our models. We adopt a hybrid stepwise approach, a combination of forward selection and backward elimination, which allows iteratively including and excluding the attributes and their levels based on their statistical significance and model fit. In order to avoid the issues associated with the stepwise approach, as detailed by Thompson (1995), we take steps to prevent overfitting the model by striking a balance between model fit and complexity. To achieve this, we employ widely recognised techniques, such as the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), to identify and eliminate variables with little predictive power resulting in a more parsimonious and robust model.

In order to ensure that our model specification is not solely based on statistical significance, we have taken a bottom-up approach firmly grounded in behaviour theory. To this end, we conduct a comprehensive review of relevant scientific and grey literature to inform the variable selection process and ensure that variables deemed meaningful and relevant to our research question are included. We rely on the conceptual framework proposed by Ashkrof et al. (2020), which characterises the primary components of drivers' behaviour, including relocation strategies. To further enrich our understanding, we incorporate empirical evidence from first-hand information shared by ride-sourcing drivers on online forums (e.g., uberpeople.net). Ultimately, we select the final model specification based on a balance between statistical fit and theoretical underpinning of expected behaviour.

4.5 Model Estimation Results

Based on the incorporated variables, four models divided into two groups are reported. At the upper level, two scenarios are defined based on the information shown to drivers (existing and hypothetical). For each scenario, two models are estimated distinguished by the variables incorporated into the choice models:

Primary: This model contains solely the variables displayed in the choice experiments.

Full: The working and socio-demographic characteristics of the drivers are added to this model.

This incremental inclusion of categories of variables enables the understanding of the impacts of different types of attributes on the repositioning decision of ride-sourcing drivers depending on the application of interest and the available information. For example, in a future application of the choice model in case that no information about the characteristics of individual drivers is available, the primary model can still be used.

Table 4-3 shows the results of the models built upon the existing and hypothetical attributes. ASC represents the alternative specific constant, the suffixes W (Waiting/staying around), S (driving to the Surge area), H (driving to the High-demand area), and C (Cruising freely) indicate the utility function for which the attribute is relevant.

Table 4-3: The results of the choice models built upon the existing and the hypothetical attributes

Parameters	**Scenario 1** (only existing attributes)		**Scenario 2** (with hypothetical attributes)	
	Primary	**Full**	**Primary**	**Full**
ASC_Waiting	0.207	-0.283	1.12***	0.988***
Waiting Time_W [min]	-0.022***	-0.019**	-0.019**	-0.017**
Number of Trips_S&H	0.080***	0.060***	0.075***	0.048***
Driver's Location_W [1=City center]	0.322**	0.315**	-0.009	-0.022
Familiarity with Neighborhood_C [1=Familiar]	-0.312**	-0.201	-0.443***	-0.334*
Parking Availability_W [1=Available]	0.286**	0.277**	0.363***	0.325**
Surge Pricing_S [$]	0.177***	0.190***	0.165***	0.166***
Drive Time to Surge Area_S [min]	-0.020***	-0.020***	-0.016*	-0.017*
Drive Time to High-Demand Area_H [min]	-0.025***	-0.037***	-0.035***	-0.042***
Working on Weekend/Friday_W	0.350***	0.427***	0.183*	0.236*
Working Shift_C [1=Beginning of the shift]	-0.764***	-0.583***	-	-
Beginners_W&C [1=Beginners]	-	-0.322**	-.	-0.018
Part-time Drivers_W [1=Part-time]	-	0.393***	-	-
High Acceptance Rate_W [1=Acceptance rate>70%]	-	-0.407***	-	-0.369***
Fully Satisfied Drivers_H [1=Fully satisfied]	-	0.371***	-	0.524***
Taxi Driving Experience_C [1=Taxi driver]	-	-0.478***	-	-0.370**
Educated Driver_W [1=Educated]	-	0.406***	-	0.003
Working Shift_W [1=Beginning of the shift]	-	-	-0.476***	-0.344**
Part-time Drivers_C [1=Part-time]	-	-	-	-0.326**
Pre-Booked Rides_W [min]	-	-	-0.021*	-0.020*
Bonus to Drive to High-Demand Area_H [$]	-	-	0.264***	0.177***
Traffic Congestion_C	-	-	-0.407**	-0.283*
Initial Log-Likelihood	**-3194.022**	**-3194.022**	**-3194.022**	**-3194.022**
Final Log-Likelihood	**-2991.151**	**-2938.735**	**-2986.493**	**-2949.844**
Rho-square	**0.064**	**0.080**	**0.065**	**0.076**
AIC	**6004.303**	**5911.471**	**6000.987**	**5939.687**
BIC	**6067.469**	**6009.092**	**6081.38**	**6054.536**

*Significance code: *p-value<0.05, **p-value<0.01, ***p-value<0.001*

We first review the results of the models estimated for the current information display setting and then proceed with reporting the results of the hypothetical scenario. The negative value of Waiting Time_W suggests that drivers tend to move to a different area in case the waiting time around the drop-off location increases. On the other hand, drivers working on weekends as well as Fridays are inclined to wait around their location. This might stem from the relatively higher demand on these days of the week (Rangel et al., 2021). Therefore, drivers can receive more requests with less driving effort (operational costs). Based on the current system setting, at the beginning of the shift, there is a strong aversion to cruise freely. This might be because the risks of self-determining movements are typically higher, therefore, drivers are willing to first try out waiting or following the platform's suggestions. Interestingly, drivers who have had the experience of being conventional taxi drivers prior to joining the platform dislike cruising on their own and have a tendency to chase the platform repositioning recommendations (i.e., high-demand/surge area) or stay at a particular location to receive a ride request. This could be attributed to their past experience in cruising as taxi drivers, leading them to opt for a system that offers more guidance.

The number of completed trips since the beginning of the shift has a positive effect on driving to the surge and high-demand areas. A satisfactory working experience can develop trust between drivers and the platform which leads to a higher willingness to follow the app recommendation. This is in line with the positive significant value of Fully Satisfied Drivers_H that suggests that highly satisfied drivers (i.e., the drivers who gave 4.5/5 out of 5 stars to the system performance) are more likely to drive to a high-demand area indicated by the platform. Moreover, the results of the first scenario suggest that beginning drivers with a working experience of less than one year (most of whom have high trust in system operations) prefer not to wait or cruise freely but drive to the surge and high-demand areas.

The chance of staying close to the current location is higher in the city centre where the probability of receiving a ride while standing still or driving around is higher compared to a suburban area. Parking availability is also a crucial factor that motivates drivers to wait at a particular location to receive a new ride request. Another influential determinant is the employment status of drivers. Part-time drivers tend to stay around. They need to minimize their operational costs during their working time which is limited by other working activities. That is why they might be more reluctant to move into new areas. Drivers who have a college degree or higher are also more inclined to wait, everything else being the same. We also examine the relation between ride acceptance behaviour and repositioning strategy. We find that drivers with an acceptance rate of more than 70% tend to move as opposed to waiting. These drivers are less selective in assessing ride requests and their intention is to find a ride as quickly as possible, paying less attention to its attractiveness.

As expected, surge pricing stimulates drivers to head to the surge area as they can expect to earn more money in the case of reaching the designated area, receiving and accepting a ride request within the surge pricing period. On the other hand, a higher distance to a surge or a high-demand area discourages drivers to follow the platform repositioning suggestions. This is because the demand-supply intensity dynamically changes and the risk of missing the opportunity is higher when the distance increases. The value of drive to the surge area which is the amount of surge pricing for every minute added to the travel time to the surge area is estimated to be roughly 0.11 $/min based on the results of the Primary model.

When drivers are provided with more information and incentives, some new alternative-specific factors start playing an essential role while the impact of some existing variables change. Moreover, even several attributes such as the driver's location, experience level, and education are no longer statistically significant at the 95% level. A strong unobserved preference for staying around is identified in the second scenario. Moreover, being familiar with the neighbourhood area increases the probability of waiting or driving to the surge or high-demand area. Presumably, this familiarity helps drivers to find suitable spots to wait or choose the best route to promptly reach the surge or high-demand area.

The existence of pre-booked rides around the drop-off location can influence the choice of drivers to stay around. This hypothetical attribute gives drivers information about the next potential client who can be picked up within their current zone. If drivers declare their interest in waiting for the incoming request, the ride will be secured for them. Nevertheless, drivers may prefer not to stay if the waiting time is relatively high. Moreover, drivers are more likely not to wait at the beginning of the shift arguably because alternative promotions including surge pricing and high-demand bonus can be expected.

Another variable included in the second scenario is the bonus for driving to a high-demand area. The positive significant value of the estimated parameter suggests that drivers are highly inclined to reach the high-demand area if a promotion is offered. Drivers are about 60% more sensitive to the high-demand bonus than towards surge pricing. This is because unlike surge pricing which is paid only if a rider is picked up, this bonus is guaranteed if the driver is driving towards the high-demand area. This has a potential implication when the platform intends to redistribute the available fleet, especially when drivers do not deliberately follow the surge area. Traffic congestion around the current location turns out to be a significant determinant. A highly congested area discourages drivers to cruise freely given that they probably get stuck in the traffic congestion without picking up passengers – increasing the operational costs. Due to the more restricted time, part-time drivers are less inclined to cruise freely and are more responsive to financial promotions and extra information offered by the platform than full-time drivers, everything else being equal.

4.6 Discussion and Conclusions

We empirically study the relocation behaviour of ride-sourcing drivers. To this end, we designed a stated choice experiment to allow investigating the behaviour of drivers under the existing system settings as well as under a hypothetical scenario exploring their potential responses in the event of new circumstances. In total, 576 qualified responses from Uber and Lyft drivers working in the United States were collected, and a series of discrete choice models were estimated. Four choice alternatives were considered: staying around the drop-off location, driving to a surge area, driving to a high-demand area, and cruising freely. Indicating surge and high-demand areas are the most well-known examples of platforms' repositioning guidance. Moreover, various existing and hypothetical incentives and information about driving conditions and demand characteristics were shared with drivers to identify the influential determinants and their potential effects. We also investigated the impacts of other aspects of driver's behaviour at the tactical level (working shift) and the operational level (ride acceptance behaviour) as well as other individual attributes.

Surge pricing - also known as dynamic pricing - is an incentive offered by platforms to redistribute the available fleet and address local imbalances in supply-demand ratios. Platforms also indicate high-demand areas where demand is relatively high but without changes to the normal rate (for both riders and drivers). In general, platform repositioning guidance is a controversial policy that provokes serious disputes. On one hand, Jing et al. (2018) and Jiao (2018) argue that the unpredictability and ambiguity of surge pricing harbour serious doubts among drivers. On the other hand, surge pricing is considered to be a near-optimal solution that can increase the match rate as well as drivers' income (Ashkrof et al., 2021; Gérard P. Cachon et al., 2017; Lu et al., 2018; Nourinejad and Ramezani, 2019). Conducting a focus group study with Uber drivers, Ashkrof et al. (2020) reported that some drivers, in particular experienced ones, distrust surge pricing as well as high-demand areas and do not follow them. Those drivers believed that the platform misleads them by not reporting surge and high-demand areas in real-time in order to relocate them to a particular location. These are in line with our findings that suggest that following the surge and high-demand area appears to be more attractive for some groups of drivers depending on their working experience, operational performances, and satisfaction level. Namely, relatively inexperienced drivers, as well as highly satisfied drivers, and drivers with a higher number of completed trips since the beginning of their shift are more likely to follow the recommended areas. The level of surge pricing and the expected travel time between the driver's location and the surge/high-demand area are recognized as the other significant determinants.

Additional repositioning guidance options which are not yet available were studied in the hypothetical scenario. Drivers were given some additional information including the existence of any pre-booked rides in the waiting area (associated with the waiting alternative), bonus for driving to the high-demand area, and the level of congestion around their location (which may impact propensity for cruising freely). We found all these variables can play a role in the relocation choice of drivers. Pre-booked rides can be shown to drivers in advance to enable them to assess whether to stay or not depending on the expected waiting time. In order to motivate drivers to relocate to a particular area such as a high-demand area, a guaranteed bonus may be offered. This guaranteed bonus is valued 60% more highly than surge pricing which is not necessarily secured. Obviously, the platform will need to determine how to set such a bonus in a way that is beneficial for its operations. Providing traffic information related to the surrounding area of the current location of drivers may help reduce idle cruising as drivers are more likely not to cruise freely when the area is highly congested. Such platform guidance policies (e.g., information on pre-booked rides as well as traffic congestion and a guaranteed bonus to follow high-demand areas) can be applied to indirectly control/steer drivers and assist them in making more informed decisions and thus possibly improve the level of service, reduce deadhead movements, which have been identified as one of the main drawbacks of ride-sourcing systems (Henao and Marshall, 2019; Tengilimoglu and Wadud, 2021), and improve the wider acceptability of ride-sourcing services.

Our findings can be used to consider the underlying determinants of drivers' behaviour in predicting their relocation choices and designing tailored drivers' incentives. For instance, educated part-time drivers with low acceptance rate who are more likely to stay around can be provided with more information about available parking spots and pre-booked rides in the vicinity, especially when working in the city centre on weekends and Fridays. In contrast, beginning drivers are more willing to respond to detailed information about surge and high-demand areas. This is in line with the findings of Tengilimoglu and Wadud (2021) that acknowledge the behavioural heterogeneity among drivers and conclude that a more effective management is needed to reduce the empty mileage of ride-sourcing services. Given that trust between individual suppliers and the platform is key in the success of such an interactive business model (Özer et al., 2018), the information shared by the platform needs to be accurate and unbiased and communicated in real-time to build the basic trust and develop it over time.

The results of this study can also be used as input to ride-sourcing simulation models to include the relocation behaviour of drivers, explore various policy designs, and investigate their impacts on system operations. Future research may validate the results of this study using revealed preference data.

Chapter 5: Ride-sourcing System Operations

Following the development of the behavioural modelling of ride-sourcing drivers in the previous chapters, Chapter 5 aims to apply the provided insights by modelling the system operations considering the interactions between supply, demand, and the platform. Using agent-based simulation modelling, we investigate the implications of drivers' ride acceptance decisions on ride-sourcing system operations where riders can revoke their requests or reject the received offers, and the platform adopts regular and surge pricing strategies.

First, Section 5.1 establishes the research territory using a comprehensive introductory description. Then, the methodology regarding the agent-based simulation framework and the experimental design is thoroughly explained in Section 5.2. The results are fully presented in Section 5.3. The chapter is concluded in Section 5.4.

This chapter is based on the following papers:

- Ashkrof, P., Ghasemi, F., Krucharski, R. de Almeida Correia, G. H., Cats, O., & van Arem, B. (2023). The Implications of Drivers' Ride Acceptance Decisions on the Daily Operations of Ride-sourcing Platforms. *Presented at the Euro Working Group Transportation (EWGT) conference in Santander, Spain.*
- Ashkrof, P., Ghasemi, F., Krucharski, R. de Almeida Correia, G. H., Cats, O., & van Arem, B. (2023). The Implications of Drivers' Ride Acceptance Decisions on the Daily Operations of Ride-sourcing Platforms. *Under review.*

5.1 Introduction

In recent years, ride-sourcing platforms – also known as Transport Network Companies (TNCs) – have received significant attention. Using a two-sided digital platform, ride-sourcing has a mediatory role in connecting passengers, who submit ride requests through the platform, with available drivers who use the app to find a ride. The ride-sourcing business model has been built upon the gig economy in which independent contractors/freelancers supply the labour market. To this end, drivers are independent service suppliers who offer their private cars to transport riders. Hence, they are not hired by the platform and are paid based on their performance. This gives both platform and service suppliers more flexibility which has been identified as a critical factor for drivers to join the platform (Ashkrof et al., 2020; Hall and Krueger, 2018).

In such a context, drivers are free to make various decisions from strategic to operational levels (Ashkrof et al., 2020). At the strategic level, drivers decide to join the platform depending on several exogenous factors, such as reservation wage (i.e., minimum expected revenue) and market competition. Working shift selection is a tactical decision typically taken based on day-to-day performance. The operational decisions consist of ride acceptance and repositioning behaviour. The former refers to the choice of drivers to accept or decline ride requests, whilst the latter pertains to their relocation strategies while being idle to find a ride. Despite this extensive freedom - labelled by Wentrup et al. (2019) as "illusionary freedom" - drivers do not appear pleased with their working conditions. Recent studies and media coverage have echoed the widespread strikes and the lawsuits filed all around the world due to unsuccessful negotiations between drivers and ride-sourcing platforms (Ashkrof et al., 2020; Robinson, 2017; Rosenblat and Stark, 2015; Techcrunch, 2019; Uberconfession, 2015).

Drivers' dissatisfaction is associated with drivers' distrust of the platform, which often accompanies the gig economy, given the app-based algorithmic communication method (Robinson, 2017; Wentrup et al., 2019). This distrust can, in return, affect drivers' decisions and thereby may have profound consequences on system operations. For instance, when drivers tend not to follow the app repositioning recommendations (e.g., surge pricing area) due to a lack of trust, they may blindly cruise idle to find a passenger which may potentially increase empty mileage (Ashkrof, Correia, *et al.* 2022, Tirachini 2020, Tengilimoglu and Wadud 2021). As another example at the operational decision-making level, once a request is rejected by a driver, it is returned to the queue to be matched with a new driver. This leads to longer waiting time for passengers and therefore a lower level of service. If the waiting time increases due to the unavailability of drivers or more ride rejections, passengers may give up on their request, resulting in a lower rate of successful matches. In this case, passengers may become dissatisfied with the platform and leave the platform altogether. A lower market share leads to fewer incoming requests, resulting in dissatisfaction among drivers, which can lead to a negative feedback loop between the quality of service and demand. This highlights the dynamic complexity and hyperconnectivity inherent to two-sided ride-sourcing systems.

In the ride-sourcing system, multiple stakeholders are involved, each of which follows their objectives resulting in conflicts with other parties' interests. Passengers aim to have a short waiting time and low trip fare. Drivers seek higher income and lower idle time. In addition, the platform intends to maximise the match rate and its profit. The inherent conflict of interests between stakeholders combined with human interactions and interventions fosters system complexity. It is, therefore, essential to consider these interactions when modelling system operations and designing guidelines and regulations.

Research into ride-sourcing has primarily focused on the demand side (Agarwal et al., 2018; Geržinič et al., 2022; Osorio, 2019; Yang et al., 2018). In the supply-side literature, three main research streams are identified. The first research stream assumes that drivers are fully compliant with platform strategies (Gérard P. Cachon et al., 2017; Z. Wang et al., 2018; Zha et al., 2016). Under this assumption, drivers make no independent decisions and completely follow what they are instructed by the platform app. The second stream focuses on an automated fleet centrally operated by the platform (Ruch *et al.* 2018, Winter *et al.* 2016, Zhang *et al.* 2016, Levin 2017, Liang *et al.* 2018, Wang *et al.* 2022). In both cases, the assumptions made on fleet characteristics appear not to be in line with current operations and simply ignore the impacts of driver's behaviour on system performance.

A third, recently emerging research stream is devoted to the study of labour behaviour and preferences of the ride-sourcing supply side. Undertaking qualitative research, Ashkrof et al. (2020) study drivers' understanding of system operations and their interaction with the platform. They propose a framework that explains the relationship between drivers' decisions and identifies the components impacting them. Ramezani et al. (2022) cluster drivers into three primary groups using revealed preference data from Didi Chuxing: (i) part-time drivers working flexible hours, (ii) part-time drivers working in the evenings, and (iii) full-time drivers. They found that such clustering improves the accuracy of the supply prediction models. Ke et al. (2019) comapre the working behaviour of ride-sourcing drivers operating with electric and gasoline vehicles. They found that the working shift decisions of EV drivers are significantly affected by the schedule of their charging time given their general reluctance to charge their vehicle in high-profitable periods.

In the context of the operational decision, Ashkrof et al. (2022) investigate the relocation strategies of ride-sourcing drivers using a unique stated preference dataset. They identify the relevant determinants and find out that drivers' repositioning behaviour significantly varies among drivers depending on their working conditions and socio-economic characteristics. Surge pricing was recognised as one of the most crucial elements to incentivise drivers to relocate to designated areas. Applying a data-driven method, Xu et al. (2018) mention that nearly 40% of ride requests in the Didi Chuxing platform on 23 January 2017 in Shangai, China, received no response. They also report that surge pricing significantly increases the probability of accepting ride requests. Analysing 576 responses collected through a stated choice survey from Uber and Lyft drivers in the US, Ashkrof et al. (2022) estimate the effects of various factors influencing ride acceptance behaviour. They suggest that part-time and beginning drivers tend to have higher acceptance rates. Based on choice model estimations, they conclude surge pricing has a higher marginal utility than trip fare per monetary unit.

On the platform side, a large body of research is focused on the design of matching and pricing strategies (Gérard P. Cachon et al., 2017; Li et al., 2022; Son, 2023; Zha et al., 2018a, 2018b). One of the focal research topics in this area is surge pricing. Surge pricing, a commonly applied strategy in ride-sourcing practices, offers a monetary bonus for drivers when the demand is excessively higher than the supply. It is often considered a black-box algorithm (Chen et al., 2015) due to the lack of transparency and the limited information shared by ride-sourcing platforms. In one of the earliest studies in this area, Chen et al. (2015) reverse-engineered surge pricing by tracking the Uber application operations on 43 mobile phones distributed through San Francisco and Manhattan. Following their research, concerns about the fairness and transparency of the system were raised. They report that most surges stay for less than 10 minutes. Moreover, they found that surge pricing has a significant negative effect on riders and a minor positive impact on drivers. Later, analysing 50 million UberX trips, Cohen et al. (2016) reported the inelasticity of users with respect to surge pricing, yielding a large consumer surplus (6.7 billion dollars in the US in 2015). Guda and Subramaniana (2019) argue that surge pricing should be applied strategically. They suggest that if there is a demand surge in a given zone, the platform should apply strategic surge pricing in a proactive manner. Similarly, if drivers are heading towards a zone with expected high demand and thereby creating a shortage in another zone, the platform should apply surge pricing in the other zone to incentivise more drivers to stay there.

Most of the abovementioned studies address a specific problem, while the interaction and dynamics between the involved parties have remained largely neglected. In order to understand and analyse the complex nature of ride-sourcing operations, the behaviour and interactions of both drivers and riders with the platform need to be considered simultaneously. Bokányi and Hannák (2020) performed agent-based simulation experiments to model a ride-hailing system at the microscopic level. They found that income inequality among drivers is higher in an oversupplied system (i.e., the number of drivers is excessively higher than what would be needed to satisfy the incoming requests) and the extent of which depends on the spatial characteristics of requests, drivers' repositioning strategies, and the platform matching algorithm. Nourinejad and Roorda (2016) study the dynamic ridesharing problem using an agent-based model and a dynamic auction-based optimisation algorithm. They observed higher cost and vehicle kilometre travelled savings for shared rides. Developing a dynamic framework that takes into account the daily participation of drivers in the platform operations, de Ruijter et al. (2022) model the emergence of substantial income disparities amongst drivers.

Given that the information on the supply side is strictly limited due to the reluctance of ride-sourcing companies to share revealed preference data and the fact that stated preference data collection is costly owing to the highly specific target group, drivers' behaviour, particularly at the operational level, is typically neglected or underestimated in simulation studies. Some studies included driver's relocation choice in the analysis of two-sided ride-sourcing platforms by directly adopting past results for taxi drivers' repositioning choices (e.g. Nahmias-Biran et al., 2019). Nonetheless, the other operational decision - ride acceptance behaviour - is rather unique to the ride-sourcing context, and there is a lack of knowledge of its implications.

The identified gap calls for developing a simulation model that incorporates the stochastic dynamic ride acceptance decision of ride-sourcing drivers into system operations while accounting for the decisions made simultaneously by other parties. This modelling approach enables devising new strategies to improve system operational management and performance analysing the consequences thereof. To the best of our knowledge, this is the first study that models in detail the within-day dynamics of a two-sided ride-sourcing platform in which drivers can either accept or decline ride requests submitted by riders in real-time to the platform. One of the key strengths of this research is that the acceptance function is obtained from a study conducted by Ashkrof et al. (2022), specifically designed to identify the variables affecting drivers' ride acceptance decisions. We also take into account riders' decisions and platform matching and pricing strategies. We systematically introduce surge pricing into the model and conduct a comprehensive analysis to investigate how the involved entities respond to this controversial pricing strategy. To this end, we adopt and adapt a discrete-event agent-based simulation framework which is able to realistically reproduce the complex and dynamic relationships between riders, drivers, and the platform. We apply our model to a real-world case study for the urban network of the city of Amsterdam, the Netherlands.

The analysis consists of several layers: First, we analyse the effects of supply-demand intensity on the system-level behaviour. Second, we contrast the performance of a decentralised fleet where individual drivers make ride acceptance decisions and a centralised fleet, where drivers are fully compliant with the system in a way that all the requests are accepted (automated fleet). Third, the implications of drivers' ride acceptance rate are analysed. Fourth, the impacts of surge pricing on system operations are discussed. In the next section, the methodology applied in this research is elaborated.

5.2 Methodology

5.2.1 Agent-based Simulation Model

In this research, we adopt a bottom-up approach for modelling emergent phenomena by means of developing and using an agent-based simulation model in which drivers, riders, and the platform are defined as the model agents. Given the immense complexity arising from the real-time interactions between the ride-sourcing actors, an agent-based simulation model allows capturing the ride-sourcing system dynamics, offers flexibility in adding the system agents with their behaviour, and provides the ability to change levels of detail as well as aggregation and simulate the complex relationship between riders, drivers, and the platform. This modelling approach has been used extensively to study demand-responsive transport modes in urban areas (Martínez et al., 2017).

To study the implications of ride-sourcing drivers' ride acceptance decisions on system performance, we adopt and adapt a within-day discrete event agent-based simulation model in which drivers are individual decision-makers on ride requests, interacting with riders and the platform and integrated into the MaaSSim simulator (Kucharski and Cats, 2022). For the needs of this study, the major simulator is extended by introducing the drivers' ride acceptance and surge pricing functionalities, as detailed below.

5.2.1.1 Matching and ride acceptance

In MaaSSim, a rider agent submits a ride request (r) with a specific origin and destination. Next, the platform agent attempts to match the requests queued in the system (Q_r) with nearby available drivers (d) in the queue (Q_d) based on the minimum pickup time (i.e., travel time between the driver's location and the rider location (P_{rd})). The match between rider and driver (M_{rd}) is calculated based on the matching function presented in Eq. 1:

$$M_{rd} = argmin\ P_{rd}\ , \qquad r \in Q_r\ , d \in Q_d \tag{1}$$

On the supply side, once a driver agent receives a request, they accept or decline it based on a logit model using a utility function. Model specification is based on the model estimation results reported in the study by Ashkrof et al. (2022b), specifically designed to analyse the ride acceptance behaviour of ride-sourcing drivers. Ride-sourcing platforms adopt various information-sharing policies leading to partial disclosure of information about ride requests. In most cases, ride-sourcing drivers make ride acceptance decisions based on limited information. For instance, trip fare and final destination are typically not shown to drivers before ride acceptanc. Therefore, we only include the typical factors related to the current system operations. To this end, the utility function consists of the driver's idle time (I_d), which is the duration between the last drop-off and the incoming request, pickup time (P_{rd}), alternative-specific constant (ASC), and the error term (ε) representing the model stochasticity in the base scenario in which the platform applies regular pricing. Eq. 2 and Eq. 3 represent the acceptance utility function specification and the corresponding probability according to a binary logit function since the driver is not able to see and assess several requests at the same time in the same platform.

$$U_{acceptance} = \text{ASC} + \beta_{I_d} * I_d + \beta_{P_{rd}} * P_{rd} + \varepsilon \tag{2}$$

$$P_{acceptance} = \frac{e^{U_{acceptance}}}{1+e^{U_{acceptance}}} \tag{3}$$

If a driver agent accepts a request, the following events take place in the simulation: heading to the passenger's location, picking them up, driving to the destination, dropping them off, staying at the drop-off point and waiting for the next ride (it is assumed that drivers stay at the drop-off location and make no repositioning decision) or ending the working shift. If the request is rejected, driver and rider agents return to the queue and wait for a possible next match.

5.2.1.2 Driver's profit

Once a ride is completed (i.e., the rider arrives at the destination), the corresponding driver and the platform receive their share of the trip fare based on the platform pricing strategy. When the platform uses regular pricing, the driver's revenue (R_d) is calculated based on the base fare (f_{base}), fare per kilometre (f_{km}), trip distance in kilometre (td_{km}), and the platform commission fee (α). The operating costs (OC_d) depend on the total driving distance (pickup distance plus trip distance) in kilometres (dd_{km}) and the total costs per kilometre (tc_{km}). These expenses consist of gas, tax, insurance, repair, maintenance, depreciation or lease payments. The subtraction of operating costs from revenue yields the driver's profit (P_d). Eq. 4 – Eq. 6 present the driver's revenue, operating costs, and profit, respectively.

$$R_d = (f_{base} + f_{km} * td_{km}) * (1 - \alpha) \tag{4}$$

$$OC_d = tc_{km} * dd_{km} \tag{5}$$

$$P_d = R_d - OC_d \tag{6}$$

5.2.1.3 Surge pricing

Once riders locally outnumber drivers, a bunch of ride requests may be left unserved, potentially harming the platform's reputation. Hence, the platform strives to balance supply and demand using multiple approaches such as surge pricing. In this study, the platform agent applies surge pricing (also known as dynamic pricing) to adjust trip fare based on the real-time ratio between demand and supply. In case surge pricing is applicable, an additional positive term associated with surge pricing (S) is added to the ride acceptance utility function (Eq. 7).

$$U_{acceptance} = \mathrm{ASC} + \beta_{I_d} * I_d + \beta_{P_{rd}} * P_{rd} + \beta_S * S + \varepsilon \tag{7}$$

For surge pricing, Uber employs a geospatial indexing system dividing cities into multiple zones where the real-time ratio between demand and supply is calculated (Chen et al., 2015). We mimic Uber's strategy for implementing surge pricing by dividing the study area into several hexagonal zones using an open-access python package known as H3 developed by Uber (Uber, 2022a). In each zone, we record the real-time ratio between demand and supply. If this ratio is greater than one, then this implies that the system is undersupplied, and surge pricing should be applied.

We consider a surge multiplier ranging from 1x to 5x with an interval of 0.1, which is in line with Uber operations (Chen et al., 2015). The multiplier is determined based on the following surge function that depends on the real-time ratio between demand and supply in zone i ($(D/S)_i$). As shown in Figure 5-1, the function is bounded by: (i) a minimum demand-supply ratio of 1 (i.e., perfect local balance between supply and demand) and an absolute maximum ratio between demand and supply (D/S_{max}) in all zones on the x-axis; (ii)- a minimum surge multiplier of 1x (i.e., regular price) and a maximum surge multiplier of 5x on the y-axis. We specify a linear function for estimating the surge multiplier based on the real-time ratio between supply and demand in any given zone. Eq. (8) mathematically presents the surge function yielding the surge multiplier in zone i (SM_i).

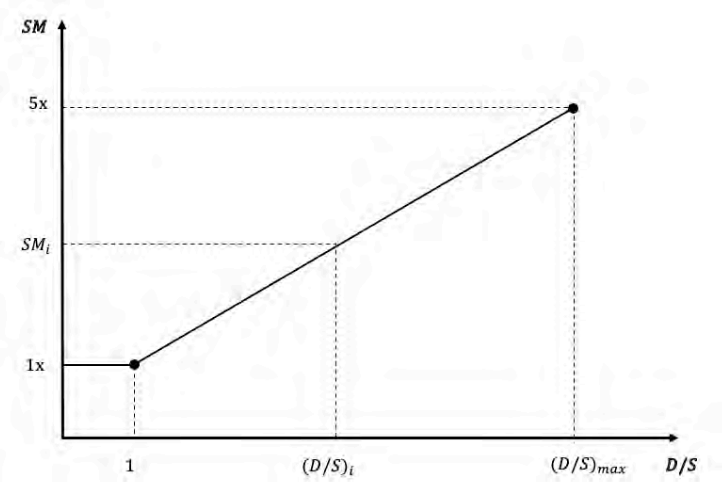


Figure 5-1: Surge Multiplier Graph

$$SM_i = \begin{cases} 1 + \frac{4*\left(\left(\frac{D}{S}\right)_i - 1\right)}{\frac{D}{S}_{max} - 1}, & \left(\frac{D}{S}\right)_i > 1 \\ 1, & \left(\frac{D}{S}\right)_i \leq 1 \end{cases} \tag{8}$$

Once the surge multiplier is determined, the trip fare is updated in the system, and the driver's revenue is calculated based on Eq. (9):

$$R_d = (f_{base} + f_{km} * td_{km}) * SM_i * (1 - \alpha) \tag{9}$$

As mentioned earlier, the surge pricing strategy aims at restoring the balance between demand and supply. This is achieved by retaining the ride requests for which the willingness to pay is the highest. To account for the impacts of surge pricing on the demand side, we adopt the demand elasticity estimated by Cohen et al. (2016), who conducted a regression discontinuity analysis. We obtain the probability of an offer being accepted by riders based on the applied surge multiplier (Figure 5-2).

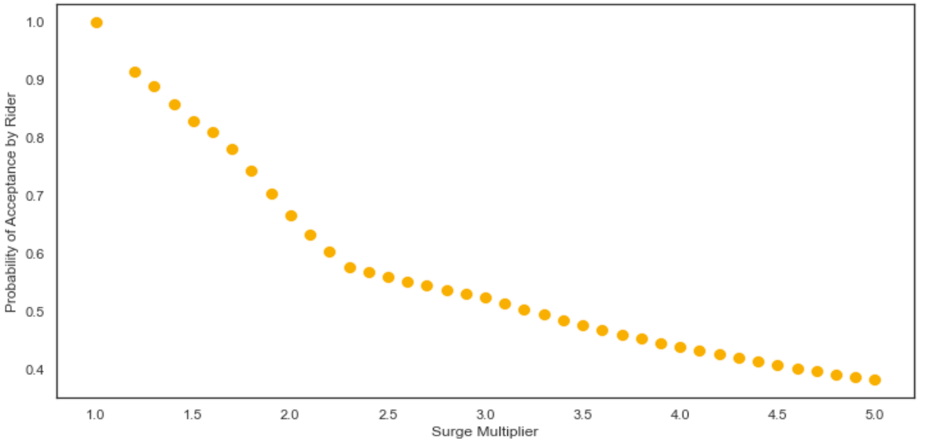


Figure 5-2: Demand elasticity based on surge multiplier (Cohen et al. 2016)

5.2.2 Experimental Design

We apply the developed simulation framework to the city of Amsterdam, the Netherlands, where merely non-shared (UberX) services are available. According to the municipality of Amsterdam (GemeenteAmsterdam, 2019), around 8 million taxi/ride-sourcing trips were made in 2019 in Amsterdam, resulting in an average of 22,000 rides per day. In order to study the within-day ride-sourcing system operations, we set the simulation starting and ending times at 8:00 and 16:00 to cover a typical working shift of 8 hours. Given the non-uniform distribution of demand within a day, we assume 10,000 ride-sourcing rides out of 22,000 daily rides are made during the simulation time. The demand is sampled from a dataset of trips of 3 kilometres or longer obtained from an updated version of the activity-based Albatross model (Arentze and Timmermans, 2004). Given that the matching time of Uber reportedly takes seconds (Medium, 2022; Uber, 2022), we assume that riders revoke their requests once no offer is given within 3 minutes.

We perform experiments for fleet sizes varying between 100 and 1000 drivers with an increment step of 100, enabling us to analyse the effects of the supply-demand intensity. Driver agents are generated based on a negative exponential distribution function to ensure more drivers are placed in the city centre where more demand is expected. Drivers' working shift matches the simulation time, i.e., no working shift decision is made. Vehicle speed is assumed to be constant at 36 km/h. We consider two types of fleets: a) a decentralised fleet in which drivers make ride acceptance decisions. b) a centralised fleet where drivers accept all the requests (fully compliant). Then, the performance of both fleets is compared to provide deeper insights into the implications of drivers' ride acceptance decisions. We assume that only one platform is operating in the city, so multi-homing (i.e., driving for multiple platforms) is not applicable.

Based on the models estimated by Ashkrof et al. (2022), the parameters of the ride acceptance functions, ASC, β_{I_d}, $\beta_{P_{rd}}$, and β_S, are set to 1.810, -0.017, -0.050, 0.101, respectively. Using the Uber price estimator tool, the base fare (f_{base}), the fare per kilometre (f_{km}) are set to €2, €1.2, and €5, respectively. The platform commission rate is 25% (α), in line with the current Uber operations in Amsterdam. The operating cost of drivers (OC_d) is set to €0.5 per kilometre (Standard mileage rates (2021)). Given the stochasticity of the simulation process, several experiment replications are needed to attain statistically robust results. The number of required replication runs is set to five as it is found to obtain results with a confidence level of 95%. We use the average values to conduct the analysis at the aggregate level.

5.3 Results

The results of the experiments are presented and analysed along four dimensions: the impacts of the supply-demand intensity on the system operations (Section 3.1), the performance of a centralised (automated) fleet versus a decentralised fleet operated by drivers making their decisions on ride requests (Section 3.2), the effects of ride acceptance rate on drivers' performance (Section 3.3) and an analysis of applying surge pricing and its consequences for system and drivers' performance (Section 3.4).

5.3.1 Supply-demand Intensity

First, we analyse the passenger waiting time as a function of the fleet size. Figure 5-3 presents each fleet size's corresponding mean, standard deviation, and kernel density estimation (KDE). What is striking is that the average passenger waiting time does not necessarily decrease for larger fleet sizes. From 100 to 300 drivers, it is observed that the average waiting time even increases with the fleet size which might be counter-intuitive. This can be explained by the trade-off between match rate (i.e., the percentage of rides matched within a specific time interval) and the match quality (i.e., the attractiveness of a ride such as pickup distance which is the distance between the driver's location and the pickup point). When the fleet size is 100, 6,224 out of 10,000 requests are rejected which results in a total match rate of 38% while the average pickup distance is 1.32 kilometres. When 100 more drivers are added to the system - resulting in a fleet size of 200 - the match rate rises to 71%, whereas the match quality decreases with an average pickup distance of 1.72 kilometres leading to a higher waiting time for the passengers. The average waiting time peaks with 300 drivers, in which the total match rate reaches 92% and the pickup distance levels up to 2.81 kilometres.

Fleet Size	Passenger Waiting Time	
	Mean (Second)	Standard Deviation
100	190.35	90.57
200	217.07	142.52
300	303.24	231.71
400	187.57	204.26
500	124.49	142.18
600	109.25	138.28
700	101.01	144.17
800	96.71	127.75
900	93.76	138.54
1000	88.73	134.74

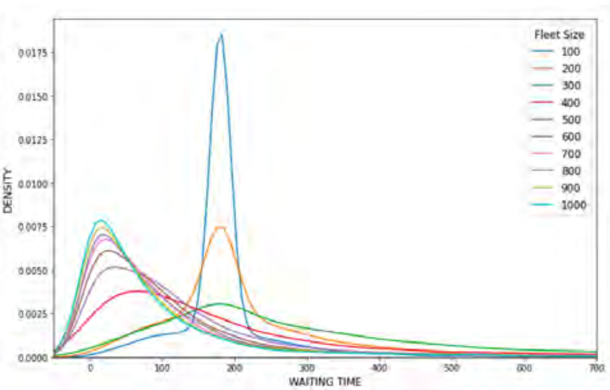


Figure 5-3: Passenger waiting time metrics

The results show that in an undersupply state where the number of requests is excessively higher than the number of available drivers (that point will depend on the network size and demand, and in our application appears to be for fleets smaller than and equal to 300 drivers), a higher match rate is achieved by a larger fleet size at the expense of match quality (i.e., higher pickup distance). When the system is extremely undersupplied with 100 drivers, most requests remain unserved due to the limited number of drivers. Therefore, once a driver is available, they are immediately matched with a nearby rider. In the moderately undersupplied state in which a total of 300 drivers are included in the system, the match rate significantly increases as more drivers are available to serve requests. Nevertheless, the system is still undersupplied and drivers are scattered across the network. In this state, the operator attempts to match more requests with the available drivers even if the pickup distance is relatively high, leading to higher waiting time for passengers. As can be seen, the average passenger waiting time is around 35% lower with 100 drivers compared to a fleet consisting of 300 drivers. In contrast, the match rate is about 55% higher in the moderately undersupplied state. Hence, the supply-demand relationship is crucial to govern the balance between match rate and quality.

With a fleet size of 400, the system seems to reach a balance between supply and demand given that all the requests during the simulation period are served (i.e., 100% match rate). Once the number of drivers reaches this threshold, a sharp drop in the passengers' average waiting time is observed. From this point onward, the waiting time pattern changes and the average value constantly decreases with the growing fleet size, as illustrated in Figure 1. This is because the number of drivers is (more than) sufficient to cover all requests with shorter pickup distances (e.g., 1.84 kilometres with 400 drivers). As the system state changes from balanced to oversupply (around 500 drivers and more), the likelihood that drivers are available in the vicinity of requests increases leading to a decrease in the average passengers' waiting time. Nonetheless, the rate of reduction decreases as the fleet size increases in the oversupply state bandwidth since fewer gains can be obtained.

Next, the performance of the ride-sourcing supply side is analysed starting with the drivers' revenue. Figure 5-4 shows the metrics associated with drivers' revenue for various fleet sizes. As expected, the average revenue of the drivers reduces as the fleet size becomes larger for a constant demand level. We do, however, observe that once the number of drivers exceeds 500, this income rate of reduction due to the joining of more drivers decreases. Another observation concerns the income variation which sharply rises once the system state changes from being undersupplied to balanced and oversupplied. This might owe to higher competition amongst drivers.

Fleet Size	Revenue	
	Mean (Euro)	Standard Deviation
100	248.38	7.55
200	234.39	8.10
300	205.29	9.46
400	168.76	38.89
500	135.09	47.17
600	112.14	45.52
700	96.28	43.31
800	84.01	43.63
900	74.73	41.20
1000	67.14	39.68

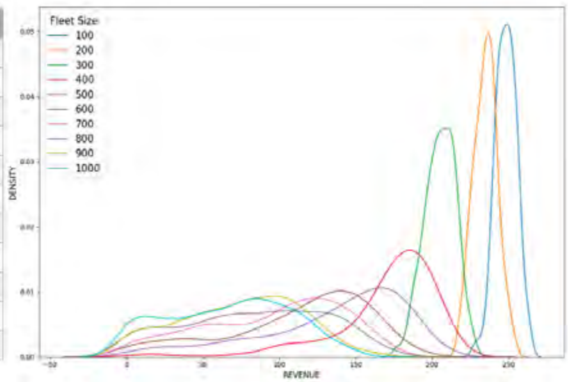


Figure 5-4: Driver's revenue metrics

Trip distance (the total distance travelled by each driver with at least a passenger during their shift) is the key determinant of the driver's income. Given that the average trip distance is similar in all the scenarios (5.5-5.9 km) regardless of the fleet size, the difference in total trip distance stems from the total number of rides made by each driver. The average number of rides per driver decreases as the fleet size increases. This is an intuitive outcome given that once fewer drivers are available in the system, more requests are assigned to each of them. Moreover, given that in the oversupplied state, the average number of rides per driver during the shift does not decrease dramatically with the increase in the fleet size, the income reduction is also more gradual.

Drivers' revenue includes the costs incurred during their operations, known as operating costs. As illustrated in Figure 5-5, we observe the same pattern in which the undersupplied system performs strikingly different. In this range (< =300 drivers), there is no notable difference in the operating costs of drivers, while a sharp drop in the operating costs occurs in the balanced and oversupply state.

Fleet Size	Operating Costs	
	Mean (Euro)	Standard Deviation
100	131.31	2.06
200	131.05	2.07
300	131.29	2.57
400	95.87	21.97
500	70.38	24.93
600	56.86	23.57
700	48.17	22.26
800	41.58	22.09
900	36.83	20.89
1000	32.88	20.01

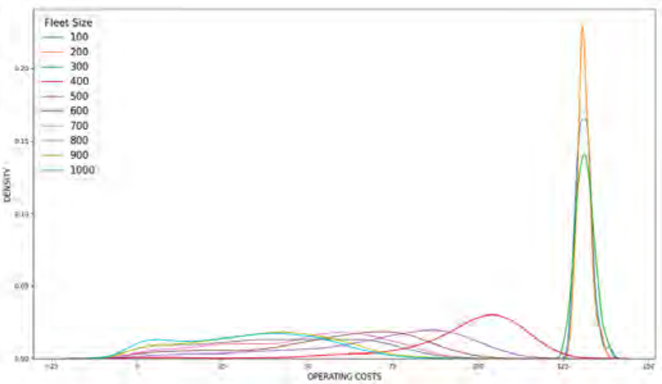


Figure 5-5: Drivers' operating costs metrics

The operating cost is obtained from driving distance consisting of pickup and trip distance (Figure 5-6). It should be highlighted that drivers are not paid for picking up passengers. Thus, pickup distance merely incurs costs for these drivers. At the same time, the average trip distance travelled in the shift decreases with a larger number of drivers.

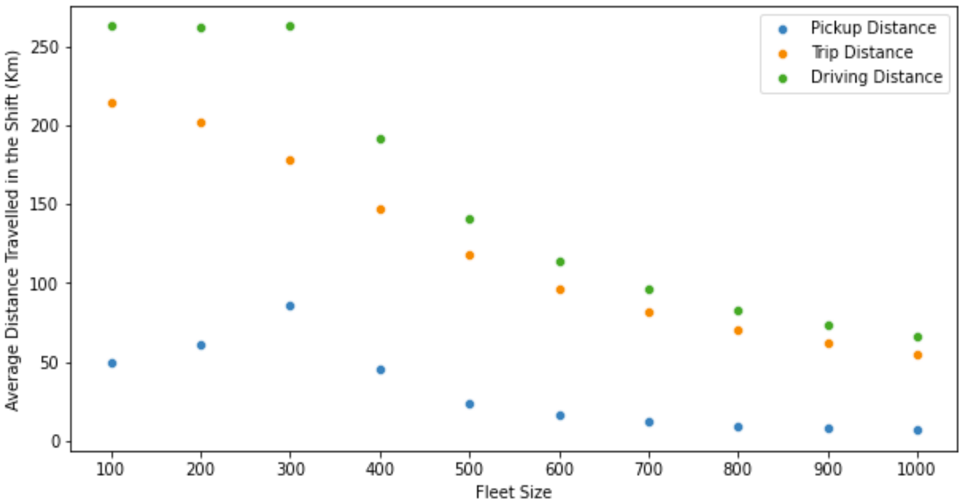


Figure 5-6: Average distance travelled in the shift

It is interesting to note that the rise in the average pickup distance in the shift is offset by the fall in the average trip distance in the shift for the fleet sizes of 100, 200, and 300. This results in similar driving distances and consequently nearly equivalent average operating costs for these drivers. Given that the average pickup distance starts decreasing with the rise in fleet size in the balanced state, there is a steep decline in operating costs due to the synergy between the decline in the pickup and trip distances in the balanced and oversupplied ranges. In addition to the mean, the cost variation between drivers grows with a fleet size of 400 and higher, probably due to higher competition between drivers.

Combining drives' revenue and operating costs leads to the analysis of the profit. What can be seen is that the drivers' average profit decreases with the increase in fleet size. When more drivers join the system, fewer requests are matched per driver leading to more limited profit opportunities. Moreover, the profit variation sharply increases once the system moves beyond the undersupply state.

Finally, the platform revenue under various scenarios of supply-demand intensity is analysed. Given the abovementioned observed trends, it is also expected that the platform revenue during the simulation time differs considerably across the scenarios., In the undersupply state, the platform revenue increases with the number of drivers but once a balance between supply and demand is achieved, the revenue does not change dramatically with the increase in the fleet size. The underlying reason is that all the requests are served in both balanced and oversupply states. Hence, the platform receives its income from all the incoming requests that are matched with drivers, implying that having more drivers in the balanced/oversupply state does not directly influence the platform revenue.

5.3.2 Centralised versus Decentralised Fleet

A widespread assumption in most of the literature concerned with ride-hailing is that a central operator makes all the decisions regarding a match between a driver and a client. This in reality implies that the fleet consists of either AVs or fully-compliant drivers who do not make independent choices, none of which reflects the current state of affairs. Rather, drivers are independent decision-makers who choose what they perceive to be in the best of their interest. In this sub-section, we analyse and compare the performance of centralised and decentralised fleets.

Figure 5-7 presents the distribution of passenger waiting time with centralised (CF) and decentralised fleets (DF) using a violin plot. It can be seen that passenger waiting time in the DF, where drivers can reject ride requests, is not necessarily higher than in the CF. It is observed that there is no substantial difference between the waiting time of passengers in both fleets in case the system is undersupplied. This is because the number of drivers in this state is not sufficient to serve all requests. Therefore, even if a request is rejected in the DF, another request (not far away from the other) is immediately offered to the driver which, if accepted, results in a shorter waiting time for another passenger. While the rejected passenger probably loses their patience and leaves the system. Once the system is in a balanced/oversupplied situation, the average and standard deviation of passenger waiting time are higher in the DF than the CF since some requests get rejected in the DF by the closest available driver, and then a farther away driver may get assigned to the request which in turn might get rejected again.

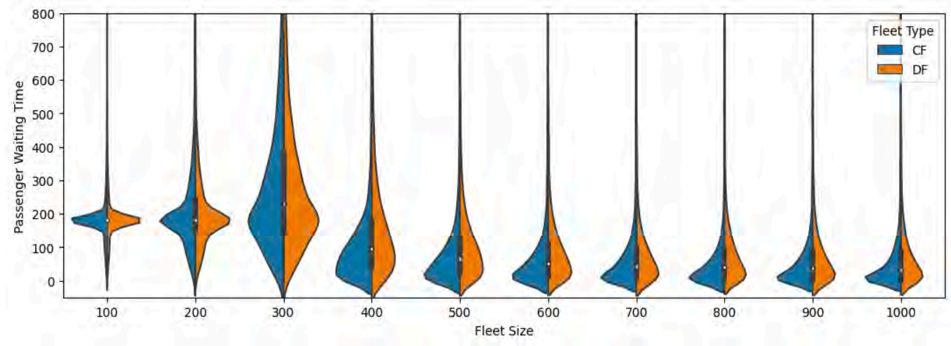


Figure 5-7: Passenger waiting time in the CF and the DF

Comparing the drivers' revenue in both fleets in Figure 5-8, we find a significantly higher income variation between the drivers of the DF in the balanced and oversupplied states. In other words, human intervention causes more income inequality as drivers seek to maximise their own income regardless of the system state. That is why the income dispersion is considerably sharper in the DF where more drivers can earn a higher income, in some cases even more than the maximum revenue in the CF. On the other hand, the number of drivers who have low revenue is higher in the oversupplied DF given the high competition. As expected, the average revenue is nearly the same in both fleet types, especially when all the requests are satisfied (equivalent total revenue). Nevertheless, the revenue is slightly higher in the CF in the undersupplied state given that more rides are served.

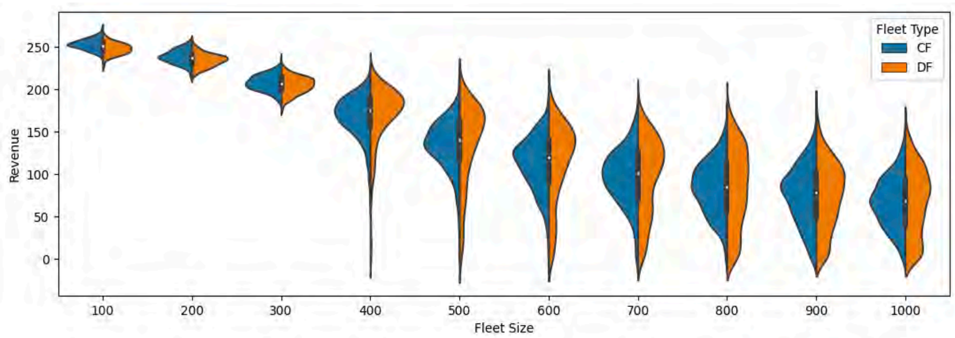


Figure 5-8: Driver's revenue in the CF and the DF

Similar to the revenue, more variation in the drivers' operating costs in the DF can be found as illustrated in Figure 5-9. Such difference is more striking in the balanced and oversupply states where the disparity in driver's ride acceptance behaviour becomes large. This is because in the DF, drivers are free to decline rides assigned based on the shortest pickup distance. Once a request is rejected, another one, which is likely to be farther away, might be matched with the driver resulting in a longer pickup distance and thereby contributing to increased operating costs.

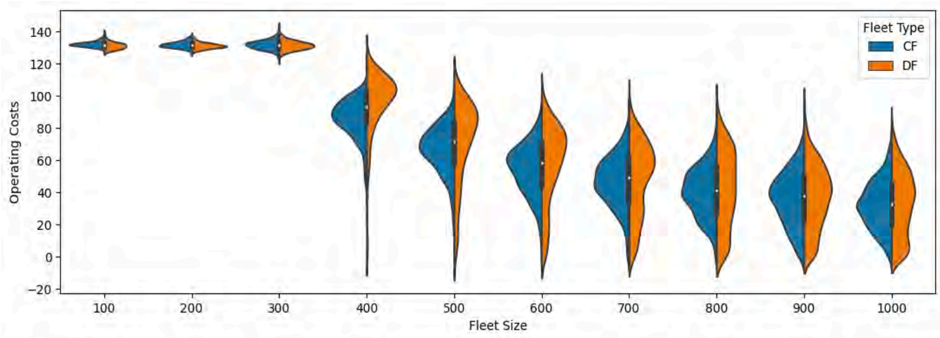


Figure 5-9: Drivers' operating costs in the CD and the DF

Following the higher variation in revenue and operating costs of drivers in the DF, drivers' profit varies more dramatically when drivers are able to make decisions on ride requests. With larger fleet sizes, the average profit is slightly higher in the CF once the number of drivers is between 100-500. As mentioned above, this is due to marginally higher revenue in the undersupply state and/or lower operating costs in the balanced state of the CF during the shift in these scenarios.

The platform revenue during the simulation time does not significantly change as far as all the requests are served. Nonetheless, driver's acceptance behaviour may result in a higher average waiting time for passengers in the balanced and oversupply state. This may decrease the platform market share which may potentially in the long term lead to lower income for a platform with a DF.

5.3.3 Ride Acceptance Rate Implications

In this section, we observe how the drivers' acceptance behaviour affects their performance. To this end we track the drivers behaviour across the simulation and classify them based on their acceptance rate, which is obtained from the ratio between the number of accepted requests and the total number of requests received during the shift. The drivers are then grouped into five segments with an acceptance rate of 60% or less, 60%-70%, 70%-80%, 80%-90%, and more than 90%. The performance of drivers is analysed for each of these groups.

First, we analyse the delay imposed on passengers by drivers rejecting rides. Figure 5-10 depicts the imposed delay in the shift for different fleet sizes based on the drivers' ride acceptance rate. In the undersupply state, none of the drivers has an acceptance rate of less than 60% given that the number of requests received during the shift is high enough. The delay imposed by a driver is the time that the corresponding passenger whose request has been rejected needs to wait to be matched with another available driver or cancel the requests because of excessing the maximum allowable waiting time. Expectedly, the imposed delay decreases when more drivers are available. In the undersupply state, the delay imposed by drivers with a low acceptance rate is much higher given that the rejected passengers should wait more owing to the low number of drivers available to serve them.

Fleet Size	Acceptance Rate				
	60 or less	60-70	70-80	80-90	90-100
100	NA	1381.00	767.55	510.66	218.83
200	NA	1119.50	631.45	369.64	139.31
300	NA	445.43	319.94	191.27	76.97
400	422.67	156.64	115.33	71.94	32.65
500	228.16	116.00	93.77	61.17	23.79
600	197.31	106.03	82.21	51.41	15.57
700	176.52	97.50	73.26	47.85	15.29
800	151.69	88.76	68.12	44.06	13.64
900	161.38	81.41	62.69	36.87	11.63
1000	122.94	78.36	60.52	36.17	12.47

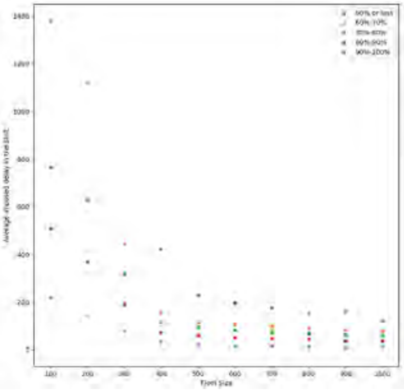


Figure 5-10: Imposed delay in the shift

Figure 5-11 presents drivers' average profit benchmarked against their acceptance rate in each fleet size. In the undersupplied state, the acceptance rate does not have a significant effect on the average profit per shift given the high number of incoming requests despite a relatively high rejection rate. Once the system is no longer in undersupply, the average profit significantly varies based on the acceptance rate. From this point onward, drivers with an acceptance rate of up to 60% have the lowest income as the idle time is higher. With 500 and more drivers, the highest income is earned by the drivers whose acceptance rate is between 80% and 90%.

Fleet Size	Acceptance Rate				
	60 or less	60-70	70-80	80-90	90-100
100	0	119.86	113.86	117.79	117.77
200	0	99.71	103.28	103.23	105.92
300	0	79.22	70.97	75.12	73.84
400	28.52	60.24	73.94	78.73	79.09
500	17.19	51.53	64.96	72.87	70.75
600	15.45	47.39	58.52	64.41	55.51
700	14.54	45.37	52.36	60.00	52.34
800	14.80	38.70	48.66	55.98	40.73
900	13.94	35.80	44.36	48.33	44.55
1000	10.89	34.08	43.33	46.33	45.32

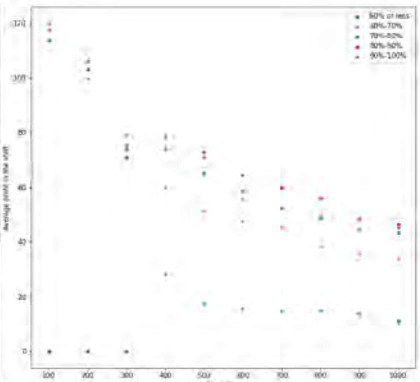


Figure 5-11: Average profit in the shift based on the acceptance rate

To gain a better understanding of the ride acceptance rate implications on drivers' profits, Figure 5-12 shows the distribution and quartiles of the profit based on drivers' acceptance rate for different fleet sizes. Interestingly, the profit of drivers with an acceptance rate of 80%-90% is either more than or equal to the other categories in each quartile once the number of drivers is 500 or higher. In the oversupply situation, a high-profit variation with an acceptance rate of 90% is seen. In other words, this group of drivers can make a profit as high as or more than the drivers with an acceptance rate of 80%-90% or as low as or less than drivers with a 60%-70% acceptance rate. To explain this, we need to investigate the performance of each driver. To this end, a scatterplot of the number of rides received by each driver against the acceptance rate is shown in Figure 5-13.

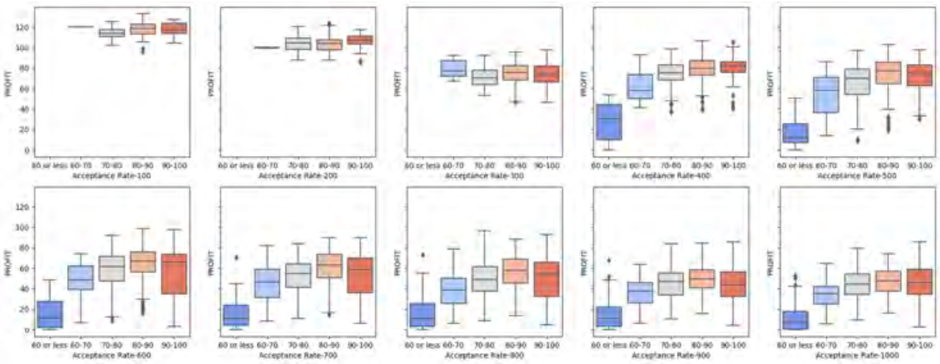


Figure 5-12: Driver's profit variation based on acceptance rate

Analysing the scatterplot, we find out that no specific pattern exists in the undersupply state. For fleet sizes of 400 or more, a pattern starts appearing, and once the number of drivers increases the pattern of receiving more requests with a higher acceptance rate emerges. Nonetheless, it is observed that a considerable number of drivers with a 100% acceptance rate in the oversupply state receives fewer requests despite accepting all of them. This may have several reasons: Drivers with a higher acceptance rate are not picky and may accept rides with a long pick up distance which are time-consuming and lead to receiving overall fewer requests during their shift. In addition, accepting all the rides increases the risk of ending up in suburban areas (given that drivers do not see the final destination when assessing a ride request) where the chance of getting a request is lower.

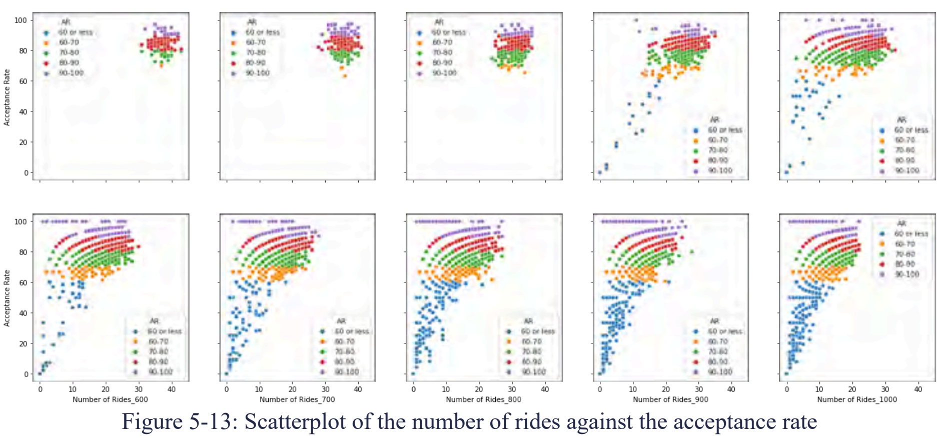


Figure 5-13: Scatterplot of the number of rides against the acceptance rate

5.3.4 Surge Pricing

At the operational level, surge pricing is one of the platform's most prevalent pricing strategies. This surge in price, applied as a multiplier or an additive value to the trip fare, is paid by riders and results in higher revenue for drivers and the platform. Some passengers may revoke their request due to their sensitivity to trip fare. Moreover, surge pricing motivates drivers to accept more rides given that they can earn more money through surge pricing in which each monetary unit is valued higher than the trip fare (Ashkrof et al., 2022). To implement surge pricing, the case study area of Amsterdam is divided into 55 hexagonal zones, and the demand-supply ratio is dynamically calculated in each zone. If a zone is undersupplied, the surge function (as explained in section 2.1.3) is used to assign a surge multiplier ranging from 1.0x to 5.0x and estimate the corresponding surge fee. Figure 5-14 illustrates the granular hyperlocal zones in Amsterdam and the calculated maximum demand-supply ratio in each zone using a colour palette ranging from dark red (high surge) to light red (low surge).

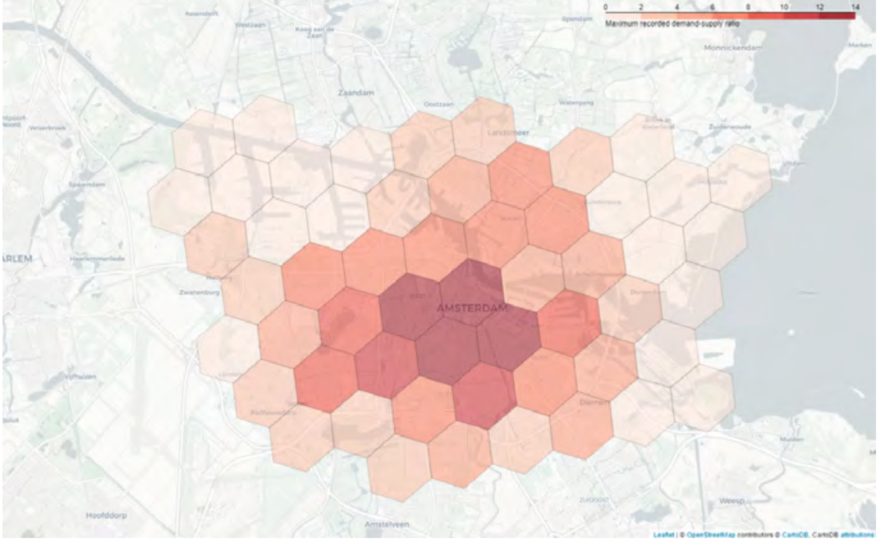


Figure 5-14: Maximum demand-supply ratio in the granular hyperlocal zones in Amsterdam

Table 5-1 presents the mean and the standard deviation of the surge multiplier and drivers' surge income (i.e., the revenue derived from surge pricing) in various fleet sizes. Simulation results indicate that surge pricing is activated only for fleet sizes of 300 or less, in which the system is undersupplied. With 69% of the rides being surged price in the extremely undersupplied state (i.e., 100 drivers), drivers have approximately 120 euros (on average) surge income during a working shift with an average surge multiplier of 1.51x. With 200 drivers, surge pricing is applied to 49% of the rides and an average driver can earn 75 euros from surge pricing with a multiplier of 1.34x. In the moderately undersupplied situation where the fleet size is 300, only 21% of the rides receive surge pricing with a multiplier of 1.15x resulting in an average surge income of 30 euros for drivers. Remarkably, the average surge multiplier and the number of rides with dynamic pricing in the moderately undersupplied fleet size scenario (300 drivers) perfectly match the corresponding indicators in real-world Uber system operations reported by Cohen et al. (2016).

Table 5-1: Summary statistics of surge multiplier and drivers' surge income

Fleet size	Surge Multiplier		Drivers' Surge Income in the Shift	
	Mean	Standard Deviation	Mean (Euros)	Standard Deviation
100	1.51x	0.08	119.83	21.71
200	1.34x	0.08	74.77	18.27
300	1.15x	0.06	29.34	12.33

Table 5-2 provides detailed information on the number of rides in each surge multiplier bucket and the total number of rides with dynamic and regular pricing. The surge multiplier of 1x implies that the price has not soared due to a real-time balance between demand and supply. Obviously, once the number of drivers increases (given the fixed demand), the number of rides with surge pricing decreases. In the case of the smallest fleet, the majority of rides receive a surge multiplier greater than 1. Once 200 drivers operate in the system, surge pricing is applied to nearly half of the total rides. In the case of 300 drivers, most of the rides are surge free. A crucial point of attention is the reduction in the total number of rides in the surge pricing scenario. Interestingly, surge pricing decreases the demand by no more than 4% in all the fleet size scenarios given the somewhat inelastic passenger demand towards surge pricing found by Cohen et al. (2016).

Table 5-2: Number of rides with dynamic and regular pricing

Fleet Size	Surge Multiplier					Number of Rides with Surge Pricing	Number of Rides with Regular Pricing
	1x	1-2x	2-3x	3-4x	4-5x		
100	1136 (31%)	2048 (55.8%)	423 (11.5%)	56 (1.5%)	4 (0.1%)	3667	3782
200	3536 (51.2%)	2754 (39.8%)	558 (8%)	42 (0.6%)	13 (0.2%)	6903	7092
300	6965 (78.6%)	1736 (19.6%)	148 (1.7%)	12 (0.1%)	0 (0.0%)	8861	9213

The analysis of drivers' income shows that the average profit in the shift increases with surge pricing by about 100%, 70%, and 30% with 100, 200, and 300 drivers, respectively. Given that no significant change in the operating cost is observed, this rise in profit stems from the higher revenue obtained from drivers' surge income. In addition, a higher variation in driver's profit is observed, implying that surge pricing reinforces income inequality.

Given that the platform charges a 25% commission per ride, the platform's revenue is higher when surge pricing is introduced. The platform can earn up to 50% higher revenue in a shift with surge pricing when the fleet size is 100. With 200 and 300 drivers in the surge pricing scenario, the platform revenue is 30% and 10% higher, respectively. Interestingly, platform's revenue reaches a peak with 300 drivers when surge pricing is applied. This means that the platform can maximise its revenue by applying surge pricing in the moderately undersupplied state even though this results in leaving about 10% of the requests unserved.

Furthermore, the platform can take advantage of having greater control over the demand-supply ratio. Platforms wish to minimise the number of unanswered ride requests and ensure riders can at least receive an offer. It appears that surge pricing can be used to serve this purpose. Given that surge pricing is paid out of riders' pockets, some riders may reject the offer due to their lower willingness to pay. As shown in Table 5-3, the number of ride requests with no offer decreases when surge pricing is applicable. This is because the ride acceptance rate is slightly higher thanks to surge pricing and some riders reject the offer, making drivers available for the next rides.

Table 5-3: Number of rides rejected by riders or receiving no offer

Fleet Size	Dynamic Pricing		Regular Pricing
	Rejected by Rider	No Offer	No Offer
100	841	5492	6218
200	1093	2004	2908
300	638	501	787

Our simulation model results suggest that surge pricing does not have a significant impact on the average passenger's waiting time. With 100 and 200 drivers, the waiting time slightly decreases, but with 300 drivers, a minor increase is observed in the surge pricing scenario. Although surge pricing primarily occurs when demand is considerably higher than supply and then a higher waiting time is expected, the drop in demand due to high surge fees can nearly offset the extra waiting time. This is in line with the findings of Cohen et al. (2016), in which they concluded that no correlation exists between passenger waiting time and surge pricing.

5.4 Discussions and Conclusions

This study sheds light on the within-day operations of a two-sided ride-sourcing platform in which the interactions between the platform, individual riders and drivers are explicitly taken into account. To this end, we adapt and adopt a discrete-event agent-based simulation for the case of Amsterdam to investigate system dynamics. To the best of our knowledge, this is the first study that models the ride acceptance decisions of ride-sourcing drivers while interacting with riders and the platform in a simulation framework.

We investigate the system performance from multiple perspectives: supply-demand intensity, centralised fleet (i.e., mandatory acceptance on each ride request) versus decentralised fleet (i.e., ride acceptance decision by each driver), ride acceptance rate implications, and surge pricing. We track and analyse several key performance indicators allowing to capture the potential effects of agents' dynamic behaviour on system operations and explain certain (ir-)regularities. The critical KPIs in this research are the platform's revenue, passengers' waiting time, drivers' revenue, operating costs, and profit.

Based on the ratio between demand and supply in a given area, the system state can be divided into three categories: undersupply (more requests than available drivers), balanced, and oversupply (more available drivers than the number of requests). The implications of such distinction are highlighted in a study by de Ruijter et al. (2022b). They establish how the ratio between supply and demand governs the balance between the matching time (i.e., request match time and driver idle time) and the match quality (i.e., average pickup distance). Furthermore, they show that the system is more efficient in an asymmetrical two-sided market (either undersupplied or oversupplied) in which one side benefits from higher match quality at the expense of higher matching time for the other side.

In our research, a distinctive pattern is observed in each state, especially in the case of undersupplied conditions. For instance, passengers' average waiting time decreases with the fleet size (for a fixed demand) except for the undersupplied condition where a larger fleet size leads to a higher match rate and a higher pickup distance resulting in longer passengers' waiting time. This suggests that the system is less reliable in the undersupplied situation. At the same time, drivers' average profit decreases when more drivers join the system regardless of the ratio between supply and demand, but the profit variation significantly rises once the system moves beyond the undersupply state given the greater competition between drivers. The within-day platform's revenue increases with a larger fleet size in the undersupplied state and does not significantly change in the balanced and oversupplied ranges.

The extent of misbalance between supply and demand is found to be critical. In an extremely undersupplied state where the number of incoming requests in a particular zone is excessively higher than the number of drivers, drivers earn significantly higher income at the expense of a low match rate and long waiting time for passengers. Conversely, an extremely oversupplied system benefits passengers, as it yields a high acceptance rate and short waiting time, but creates intense competition between drivers resulting in longer idle times and, consequently, a lower income. The platform may adopt measures to mitigate the emergence of such extreme situations. When the system is moderately misbalanced, both sides can asymmetrically benefit from the system. Under a moderately undersupply state passengers experience long waiting times caused by a higher match rate. In a near-balanced or slightly oversupplied situation, the competition between drivers is not as fierce as in the highly oversupply situation resulting in a higher income/satisfaction, and at the same time, the number of drivers is sufficient to handle all the requests with a relatively short waiting time for passengers. The platform can also benefit directly from the revenue obtained from serving all the requests and indirectly from having a potentially higher market share, given the higher level of service provisioned.

Comparing the performance of a centralised and a decentralised fleet, we argue that the type of fleet associated with drivers' ride acceptance behaviour plays a crucial role in system operations. In the balanced and oversupplied condition, passengers' average waiting time is higher in a DF given that each rejection imposes a delay to the system. This increase in waiting time can reduce the system's capacity and efficiency. This is in line with the findings of Nahmias-Biran et al. (2019) that suggest that a centralised fleet operated by automated vehicles, which dutifully follow the platform instructions on repositioning, performs more efficiently than a decentralised human-driven fleet. They found that such higher efficiency increases the platform market share by four times once an automated fleet takes over the operations. Regarding the relation between drivers' profit and fleet type, we find that human interventions as manifested in ride acceptance decisions cause higher income inequality leading to drivers of a DF having higher income variation, especially if the system is not undersupplied. Such operational differences in CF and DF suggest that ignoring drivers' behaviour when analysing the within-day operations of real-world two-sided ride-sourcing system potentially leads to misrepresentation of the system performance.

Analysing the impacts of surge pricing on system operations suggests that dynamic pricing can be beneficial for drivers and the platform while having mixed effects on the demand side. On the one hand, an inflated price decreases the utility of a ride for passengers, leading to some offers being rejected by riders. On the other hand, this reduction in the total number of requests leaves the remaining passengers better off as it creates more balance between supply and demand, enhancing the chance of those passengers to receive a ride. This can improve the matching efficiency by allocating the rides to passengers with a high willingness to pay when drivers are scarce (Castillo, 2018). According to Uber, surge pricing is meant to help passengers find a reliable ride by restoring the balance between supply and demand (Uber Marketplace Surge pricing, 2022). In fact, Uber strives to minimise the number of requests that receive no response. Using surge pricing, the platform nudges riders with a lower willingness to pay (e.g. due to differences in urgency, income or quality of alternatives) to opt out. Regardless of the final decision, this choice can boost riders' surplus. Moreover, the platform benefits from higher revenue due to higher trip fares.

From the suppliers' perspective, drivers, on average, earn significantly higher average profits during surge pricing, the extent of which depends on the ratio between demand and supply. In addition, surge pricing reinforces income inequality between drivers. Overall, it seems that surge pricing can offer benefits to all parties at the aggregate level, albeit their advantages are asymmetric. However, the surge pricing mechanism is reportedly not transparent, leading to complaints and mistrust (Ashkrof et al., 2020; Castillo, 2018).

In this study, we included the ride acceptance behaviour of drivers in the system operations of a two-sided ride-sourcing platform. The other operational decision of drivers (i.e., relocation strategy) can be added to the system enabling a more comprehensive analysis at the operational level. The focus of this study was on within-day operations while demand and supply are assumed fixed. A promising avenue for future research is to integrate the within-day and day-to-day decisions of both the demand and supply sides of the ride-sourcing market.

Chapter 6: Conclusions

The research presented in this dissertation has been devoted to unravelling the supply-side operations and behavioural dynamics of two-sided ride-sourcing systems in which drivers and riders interact through a digital platform. We have provided in-depth insights into drivers' decisions, identified the key factors affecting them, and analysed their consequences for system operations. This final chapter synthesises the main findings from this thesis in Section 6.1, an overall reflection on the research procedure and outputs in Section 6.2, the corresponding implications for practice in Section 6.3, and future research directions in Section 6.4.

6.1 Main Findings

In this section, we provide answers to the research questions raised in Section 1.3 and briefly present the key findings:

RQ1: What are drivers' perception of and their interactions with ride-sourcing platforms?

This research question studied in Chapter 2 is centred around drivers' comprehension of the system operations, their corresponding responses, the relationships between their choices, and understanding their concerns and expectations. A focus group approach was used to facilitate gaining detailed insights. During the focus group sessions, we delved into drivers' daily work and their interactions with the information and instructions given in the app. The lack of an effective line of communication between drivers and the platform given the constant changes and new functionalities in the app significantly increases the risk of misunderstanding system operations we found, and also fuels the mistrust of drivers toward the platform, resulting in unexpected behaviour and counter-productive outcomes for the system.
Using the focus groups, we also found that platform strategies, drivers' characteristics, riders' attributes, and exogenous factors could affect drivers' decisions in terms of ride acceptance, relocation strategies, working shift and area selection. Flexible working conditions enabling drivers to make independent decisions based on their preferences/objectives were identified as the principal reason for joining the system. While all drivers strive to maximise their revenue, their strategies may greatly differ, depending on their characteristics. Part-time and full-time drivers, as well as experienced and beginning drivers, are characterised by distinctive behaviour. For instance, full-time drivers are more flexible in determining their working hours and dynamically respond to possible transport system issues such as disruption in public transport while part-time drivers have more time limits due to their other scheduled activities. Experienced drivers are more selective in the options offered by the platform (e.g., ride requests and repositioning guidance). We also proposed a conceptual model that explains the relationship between the tactical (i.e., working shift and area selection) and drivers' operational decisions (i.e., ride acceptance and relocation strategies).

RQ2: What components govern the relationship between the information sharing about a ride request and the decision of ride-sourcing drivers on accepting/declining requests?

Using a stated choice experiment designed based on the existing literature and the findings of the previous chapter, we investigated drivers' ride acceptance behaviour in Chapter 3. We collected a unique dataset from ride-sourcing drivers working in the United States and the Netherlands through a cross-sectional survey designed based on disparate information conveyed to the respondents. Pickup time (i.e., the travel time between the driver's location and the rider's pickup spot) was found to be the most critical determinant and has a significant adverse effect on ride acceptance. In addition to surge pricing, which is the only monetary information that is shared in the current operations, we devised a potential information-sharing policy in which the information on the trip fare and guaranteed tip (i.e., the minimum amount of tip that is indicated upfront by the prospective rider) are disclosed to drivers in our experiment. It turns out the additional income due to guaranteed tip and surge pricing is valued considerably higher than trip fare per monetary unit.
Regarding the individual-specific determinants, employment status, experience level, and working shift are found to be the key components of drivers' ride acceptance. Part-time and beginning drivers who work on midweek days have a higher tendency to accept ride requests. Full-time drivers are less sensitive to pickup time and more disposed to guaranteed tip than their

part-time counterparts. Moreover, we examined the implications of the outbreak using an Integrated Choice and Latent Variable (ICLV). In both information-sharing scenarios, the results suggest that the higher sensitivity of drivers to the COVID-19 effects increases the chance of rejection rate with the extent of which depending on their personal characteristics. For example, beginning and full-time drivers are less sensitive to the COVID-19 impacts, leading to a higher acceptance rate.

RQ3: What factors, and to what extent, affect the relocation strategies of the ride-sourcing drivers?

The relocation strategies of ride-sourcing drivers discussed in Chapter 4 refer to their choices in the idle status to find a new ride. We examine four relocation alternatives: waiting at the drop-off location, driving to the surge area in which surge pricing is applied, heading to the high-demand area where more demand is expected while regular pricing is applied, and cruising freely based on experience/intuition. The results reveal that drivers' relocation strategies substantially change with their career profiles and working conditions. Beginning, as well as highly satisfied drivers, and drivers with a higher number of completed trips since the beginning of their shift, are more likely to follow the platform repositioning recommendations (i.e., surge and high-demand area). The key significant determinants are identified as surge value and the expected travel time between the driver's location and the surge/high-demand area.
We also investigate the impacts of additional repositioning guidance in the experiment, which is not currently available in the ride-sourcing settings, to analyse drivers' possible reactions. For instance, if drivers are informed upfront about the existence and the schedule of a pre-booked ride in the neighbourhood of the drop-off location, the probability of staying around the drop-off location is affected depending on the expected waiting time. Given the existing issues with surge pricing such as drivers' mistrust due to its dynamic nature, the platform may offer a guaranteed bonus to incentivise drivers to head to a particular area (e.g., high-demand area) when needed. It is found that this guaranteed bonus is valued 60% higher than surge pricing, which is not necessarily secure. Moreover, drivers appreciate receiving real-time and accurate traffic information in the surrounding area of the current location, which is potentially helpful in reducing idle cruising, especially when the area is congested.

RQ4: To what extent does drivers' ride acceptance behaviour play a role in ride-sourcing system operational performance with/without surge pricing?

This is one of the research questions answered in Chapter 5 in which ride-sourcing within-day system operations were simulated using an agent-based modelling framework enabling the platform to apply regular and surge pricing strategies, drivers to make ride acceptance decisions, and riders to submit and revoke ride requests and also reject offers due to surge pricing. We found out that supply-demand intensity resulting in an undersupplied, balanced, or oversupplied system, governs the interactions between the agents and the system operations in general. The analysis of the KPIs suggests that the system performance is noticeably different once the system is undersupplied. For instance, passengers' waiting time is generally expected to decrease when more drivers join the system, assuming the demand is fixed. Nonetheless, the results reveal that in the undersupply state, passengers' waiting time increases with a larger fleet size due to a higher match rate at the expense of higher pickup time.
Analysing the ride acceptance rate implications, we find that the drivers' average profit does not significantly vary with the ride acceptance behaviour once the system is undersupplied. This is because the high number of incoming requests offsets the effects of a high rejection rate. Once the system is no longer undersupplied, the average income changes depending on the ride

acceptance behaviour. Drivers with an acceptance rate of 60% or lower have the lowest income. In the oversupplied ranges, drivers with an acceptance rate of 80%-90% earn the highest income. This shows that when the competition between drivers is relatively high, drivers who control their operating costs by rejecting the least profitable rides have higher income.
We also introduced surge pricing in our simulation framework in order to analyse its impacts on system operations. We found that surge pricing is asymmetrically in favour of the parties when the system is undersupplied, even though several adverse effects on the demand side due to higher trip fare are inevitable. Surge pricing unloads the excessive demand burden and allows passengers to accept or decline the offer depending on their willingness to pay. Moreover, the lower demand due to surge pricing enhances the chance of other passengers receiving a ride, potentially improving the matching efficiency (higher match rate) and, thus, the platform revenue given the higher trip fare. Furthermore, the supply-side highly appreciates surge pricing that significantly increases drivers' average profit. Nonetheless, income inequality is noticeably higher when surge pricing is applied.

RQ5: What is the difference in performance between a fully centralised (automated/fully compliant) and a decentralised (human-driven/choice-based) fleet once accounting for ride acceptance?

Using the simulation framework presented in Chapter 5, we conducted a comparison between a centralised fleet, where all requests are accepted by either automated vehicles or fully complied drivers and a decentralised fleet in which individual drivers make ride acceptance decisions. The results suggest that the fleet type associated with drivers' acceptance behaviour, next to the fleet size, plays a crucial role in the system operations with the extent of which depending on the ratio between supply and demand. In the balanced and oversupply states, passengers in a decentralised fleet have a longer average waiting time given that each rejection causes a delay in the system and the declined request returns to the queue of pending requests, which reduces the efficiency and capacity. We found out that driver's income inequality is higher in a decentralised fleet where drivers make independent decisions to maximise their profit. These operational differences between centralised and decentralised fleets highlight the impacts of individual drivers' decisions on the system performance.

6.2 Reflection

Throughout the course of my research project, we encountered numerous challenges primarily related to the scarcity of available literature and reliable revealed preference datasets on the ride-sourcing supply side. As a result, we needed to utilise a range of qualitative and quantitative data collection methods to obtain sufficient data for the analysis. Additionally, finding inclusive panel providers to facilitate data collection was a tedious task due to the highly specific nature of the target group.
To address these challenges, each phase of the study was meticulously planned with expert advice and support from the supervisory team. This involved following various strategies, such as leveraging personal and professional networks to recruit participants and panel providers, using multiple data collection methods to obtain a diverse range of perspectives, and collaborating with other research groups to develop effective research methodologies.
The methodologies adopted in this study were chosen based on their appropriateness and ability to allow for a comprehensive investigation of ride-sourcing drivers' behaviour and analysing of the corresponding consequences for the system. Applying a mixed-methods approach allowed triangulation of the data obtained from different sources, reducing the risk of bias and enhancing the generalisability of the results. The focus group study and stated choice experiments yielded

rich data and valuable insights into ride-sourcing drivers' decision-making processes, while the agent-based simulation model provided a powerful tool for explaining the system dynamics.
In this thesis, we obtained in-depth empirical knowledge of drivers' responses to the platform strategies based on the existing/potential system operations. We developed theories regarding drivers' decision-making process, modelled their operational choices (i.e., ride acceptance behaviour and relocation strategies) and identified the factors influencing them. Using behavioural insights, we simulate the operations of a ride-sourcing platform supplied by individual drivers who make ride acceptance decisions.
We conclude that ride-sourcing system operations are governed by the collective choices of drivers as service suppliers. Ride-sourcing platforms need to adopt various strategies to efficiently manage the fleet. These measures must be transparent and well-communicated to reduce the existing mistrust in the gig economy business model and ensure drivers have a proper understanding of the system operation. We believe that ignoring drivers' role when analysing the operations of a two-sided ride-sourcing platform potentially leads to misrepresentation of the system and thus results in a biased analysis. We acknowledge that our research, like any other research, has several limitations outlined in Section 6.4.

6.3 Implications for Practice

Ride-sourcing, as a new phenomenon in the mobility market, is still in the development stage. Therefore, we not only delved into the current system operations and the associated implications but also investigated the potential operational strategies and analysed drivers' respective responses. In both dimensions, this research provides practical insights into the behavioural and operational aspects of the supply-side interacting with the platform and the demand side:

- *Matching algorithm*

The findings of the ride acceptance study presented in Chapter 3 enable the platform to introduce a tailored matching algorithm that initially calculates the ride acceptance probability of nearby drivers and then sends the request to the driver with the highest acceptance likelihood. This can significantly increase the match efficiency and the level of service. In the current operations, passengers can tip drivers after the ride. As a potential feature, a guaranteed tip can be launched in the app as a self-determined discriminatory pricing algorithm enabling riders who desperately seek a quick match to offer a minimum tip to available drivers increasing the chance of acceptance due to the high eagerness of drivers to tips. Unlike trip fare and surge pricing, tipping is not forced by the platform and is considered a voluntary action which makes it less unfavourable for the riders. This can also be part of the platform pricing strategy in which the trip fare and possibly surge pricing is optimally calculated based on the amount of the guaranteed tip determined by riders. This strategy increases the chance of riders getting a faster pickup (i.e., a higher level of service) thanks to drivers' higher acceptance probability.

- *Repositioning guidance*

In the context of ride-sourcing, the findings presented in Chapter 4 could be used to design customised repositioning guidance based on a prediction model obtained from the identified determinants of ride-sourcing drivers' relocation behaviour. For example, educated part-time drivers with low acceptance rate are more inclined to wait around the drop-off location. Therefore, the platform can provide more specific information about available parking spots and pre-booked rides in the neighbourhood. Conversely, detailed information on the surge and high-demand areas could be conveyed to beginners, who are more likely to follow. The potential repositioning guidance introduced and analysed in this thesis (i.e., information on pre-booked rides as well as traffic congestion and a guaranteed bonus to follow high-demand areas) can facilitate a more efficient indirect control of individual drivers. For instance, once a driver is informed that a request will pop up soon around the drop-off location, the chance of staying around is higher. This helps drivers make more informed decisions and consequently improves the system performance in terms of the level of service and users' (i.e., drivers and riders) satisfaction and possibly reduces deadhead movements and the associated traffic congestion as the critical pitfalls of ride-sourcing systems.

- *Effective communications*

In Chapter 5, we argue that surge pricing is potentially an effective approach to improve the balance between supply and demand and benefit all the parties by reducing the number of the requests that receive no response, improving the match rate, and increasing drivers' earnings and the platform's revenue. The key point highlighted in Chapter 2 is that drivers' misunderstanding of the system operations, specifically surge pricing, may downgrade the corresponding benefits. Therefore, the platform needs to provide both riders and drivers with sufficient explanations and consequences of surge pricing, receive their feedback, improve the system accordingly, and communicate accurate, unbiased, and real-time information. Based on the analysis conducted in Chapter 5, the platform needs to implement the necessary measures to keep the ratio between supply and demand at the balanced or slightly over-supplied ranges in which the passengers' average waiting time, the driver's average profit, and the platform revenue appear relatively satisfactory while all the requests are served.

6.4 Study Limitations and Future Research Directions

In this section, we formulate several recommendations for future research based on the insights gained in this research and in order to address the limitations thereof:

- **Conducting comprehensive analyses of drivers' decisions using revealed preference data**

In this research, the supply-side behavioural dynamics have been studied using stated preference data. Although the stated choice experiments provide an opportunity to investigate hypothetical scenarios, they may impose bias due to respondents' potential misunderstanding of the survey or their political responses. Revealed preference data is a fertile source to further investigate the choices of the target group based on the existing development. Notwithstanding, the reluctance of ride-sourcing platforms to share the supply-side data due to their fragile relationship with drivers and commercial reasons is a significant barrier. If accessible, analysing big data from drivers' activities including participation choice, working hours, received requests, and the characteristics of the rides (e.g., pickup point, drop-off location, and rider's rating) is expected to yield remarkable insights.

- **Replicating the undertaken research in other contexts**

Ride-sourcing operations and strategies vary across countries based on local rules, working conditions, and user profiles. For instance, the information about trip fare might be disclosed or hidden, depending on the platform information sharing policy in that country. In this thesis, we focused on ride-sourcing operations in the US and the Netherlands. It will be insightful to conduct a similar analysis in other countries where a competitive market exists and then compare the results with the findings of this research. This allows for drawing more universal conclusions. Additionally, it is crucial to acknowledge that a portion of our research was conducted during the COVID-19 pandemic, a period that had a profound impact on numerous industries, including transportation, and more specifically, the ride-sourcing system as a component of shared mobility. The immediate and lasting consequences of the pandemic on user behaviour, driven by considerations related to hygiene and the financial ramifications of the outbreak, may have also exerted an influence on the supply side. Drivers likely found it necessary to implement additional hygienic and preventive measures, such as installing barriers between passengers and themselves, equipping their vehicles with disinfectants, and exercising heightened caution when accepting ride requests, among other adaptations. Furthermore, changes occurred in both the volume and nature of trips, particularly the absence of shared rides, during the pandemic, which could have significant implications for system operations. Consequently, revisiting these studies on drivers' behaviour outside the context of the pandemic could provide novel insights and a more comprehensive understanding of the factors in play.

- **Investigation of the impacts of shared rides on drivers' decisions**

This research has been centred around private rides, involving only one main passenger requesting a ride. Offering shared rides (i.e., transporting at least two main passengers simultaneously) has been recognised as an effective measure to make ride-sourcing operations more efficient. Nevertheless, in case the demand remains unchanged, fewer vehicles are needed which may negatively affect drivers' interests. Hence, the behaviour of drivers in response to shared rides and the associated consequences (e.g., more complexity, routing issues, possible delays, etc.) which are largely unknown in the literature, can be a promising research direction.

- **The implications of drivers' relocations strategies on system performance (with surge pricing)**

Based on the current operations as well as several potential scenarios, we identified the key factors affecting drivers' relocation choices. Given the increasing criticism of ride-sourcing's deadheading, which potentially contributes to traffic congestion, a future research path can be to focus on the impacts of drivers' repositioning behaviour on ride-sourcing system operations where the actors interact with each other, and introduce some measures to minimise deadheading.

- **Empirical behavioural knowledge on ride-sourcing drivers' tactical decisions and modelling day-to-day ride-sourcing system operations governed by the within-day decisions of drivers**

Operational choices of drivers (ride acceptance behaviour and relocation strategies), associated with with-day decisions, have been the centre of attention in this thesis. As explained, tactical decisions (i.e., working shift and area selection), attributed to day-to-day choices, have a reciprocal relationship with operational decisions. Identifying the critical determinants of drivers' tactical choices, modelling their interactions with operational decisions and analysing the possible consequences in a simulation framework where the platform uses various matching and pricing strategies for managing a dynamic supply and demand can be highly elaborate.

- **Carrying out periodic qualitative research into drivers' understanding of system operations and the platform strategies**

Following the constant development of ride-sourcing systems due to advancements in technology and the applied algorithms, it is crucial first to ensure that service providers are sufficiently briefed and then receive their feedback to assess whether a common ground exists and find how to improve the system functionalities with their collaborations. To do so, systematic qualitative research in this field is needed (as proposed in Figure 1-2) to gain in-depth insights into drivers' understanding of system operations and platform strategies.

Appendix A

Primary model estimation with main-effects-only

Name	BIP			AIP		
	Value	T-value	P-value	Value	T-value	P-value
ASC_Accept	1.620	6.810	0.000	1.340	4.820	0.000
Pickup time [min]	-0.044	-5.890	0.000	-0.050	-5.600	0.000
Idle time [min]	-0.020	-3.060	0.002	-0.005	-0.561	0.575
Working time [1=Peak hours]	-0.570	-5.490	0.000	-0.067	-0.557	0.577
Working day [1=Weekend/Friday]	-0.443	-5.700	0.000	-0.511	-5.970	0.000
Shift segment [1=At the beginning of the shift]	-0.208	-2.520	0.012	-0.115	-1.230	0.217
Driver's location [1=City centre]	-0.115	-1.490	0.137	-0.041	-0.923	0.356
Last request status [1=Declined]	0.150	1.850	0.065	-0.022	-0.242	0.809
Long trip [1=30+ min]	0.114	1.290	0.197	0.188	1.830	0.067
Rider rating [star]	0.030	0.581	0.561	0.060	1.040	0.296
Type of request [1=UberX]	0.108	1.270	0.204	0.090	0.867	0.386
Surge pricing [USD]	0.090	2.580	0.010	0.049	1.120	0.262
Trip fare [USD]	-	-	-	0.038	4.250	0.000
Guaranteed tip [USD]	-	-	-	0.068	1.890	0.059
Traffic congestion [min]	-	-	-	-0.010	-2.700	0.007
Initial Log-Likelihood		-2395.517			-2395.517	
Final Log-Likelihood		-2031.219			-1751.637	
Rho-square		0.152			0.269	
AIC		4086.438			3533.274	
BIC		4160.212			3625.492	

Appendix B

Results of the integrated Dutch-US model for the AIP scenario

Name	Value	T-value	P-value
ASC_Accept	1.180	8.040	0.000
Pickup time [min]	-0.049	-6.110	0.000
Idle time [min]	-0.001	-0.106	0.916
Driver's location * Shift segment [1= City centre and Beginning of the shift]	-0.135	-1.400	0.161
UberX*Long ride*Rating*Declined ride	0.009	0.896	0.370
Surge pricing [USD]	0.063	1.810	0.070
Trip fare_NL [USD]	0.074	5.260	0.000
Trip fare_US [USD]	0.045	5.650	0.000
Guaranteed tip [USD]	0.060	1.780	0.075
Traffic congestion_NL [min]	-0.079	-6.840	0.000
Traffic congestion_US [min]	-0.008	-2.240	0.025
Initial Log-Likelihood		-2636.732	
Final Log-Likelihood		-1956.091	
Rho-Square		0.258	
AIC		3934.181	
BIC		4002.863	

- NL and US refer to the Netherlands and the US, respectively.

Appendix C

Full estimation of the ICLV model

Name	BIP		AIP	
	Value	P-value	Value	P-value
ASC_Accept	-0.351	0.084	-0.475	0.069
$\boldsymbol{\beta}$ _Ride-related COVID-19 attitudes	-0.579	0.000	-0.529	0.000
$\boldsymbol{\beta}$ _General COVID-19 attitudes	-0.418	0.000	-0.472	0.000
$\boldsymbol{\beta}$ _Pickup time*Full-time drivers [min]	-0.027	0.011	-0.021	0.102
$\boldsymbol{\beta}$ _Pickup time*Part-time drivers [min]	-0.072	0.000	-0.076	0.000
$\boldsymbol{\beta}$ _Idle time [min]	-0.018	0.004	-0.005	0.575
$\boldsymbol{\beta}$ _Working time [1=Peak hours]	-0.347	0.001	0.046	0.711
$\boldsymbol{\beta}$ _Working day [1=Weekend/Friday]	-0.247	0.005	-0.350	0.000
$\boldsymbol{\beta}$ _Uberx*Long ride*Rating*Declined ride	0.099	0.000	0.081	0.016
$\boldsymbol{\beta}$ _Driver's location*shift segment [1= City centre and Beginning of the shift]	-0.295	0.005	-0.159	0.184
$\boldsymbol{\beta}$ _Surge pricing [USD]	0.108	0.001	0.068	0.077
$\boldsymbol{\beta}$ _Trip fare [USD]	-	-	0.040	0.000
$\boldsymbol{\beta}$ _Guaranteed tip*Full-time drivers [USD]	-	-	0.211	0.000
$\boldsymbol{\beta}$ _ Guaranteed tip *Part-time drivers [USD]	-	-	0.016	0.737
$\boldsymbol{\beta}$ _Traffic congestion [min]	-	-	-0.012	0.001
$\boldsymbol{\beta}$ _Employment status [1=Part-time drivers]	1.230	0.000	1.150	0.000
$\boldsymbol{\beta}$ _Experience [1=Beginners]	0.072	0.546	-0.029	0.824
$\boldsymbol{\beta}$ _Gender [1=Male]	0.361	0.000	0.072	0.470
$\boldsymbol{\beta}$ _Satisfaction level [1=Fully satisfied]	0.543	0.000	0.140	0.112
$\boldsymbol{\beta}$ _Education [1=Educated]	-0.203	0.025	0.243	0.014
$\boldsymbol{\gamma_{0r}}$_Ride-related COVID-19 attitudes	-1.740	0.000	-1.730	0.000

γ_{r}_ Education [1=Educated]	-0.510	0.000	-0.512	0.000
γ_{r}_Age	0.036	0.000	0.035	0.000
γ_{r}_Acceptance rate	0.639	0.000	0.625	0.000
η_{1}^{*}_Ride-related COVID-19 attitudes	0.900	0.000	0.895	0.000
α_{0r}_Accepting more rides	-0.230	0.000	-0.228	0.000
α_{r}_Accepting more rides	0.827	0.000	0.829	0.000
υ_{1}^{*}_Accepting more rides	1.270	0.000	1.260	0.000
α_{0r}_No changes in work	0.035	0.253	0.036	0.236
α_{r}_No changes in work	0.930	0.000	0.932	0.000
υ_{2}^{*}_No changes in work	1.100	0.000	1.100	0.000
γ_{0g}_General COVID-19 attitudes	1.510	0.000	1.460	0.000
γ_{g}_Age	-0.063	0.000	-0.062	0.000
γ_{g}_Acceptance rate	-1.100	0.000	-1.100	0.000
γ_{g}_Taxi driving experience [1=Taxi driver]	-0.759	0.000	-0.697	0.000
γ_{g}_ Employment status [1=Part-time drivers]	0.336	0.000	0.331	0.000
γ_{g}_ Experience [1=Beginners]	-0.702	0.000	-0.695	0.000
η_{2}^{*}_General COVID-19 attitudes	-1.530	0.000	-1.520	0.000
α_{0g}_Negative impact	-1.250	0.000	-1.250	0.000
α_{g}_Negative impact	0.258	0.000	0.258	0.000
υ_{4}^{*}_Negative impact	1.440	0.000	1.430	0.000
α_{0g}_Taking preventive measures	-1.210	0.000	-1.200	0.000
α_{g}_Taking preventive measures	0.302	0.000	0.304	0.000
υ_{5}^{*}_Taking preventive measures	1.050	0.000	1.050	0.000
delta_1*	0.564	0.000	0.561	0.000
delta_2*	1.300	0.000	1.290	0.000
ec_sigma*	0.823	0.000	0.820	0.000
Initial Log-Likelihood	-44567.850		-44567.850	
Final Log-Likelihood	-28734.390		-28497.320	
Rho-Square	0.355		0.361	
AIC	57554.780		57088.630	
BIC	57819.130		57377.580	

- η^{*}, υ^{*} are the scale of the error terms of the structural and measurement equations.
- δ_1 and δ_2 are two positive parameters used to account for the 5-point Likert scale of the measures.
- ec_sigma is an error component capturing the panel effects.

Bibliography

Agarwal, S., Charoenwong, B., Cheng, S.-F., Keppo, J., 2018. Fickle Fingers: Ride-Hail Surge Factors and Taxi Bookings. SSRN Electron. J. 1–42. https://doi.org/10.2139/ssrn.3157378

Arentze, T.A., Timmermans, H.J.P., 2004. A learning-based transportation oriented simulation system. Transp. Res. Part B Methodol. 38, 613–633. https://doi.org/10.1016/j.trb.2002.10.001

Ashkrof, P., Correia, G.H. de A., Cats, O., van Arem, B., 2023. On the Relocation Behaviour of Ride-sourcing Drivers. Transp. Lett. 1–8. https://doi.org/10.1080/19427867.2023.2192581

Ashkrof, P., Correia, G.H. de A., Cats, O., van Arem, B., 2020. Understanding ride-sourcing drivers' behaviour and preferences: Insights from focus groups analysis. Res. Transp. Bus. Manag. 37, 100516. https://doi.org/10.1016/j.rtbm.2020.100516

Ashkrof, P., Homem de Almeida Correia, G., Cats, O., van Arem, B., 2022. Ride acceptance behaviour of ride-sourcing drivers. Transp. Res. Part C Emerg. Technol. 142, 103783. https://doi.org/10.1016/j.trc.2022.103783

Azar, O.H., 2003. The implications of tipping for economics and management. Int. J. Soc. Econ. 30, 1084–1094. https://doi.org/10.1108/03068290310492878

Baron, D.P., 2018. Disruptive Entrepreneurship and Dual Purpose Strategies: The Case of Uber. Strateg. Sci. 3, 439–462. https://doi.org/10.1287/stsc.2018.0059

Battifarano, M., Qian, Z. (Sean), 2019. Predicting real-time surge pricing of ride-sourcing companies. Transp. Res. Part C Emerg. Technol. 107, 444–462. https://doi.org/10.1016/j.trc.2019.08.019

Ben-Akiva, M., Walker, J., Bernardino, A.T., Gopinath, D.A., Morikawa, T., Polydoropoulou, A., 2002. Integration of Choice and Latent Variable Models, In Perpetual Motion. https://doi.org/10.1016/b978-008044044-6/50022-x

Beojone, C.V., Geroliminis, N., 2021. On the inefficiency of ride-sourcing services towards urban congestion. Transp. Res. Part C Emerg. Technol. 124, 102890. https://doi.org/10.1016/j.trc.2020.102890

Besbes, O., Castro, F., Lobel, I., 2021. Surge pricing and its spatial supply response. Manage. Sci. 67, 1350–1367. https://doi.org/10.1287/mnsc.2020.3622

Bierlaire, M., 2020. A Short Introduction to PandasBiogeme. Ec. Polytech. Fed. Lausanne 13–43.

Bierlaire, M., Lurkin, V., 2020. Introduction to choice models [WWW Document]. URL https://www.edx.org/course/introduction-to-discrete-choice-models

Bliemer, M.C.J., Rose, J.M., 2010. Construction of experimental designs for mixed logit models allowing for correlation across choice observations. Transp. Res. Part B Methodol. https://doi.org/10.1016/j.trb.2009.12.004

Bloomberg, M.R., Yassky, D., 2014. 2014 Taxicab Factbook. Taxicab Factb. 1–13.

Bokányi, E., Hannák, A., 2020. Understanding Inequalities in Ride-Hailing Services Through Simulations. Sci. Rep. 10, 1–11. https://doi.org/10.1038/s41598-020-63171-9

Braverman, A., Dai, J.G., Liu, X., Ying, L., 2019. Empty-car routing in ridesharing systems. Oper. Res. 67, 1437–1452. https://doi.org/10.1287/opre.2018.1822

Bryan, K.A., Gans, J.S., 2019. A theory of multihoming in rideshare competition. J. Econ. Manag. Strateg. 28, 89–96. https://doi.org/10.1111/jems.12306

Cachon, G.P., Daniels, K.M., Lobel, R., 2017. The role of surge pricing on a service platform with self-scheduling capacity. Manuf. Serv. Oper. Manag. 19, 368–384. https://doi.org/10.1287/msom.2017.0618

Cachon, Gérard P., Daniels, K.M., Lobel, R., 2017. The role of surge pricing on a service platform with self-scheduling capacity. Manuf. Serv. Oper. Manag. 19, 368–384. https://doi.org/10.1287/msom.2017.0618

Cahuc, P., Carcillo, S., Zylberberg, A., 2014. Labor economics.

Carvalho, I., Costa, P.L., Simoes, R., Silva, A., Silva, S.A., 2016. Qualitative analysis of vehicle needs and perceptions towards the adoption of a reconfigurable vehicle. Res. Transp. Bus. Manag. 18, 85–104. https://doi.org/10.1016/j.rtbm.2016.03.007

Castillo, J.C., 2018. Who Benefits from Surge Pricing? SSRN Electron. J. https://doi.org/10.2139/ssrn.3245533

Chandar, B., Gneezy, U., List, J.A., Muir, I., 2019. The Drivers of Social Preferences : Evidence from a Nationwide Tipping Field Experiment.

Chen, L., Mislove, A., Wilson, C., 2015. Peeking beneath the hood of uber. Proc. ACM SIGCOMM Internet Meas. Conf. IMC 2015-October, 495–508. https://doi.org/10.1145/2815675.2815681

Chen, M.K., Sheldon, M., 2015. Dynamic Pricing in a Labor Market : Surge Pricing and Flexible Work on the Uber. Ssrn 1–19.

Chen, X. (Michael), Zheng, H., Ke, J., Yang, H., 2020. Dynamic optimization strategies for on-demand ride services platform: Surge pricing, commission rate, and incentives. Transp. Res. Part B Methodol. 138, 23–45. https://doi.org/10.1016/j.trb.2020.05.005

Chen, Xiqun, Chen, Xiaowei, Zheng, H., Xiao, F., 2021. Efficient dispatching for on-demand ride services : Systematic optimization via Monte-Carlo tree search. Transp. Res. Part C 127, 103156. https://doi.org/10.1016/j.trc.2021.103156

Chen, Y., Hu, M., 2020. Pricing and matching with forward-looking buyers and sellers. Manuf. Serv. Oper. Manag. 22, 717–734. https://doi.org/10.1287/msom.2018.0769

ChoiceMetrics, 2018. Ngene 1.2 USER MANUAL & REFERENCE GUIDE The Cutting Edge in Experimental Design End-User License Agreement 241.

Chu, L.Y., Wan, Z., Zhan, D., 2018. Harnessing the Double-Edged Sword via Routing: Information Provision on Ride-Hailing Platforms. SSRN Electron. J. https://doi.org/10.2139/ssrn.3266250

Ciari, F., Janzen, M., Ziemlicki, C., 2020. Planning shared automated vehicle fleets, Demand for Emerging Transportation Systems. Elsevier Inc. https://doi.org/10.1016/b978-0-12-815018-4.00008-5

Cohen, P., Hahn, R., Hall, J., Levitt, S., Metcalfe, R., 2016. Using Big Data To Estimate Consumer Surplus. Nber Work. Pap. Ser. 42.

Contreras, S.D., Paz, A., 2018. The effects of ride-hailing companies on the taxicab industry in Las Vegas, Nevada. Transp. Res. Part A Policy Pract. 115, 63–70. https://doi.org/10.1016/j.tra.2017.11.008

Conway, M., Salon, D., King, D., 2018. Trends in Taxi Use and the Advent of Ridehailing, 1995–2017: Evidence from the US National Household Travel Survey. Urban Sci. 2, 79. https://doi.org/10.3390/urbansci2030079

Cramer, J., Krueger, A.B., 2016. Disruptive change in the taxi business: The case of uber. Am. Econ. Rev. 106, 177–182. https://doi.org/10.1257/aer.p20161002

Davison, L., Enoch, M., Ryley, T., Quddus, M., Wang, C., 2012. Identifying potential market niches for Demand Responsive Transport. Res. Transp. Bus. Manag. 3, 50–61. https://doi.org/10.1016/j.rtbm.2012.04.007

de Ruijter, A., Cats, O., Kucharski, R., van Lint, H., 2022a. Evolution of labour supply in ridesourcing. Transp. B 10, 599–626. https://doi.org/10.1080/21680566.2021.2024917

de Ruijter, A., Cats, O., van Lint, H., 2022b. Emerging Dynamics in Ridesourcing Markets. SSRN Electron. J. https://doi.org/10.2139/ssrn.4258151

Du, J., Rakha, H., 2021. Impact of COVID-19 on Ridehailing and Other Modes of Transportation [WWW Document]. URL https://www.morgan.edu/school_of_engineering/research_centers/urban_mobility_and_equity_center/research/new_research/covid_and_ridehailing.html (accessed 5.13.21).

Elliott, D., Tomasini, M., Oliveira, M., Menezes, R., 2018. Tippers and stiffers: An analysis of tipping behavior in taxi trips. 2017 IEEE SmartWorld Ubiquitous Intell. Comput. Adv. Trust. Comput. Scalable Comput. Commun. Cloud Big Data Comput. Internet People Smart City Innov. SmartWorld/SCALCOM/UIC/ATC/CBDCom/IOP/SCI 2017 - 1–8. https://doi.org/10.1109/UIC-ATC.2017.8397523

Elo, S., Kyngäs, H., 2008. The qualitative content analysis process. J. Adv. Nurs. 62, 107–115. https://doi.org/10.1111/j.1365-2648.2007.04569.x

Faber, K., van Lierop, D., 2020. How will older adults use automated vehicles? Assessing the role of AVs in overcoming perceived mobility barriers. Transp. Res. Part A Policy Pract. 133, 353–363. https://doi.org/10.1016/j.tra.2020.01.022

Farber, H.S., 2015. Why you Can't Find a Taxi in the Rain and Other Labor Supply Lessons from Cab Drivers. Q. J. Econ. 130, 1975–2026. https://doi.org/10.1093/qje/qjv026

Ferrer, S., Ruiz, T., 2018. The impact of the built environment on the decision to walk for short trips: Evidence from two Spanish cities. Transp. Policy 67, 111–120. https://doi.org/10.1016/j.tranpol.2017.04.009

Fielbaum, A., Tirachini, A., 2020. The sharing economy and the job market: the case of ride-hailing drivers in Chile. Transportation (Amst). https://doi.org/10.1007/s11116-020-10127-7

Fistman, R., Luca, M., 2016. Fixing Discrimination in Online Marketplaces - Article - Harvard Business School [WWW Document]. Harvard Bus. Sch. URL https://www.hbs.edu/faculty/Pages/item.aspx?num=51982 (accessed 10.24.19).

Flath, D., 2012. Why Do We Tip Taxicab Drivers? Japanese Econ. 39, 69–76. https://doi.org/10.2753/jes1097-203x390304

Flora, D.B., LaBrish, C., Chalmers, R.P., 2012. Old and new ideas for data screening and assumption testing for exploratory and confirmatory factor analysis. Front. Psychol. 3, 1–21. https://doi.org/10.3389/fpsyg.2012.00055

Gao, Y., Jiang, D., Xu, Y., 2018. Optimize taxi driving strategies based on reinforcement learning. Int. J. Geogr. Inf. Sci. 32, 1677–1696. https://doi.org/10.1080/13658816.2018.1458984

Gaskin, C.J., Happell, B., 2014. On exploratory factor analysis: A review of recent evidence, an assessment of current practice, and recommendations for future use. Int. J. Nurs. Stud. 51, 511–521. https://doi.org/10.1016/j.ijnurstu.2013.10.005

Ge, Y., Knittel, C., MacKenzie, D., Zoepf, S., 2016. Racial and Gender Discrimination in Transportation Network Companies. NBER Work. Pap. No. 22776 9 pages. https://doi.org/10.3386/w22776

GemeenteAmsterdam, 2019. Agenda Taxi 2020–2025. Technical Report. Verkeer en Openbare

Ruimte, Gemeente Ams- terdam.
Geržinič, N., van Oort, N., Hoogendoorn-Lanser, S., Cats, O., Hoogendoorn, S., 2022. Potential of on-demand services for urban travel, Transportation. Springer US. https://doi.org/10.1007/s11116-022-10278-9
Godfrey, G.A., Powell, W.B., 2002. An adaptive dynamic programming algorithm for dynamic fleet management, I: Single period travel times. Transp. Sci. 36, 21–39. https://doi.org/10.1287/trsc.36.1.21.570
Guda, H., Subramaniana, U., 2019. Your uber is arriving: Managing on-demand workers through surge pricing, forecast communication, and worker incentives. Manage. Sci. 65, 1995–2014. https://doi.org/10.1287/mnsc.2018.3050
Hall, J. V., Krueger, A.B., 2018. An Analysis of the Labor Market for Uber's Driver-Partners in the United States. ILR Rev. 71, 705–732. https://doi.org/10.1177/0019793917717222
Hamilton, I., Hernbroth, M., 2019. Uber drivers across the world are striking about pay, conditions, and the firm's "orgy of greed" [WWW Document]. businessinsider. URL https://www.businessinsider.nl/photos-uber-drivers-go-on-strike-around-the-world-2019-5?international=true&r=US (accessed 5.6.21).
He, Z., 2021. Portraying ride-hailing mobility using multi-day trip order data: A case study of Beijing, China. Transp. Res. Part A Policy Pract. 146, 152–169. https://doi.org/10.1016/j.tra.2021.01.017
Henao, A., Marshall, W.E., 2019. An analysis of the individual economics of ride-hailing drivers. Transp. Res. Part A 130, 440–451. https://doi.org/10.1016/j.tra.2019.09.056
Hensher, D.A., Rose, J.M., Rose, J.M., Greene, W.H., 2005. Applied Choice Analysis, Cambridge University Press.
Henson, R.K., Roberts, J.K., 2006. Use of Exploratory Factor Analysis in Published Research. Educ. Pschological Meas. 66, 11–14. https://doi.org/10.1177/0013164405282485
Hörl, S., Ruch, C., Becker, F., Frazzoli, E., Axhausen, K.W., 2019. Fleet operational policies for automated mobility: A simulation assessment for Zurich. Transp. Res. Part C Emerg. Technol. 102, 20–31. https://doi.org/10.1016/j.trc.2019.02.020
Iglesias, R., Rossi, F., Zhang, R., Pavone, M., 2019. A BCMP network approach to modeling and controlling autonomous mobility-on-demand systems. Int. J. Rob. Res. 38, 357–374. https://doi.org/10.1177/0278364918780335
Jacobsson, S., Arnäs, P.O., Stefansson, G., 2017. Access management in intermodal freight transportation: An explorative study of information attributes, actors, resources and activities. Res. Transp. Bus. Manag. 23, 106–124. https://doi.org/10.1016/j.rtbm.2017.02.012
Jiang, Z.-Z., Kong, G., Zhang, Y., 2018. Making the Most of Your Regret: A Behavioral Investigation of Workers' Relocation in On-Demand Platforms by Zhong-Zhong Jiang, Guangwen Kong, Yinghao Zhang :: SSRN. SSRN Electron. J.
Jiao, J., 2018. Investigating Uber price surges during a special event in Austin, TX. Res. Transp. Bus. Manag. 29, 101–107. https://doi.org/10.1016/j.rtbm.2018.02.008
Kaiser, H.F., 1974. An index of factorial simplicity. Psychometrika 39, 31–36. https://doi.org/10.1007/BF02291575
Kapoor, A., Tucker, C.E., 2017. How Do Platform Participants Respond to an Unfair Rating? An Analysis of a Ride-Sharing Platform Using a Quasi-Experiment. SSRN Electron. J. https://doi.org/10.2139/ssrn.3061385
Ke, J., Cen, X., Yang, H., Chen, X., Ye, J., 2019. Modelling drivers' working and recharging schedules in a ride-sourcing market with electric vehicles and gasoline vehicles. Transp. Res. Part E Logist. Transp. Rev. 125, 160–180. https://doi.org/10.1016/j.tre.2019.03.010
Ke, J., Zheng, Z., Yang, H., Ye, J., 2021. Data-driven analysis on matching probability, routing distance and detour distance in ride-pooling services. Transp. Res. Part C Emerg. Technol.

124, 102922. https://doi.org/10.1016/j.trc.2020.102922
Krueger, R.A., Casey, M.A., 2014. Focus groups: A practical guide for applied research. Sage publications, 2014.
Kucharski, R., Cats, O., 2022. Simulating two-sided mobility platforms with MaaSSim. PLoS One 17, 1–20. https://doi.org/10.1371/journal.pone.0269682
Kucharski, R., Cats, O., 2020. Exact matching of attractive shared rides (ExMAS) for system-wide strategic evaluations. Transp. Res. Part B Methodol. 139, 285–310. https://doi.org/10.1016/j.trb.2020.06.006
Kyngäs, H., 2020. Inductive Content Analysis. Appl. Content Anal. Nurs. Sci. Res. 13–21. https://doi.org/10.1007/978-3-030-30199-6_2
Leng, B., Du, H., Wang, J., Li, L., Xiong, Z., 2016. Analysis of taxi drivers' behaviors within a battle between two taxi apps. IEEE Trans. Intell. Transp. Syst. 17, 296–300. https://doi.org/10.1109/TITS.2015.2461000
Levin, M.W., 2017. Congestion-aware system optimal route choice for shared autonomous vehicles. Transp. Res. Part C Emerg. Technol. 82, 229–247. https://doi.org/10.1016/j.trc.2017.06.020
Li, J., 2018. Residential and transit decisions: Insights from focus groups of neighborhoods around transit stations. Transp. Policy 63, 1–9. https://doi.org/10.1016/j.tranpol.2017.10.012
Li, M., Jiang, G., Lo, H.K., 2022. Pricing strategy of ride-sourcing services under travel time variability. Transp. Res. Part E Logist. Transp. Rev. 159, 102631. https://doi.org/10.1016/j.tre.2022.102631
Liang, X., Correia, G.H. de A., An, K., van Arem, B., 2020. Automated taxis' dial-a-ride problem with ride-sharing considering congestion-based dynamic travel times. Transp. Res. Part C Emerg. Technol. 112, 260–281. https://doi.org/10.1016/j.trc.2020.01.024
Liang, X., Homem de Almeida Correia, G., van Arem, B., 2018. Applying a Model for Trip Assignment and Dynamic Routing of Automated Taxis with Congestion: System Performance in the City of Delft, The Netherlands. Transp. Res. Rec. https://doi.org/10.1177/0361198118758048
Litman, T., 2022. Autonomous Vehicle Implementation Predictions: Implications for Transport Planning. Transp. Res. Board Annu. Meet. 42, 1–39.
Lu, A., Frazier, P., Kislev, O., 2018. Surge Pricing Moves Uber's Driver Partners. SSRN Electron. J. i. https://doi.org/10.2139/ssrn.3180246
Marshall, M.N., 1996. Sampling for qualitative research. Fam. Pract. 13, 522–525. https://doi.org/10.1093/fampra/13.6.522
Martínez, L.M., Correia, G.H. de A., Moura, F., Mendes Lopes, M., 2017. Insights into carsharing demand dynamics: Outputs of an agent-based model application to Lisbon, Portugal. Int. J. Sustain. Transp. 11, 148–159. https://doi.org/10.1080/15568318.2016.1226997
Mayring, P., 2000. Qualitative content analysis [WWW Document]. Forum Qual. Sozialforsch. / Forum Qual. Soc. Res. 1(2). URL http://www.qualitative-research.net/index.php/fqs/article/viewArticle/1089/2385 (accessed 5.29.20).
McFadden, D., 1974. Conditional Logit Analysis of Qualitative Choice Behaviour, in: Frontiers of Econometrics.
Meduim, 2022. Uber's Marketplace Matching: Case Study | by Vithika Karan | MLearning.ai | Medium [WWW Document]. URL https://medium.com/mlearning-ai/ubers-marketplace-matching-algorithm-case-study-441853410a6b (accessed 12.27.22).
Miranda, F., Muñoz, J.C., De dios Ortúzar, J., 2008. Identifying transit driver preferences for work shift structures: An econometric analysis. Transp. Sci. 42, 70–86. https://doi.org/10.1287/trsc.1070.0199

Morshed, S.A., Khan, S.S., Tanvir, R.B., Nur, S., 2021a. Impact of COVID-19 pandemic on ride-hailing services based on large-scale Twitter data analysis. J. Urban Manag. https://doi.org/10.1016/j.jum.2021.03.002

Morshed, S.A., Khan, S.S., Tanvir, R.B., Nur, S., 2021b. Impact of COVID-19 pandemic on ride-hailing services based on large-scale Twitter data analysis. J. Urban Manag. 10, 155–165. https://doi.org/10.1016/j.jum.2021.03.002

Nahmias-Biran, B.H., Oke, J.B., Kumar, N., Basak, K., Araldo, A., Seshadri, R., Akkinepally, A., Azevedo, C.L., Ben-Akiva, M., 2019. From Traditional to Automated Mobility on Demand: A Comprehensive Framework for Modeling On-Demand Services in SimMobility. Transp. Res. Rec. 2673, 15–29. https://doi.org/10.1177/0361198119853553

Narayan, J., Cats, O., van Oort, N., Hoogendoorn, S.P., 2021. Fleet size determination for a mixed private and pooled on-demand system with elastic demand. Transp. A Transp. Sci. 17, 897–920. https://doi.org/10.1080/23249935.2020.1819910

Nicolas Vega (New York Post), 2019. Rush-hour Uber and Lyft driver strike was a flop in NYC [WWW Document]. URL https://nypost.com/2019/05/08/rush-hour-uber-and-lyft-driver-strike-was-a-flop-in-nyc/?utm_source=whatsapp_sitebuttons (accessed 5.10.19).

Nikitas, A., Wang, J.Y.T., Knamiller, C., 2019. Exploring parental perceptions about school travel and walking school buses: A thematic analysis approach. Transp. Res. Part A Policy Pract. 124, 468–487. https://doi.org/10.1016/j.tra.2019.04.011

Norris, M., Lecavalier, L., 2010. Evaluating the use of exploratory factor analysis in developmental disability psychological research. J. Autism Dev. Disord. 40, 8–20. https://doi.org/10.1007/s10803-009-0816-2

Noulas, A., Salnikov, V., Hristova, D., Mascolo, C., Lambiotte, R., 2019. Developing and deploying a taxi price comparison mobile app in the wild: Insights and challenges. Proc. - 2018 IEEE 5th Int. Conf. Data Sci. Adv. Anal. DSAA 2018 424–430. https://doi.org/10.1109/DSAA.2018.00055

Nourinejad, M., Ramezani, M., 2019. Ride-Sourcing Modeling and Pricing in Non-Equilibrium Two-Sided Markets. Transp. Res. Part B 00, 24–26. https://doi.org/10.1016/j.trb.2019.05.019

Nourinejad, M., Roorda, M.J., 2016. Agent based model for dynamic ridesharing. Transp. Res. Part C Emerg. Technol. 64, 117–132. https://doi.org/10.1016/j.trc.2015.07.016

Oh, S., Seshadri, R., Le, D.-T., Zegras, P.C., Ben-Akiva, M.E., 2020. Evaluating Automated Demand Responsive Transit Using Microsimulation. IEEE Access 8, 82551–82561. https://doi.org/10.1109/access.2020.2991154

Onwuegbuzie, A.J., Dickinson, W.B., Leech, N.L., Zoran, A.G., 2009. A Qualitative Framework for Collecting and Analyzing Data in Focus Group Research. Int. J. Qual. Methods 8, 1–21. https://doi.org/10.1177/160940690900800301

Osorio, C., 2019. Dynamic origin-destination matrix calibration for large-scale network simulators. Transp. Res. Part C Emerg. Technol. 98, 186–206. https://doi.org/10.1016/j.trc.2018.09.023

Özer, Ö., Subramanian, U., Wang, Y., 2018. Information sharing, advice provision, or delegation: What leads to higher trust and trustworthiness? Manage. Sci. 64, 474–493. https://doi.org/10.1287/mnsc.2016.2617

Peters, D.A., 1993. Improving quality requires consumer input: Using focus group. J. Nurs. Care Qual. 7, 34–41.

Price, L.R., 2017. Psychometric Methods: Theory into Practice [WWW Document]. Meas. Interdiscip. Res. Perspect. URL https://lccn.loc.gov/2016013346 (accessed 4.14.21).

Pudāne, B., Rataj, M., Molin, E.J.E., Mouter, N., van Cranenburgh, S., Chorus, C.G., 2018. How will automated vehicles shape users' daily activities? Insights from focus groups with commuters in the Netherlands. Transp. Res. Part D Transp. Environ. 1–14.

https://doi.org/10.1016/j.trd.2018.11.014
Ramezani, M., Yang, Y., Elmasry, J., Tang, P., 2022. An empirical study on characteristics of supply in e-hailing markets: a clustering approach. https://doi-org.tudelft.idm.oclc.org/10.1080/19427867.2022.2079869. https://doi.org/10.1080/19427867.2022.2079869
Rangel, T., Gonzalez, J.N., Gomez, J., Romero, F., Vassallo, J.M., 2021. Exploring ride-hailing fares: an empirical analysis of the case of Madrid. Transportation (Amst). https://doi.org/10.1007/s11116-021-10180-w
Rayle, L., Dai, D., Chan, N., Cervero, R., Shaheen, S., 2016. Just a better taxi? A survey-based comparison of taxis, transit, and ridesourcing services in San Francisco. Transp. Policy 45, 168–178. https://doi.org/10.1016/j.tranpol.2015.10.004
Reuters, 2022. Uber, Lyft drivers claim price-fixing in lawsuit against companies | Reuters.
Robinson, H.C., 2017. Making a Digital Working Class: Uber Drivers in Boston, 2016- 2017. Dr. diss., Progr. Sci. Technol. Soc. MIT 1–195.
Romanyuk, G., 2016. Ignorance Is Strength : Improving Performance of Matching Markets by Limiting Information. Job Mark. Pap. 1–43.
Rose, J.M., Bliemer, M.C.J., 2009. Incorporating model uncertainty into the generation of efficient stated choice experiments: A model averaging approach, in: International Choice Modelling Conference, March 30-April 1, Yorkshire U.K.
Rose, J.M., Bliemer, M.C.J., Hensher, D.A., Collins, A.T., 2008. Designing efficient stated choice experiments in the presence of reference alternatives. Transp. Res. Part B Methodol. 42, 395–406. https://doi.org/10.1016/j.trb.2007.09.002
Rosenblat, A., Stark, L., 2015. Algorithmic Labor and Information Asymmetries: A Case Study of Uber's Drivers. Ssrn 10, 3758–3784. https://doi.org/10.2139/ssrn.2686227
Ruch, C., Sebastian, H., Frazzoli, E., 2018. AMoDeus , a Simulation-Based Testbed for Autonomous Mobility-on-Demand Systems 3639–3644.
SAE International, 2021. Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles - SAE International.
SAE International, 2018. Surface Vehicle Recommended Practice.
Serafimova, T., 2020. Covid-19: An Opportunity to Redesign Mobility Towards Greater Sustainability and Resilience? 8.
Shaheen, S.A., Mallery, M.A., Kingsley, K.J., 2012. Personal vehicle sharing services in North America. Res. Transp. Bus. Manag. 3, 71–81. https://doi.org/10.1016/j.rtbm.2012.04.005
Shen, H., Zou, B., Lin, J., Liu, P., 2020. Modeling travel mode choice of young people with differentiated E-hailing ride services in Nanjing China. Transp. Res. Part D Transp. Environ. 78, 102216. https://doi.org/10.1016/j.trd.2019.102216
Shierholdz, H., Cooper, D., Wolfe, J., Zipperer, B., 2017. Employers would pocket $5.8 billion of workers' tips under Trump administration's proposed 'tip stealing' rule [WWW Document]. A Rep. by Econ. Policy Institute, Washingt. DC. URL https://www.epi.org/publication/employers-would-pocket-workers-tips-under-trump-administrations-proposed-tip-stealing-rule/ (accessed 4.29.21).
Smart, R., Rowe, B., Hawken, A., 2015. Faster and Cheaper: How Ride-Sourcing Fills a Gap in Low-Income Los Angeles Neighborhoods.
Son, D.H., 2023. On-demand ride-sourcing markets with cryptocurrency-based fare-reward scheme. Transp. Res. Part E Logist. Transp. Rev. 171, 103027. https://doi.org/10.1016/j.tre.2023.103027
Spearman, C., 1904. " General Intelligence ," Objectively Determined and Measured Author (s): C . Spearman Source : The American Journal of Psychology , Vol . 15 , No . 2 (Apr ., 1904), pp . 201-292 Published by : University of Illinois Press Stable URL : http://www.jsto. Am. J. Psychol. 15, 201–292.

Standard mileage rates for 2021 | Internal Revenue Service [WWW Document], n.d. . IRS. URL https://www.irs.gov/newsroom/irs-issues-standard-mileage-rates-for-2021 (accessed 10.31.22).

Techcrunch, 2019. Uber and Lyft drivers are striking ahead of Uber's IPO | TechCrunch [WWW Document]. URL https://techcrunch.com/2019/05/06/uber-and-lyft-drivers-are-striking-ahead-of-ubers-ipo/?guce_referrer=aHR0cHM6Ly93d3ctbmF0dXJlLWNvbS50dWRlbGZ0LmlkbS5vY2xjLm9yZy8&guce_referrer_sig=AQAAAIBFzlo0ByTPoYMLW4UTk0bdc2jtsqY_taMrShkwgyABAy3C_2C02xUjy4eNoyHqYAjyS_ (accessed 12.1.22).

Tengilimoglu, O., Wadud, Z., 2021. Evaluating the mileage and time efficiency of ridesourcing services: Austin, Texas case. Transp. Lett. 00, 1–14. https://doi.org/10.1080/19427867.2021.1892936

The Guardian, 2021. Uber and Lyft drivers join day-long strike over working conditions | Uber | The Guardian [WWW Document]. URL https://www.theguardian.com/technology/2021/jul/21/uber-lyft-drivers-strike-app-based-work-gig-economy (accessed 11.21.22).

Thompson, B., 1995. Stepwise Regression and Stepwise Discriminant Analysis Need Not Apply here: A Guidelines Editorial. http://dx.doi.org.tudelft.idm.oclc.org/10.1177/0013164495055004001 55, 525–534. https://doi.org/10.1177/0013164495055004001

Tirachini, A., 2020. Ride-hailing, travel behaviour and sustainable mobility: an international review. Transportation (Amst). 47, 2011–2047. https://doi.org/10.1007/s11116-019-10070-2

Traffic Index by Country, 2021. Traffic Index by Country 2021 [WWW Document]. URL https://www.numbeo.com/traffic/rankings_by_country.jsp (accessed 5.13.21).

Uber, 2022a. H3: Uber's Hexagonal Hierarchical Spatial Index | Uber Blog [WWW Document]. URL https://www.uber.com/en-NL/blog/h3/ (accessed 12.30.22).

Uber, 2022b. Uber Marketplace Matching | Uber [WWW Document]. URL https://www.uber.com/us/en/marketplace/matching/ (accessed 12.27.22).

Uber Marketplace Surge pricing, 2022. Uber Marketplace Surge pricing [WWW Document]. URL https://www.uber.com/us/en/marketplace/pricing/surge-pricing/ (accessed 12.22.22).

Uberconfession, 2015. Confessions of an Uber Driver – Empty Promises [WWW Document]. URL https://uberconfession.tumblr.com/post/108296995865/empty-promises (accessed 12.1.22).

Vazifeh, M.M., Santi, P., Resta, G., Strogatz, S.H., Ratti, C., 2018. Addressing the minimum fleet problem in on-demand urban mobility. Nature 557, 534–538. https://doi.org/10.1038/s41586-018-0095-1

Vij, A., Walker, J.L., 2016. How, when and why integrated choice and latent variable models are latently useful. Transp. Res. Part B Methodol. 90, 192–217. https://doi.org/10.1016/J.TRB.2016.04.021

Walker, J.L., Wang, Y., Thorhauge, M., Ben-Akiva, M., 2018. D-efficient or deficient? A robustness analysis of stated choice experimental designs. Theory Decis. 84, 215–238. https://doi.org/10.1007/s11238-017-9647-3

Wang, D., Zhang, J., Cao, W., Li, J., Zheng, Y., 2018. When will you arrive? Estimating travel time based on deep neural networks. 32nd AAAI Conf. Artif. Intell. AAAI 2018 2500–2507.

Wang, H., Yang, H., 2019. Ridesourcing systems: A framework and review. Transp. Res. Part B Methodol. 129, 122–155. https://doi.org/10.1016/j.trb.2019.07.009

Wang, S., Correia, G.H. de A., Lin, H.X., 2022. Modeling the competition between multiple Automated Mobility on-Demand operators: An agent-based approach. Phys. A Stat. Mech. its Appl. 605, 128033. https://doi.org/10.1016/j.physa.2022.128033

Wang, S., Smart, M., 2020. The disruptive effect of ridesourcing services on for-hire vehicle drivers' income and employment. Transp. Policy 89, 13–23. https://doi.org/10.1016/j.tranpol.2020.01.016

Wang, T., Zhang, Y., Fu, X., Li, X., Liu, L., 2020. Finding taxi service management opportunities based on the analysis of choice behavior for passengers with different travel distances. Res. Transp. Bus. Manag. 100457. https://doi.org/10.1016/j.rtbm.2020.100457

Wang, Z., Fu, K., Ye, J., 2018. Learning to estimate the travel time. Proc. ACM SIGKDD Int. Conf. Knowl. Discov. Data Min. 858–866. https://doi.org/10.1145/3219819.3219900

Wen, J., Zhao, J., Jaillet, P., 2018. Rebalancing shared mobility-on-demand systems: A reinforcement learning approach. IEEE Conf. Intell. Transp. Syst. Proceedings, ITSC 2018-March, 220–225. https://doi.org/10.1109/ITSC.2017.8317908

Wentrup, R., Nakamura, H.R., Ström, P., 2019. Uberization in Paris – the issue of trust between a digital platform and digital workers. Crit. Perspect. Int. Bus. 15, 20–41. https://doi.org/10.1108/cpoib-03-2018-0033

Williamson, K., Given, L.M., Scifleet, P., 2018. Qualitative data analysis, Research Methods: Information, Systems, and Contexts: Second Edition. Elsevier Ltd. https://doi.org/10.1016/B978-0-08-102220-7.00019-4

Winter, K., Cats, O., Correia, G.H. de A., van Arem, B., 2016. Designing an Automated Demand-Responsive Transport System: Fleet Size and Performance Analysis for a Campus–Train Station Service. Transp. Res. Rec. J. Transp. Res. Board 2542, 75–83. https://doi.org/10.3141/2542-09

Winter, K., Cats, O., Martens, K., van Arem, B., 2020. Relocating shared automated vehicles under parking constraints: assessing the impact of different strategies for on-street parking. Transportation (Amst). https://doi.org/10.1007/s11116-020-10116-w

Xu, K., Sun, L., Liu, J., Wang, H., 2018. An empirical investigation of taxi driver response behavior to ride-hailing requests: A spatio-temporal perspective. PLoS One 13, 1–17. https://doi.org/10.1371/journal.pone.0198605

Xu, Z., 2020. On the Empty Miles of Ride-Sourcing Services: Theory, Observation and Countermeasures [WWW Document]. Univ. Michigan. URL https://deepblue.lib.umich.edu/handle/2027.42/163209 (accessed 2.5.22).

Xu, Z., A.M.C. Vignon, D., Yin, Y., Ye, J., 2020. An empirical study of the labor supply of ride-sourcing drivers. Transp. Lett. 1–4. https://doi.org/10.1080/19427867.2020.1788761

Xue, Z., Zeng, S., Ma, C., 2021. Economic modeling and analysis of the ride-sourcing market considering labor supply. Res. Transp. Bus. Manag. 38, 100530. https://doi.org/10.1016/j.rtbm.2020.100530

Yang, H., Shao, C., Wang, H., Ye, J., 2018. Integrated reward scheme and surge pricing in a ride-sourcing market. Transp. Syst. Connect. Era - Proc. 23rd Int. Conf. Hong Kong Soc. Transp. Stud. HKSTS 2018 209–218. https://doi.org/10.2139/ssrn.3198081

Zha, L., Yin, Y., Du, Y., 2018a. Surge pricing and labor supply in the ride-sourcing market. Transp. Res. Part B Methodol. 117, 708–722. https://doi.org/10.1016/j.trb.2017.09.010

Zha, L., Yin, Y., Xu, Z., 2018b. Geometric matching and spatial pricing in ride-sourcing markets. Transp. Res. Part C Emerg. Technol. 92, 58–75. https://doi.org/10.1016/j.trc.2018.04.015

Zha, L., Yin, Y., Yang, H., 2016. Economic analysis of ride-sourcing markets. Transp. Res. Part C Emerg. Technol. 71, 249–266. https://doi.org/10.1016/j.trc.2016.07.010

Zhang, R., Pavone, M., 2016. Control of robotic mobility-on-demand systems: A queueing-theoretical perspective. Int. J. Rob. Res. 35, 186–203.

https://doi.org/10.1177/0278364915581863
Zhang, R., Rossi, F., Pavone, M., 2016. Model predictive control of autonomous mobility-on-demand systems. Proc. - IEEE Int. Conf. Robot. Autom. 2016-June, 1382–1389. https://doi.org/10.1109/ICRA.2016.7487272
Zhong, Y., Wan, Z., Shen, Z.-J.M., 2020. Queueing Versus Surge Pricing Mechanism: Efficiency, Equity, and Consumer Welfare. SSRN Electron. J. https://doi.org/10.2139/ssrn.3699134
Zuniga-Garcia, N., Tec, M., Scott, J.G., Ruiz-Juri, N., Machemehl, R.B., 2020. Evaluation of ride-sourcing search frictions and driver productivity: A spatial denoising approach. Transp. Res. Part C Emerg. Technol. 110, 346–367. https://doi.org/10.1016/j.trc.2019.11.021

Summary

Emerging from recent technological developments, ride-sourcing platforms have penetrated the transportation market. Ride-sourcing is a two-sided digital platform acting as a mediator between individual passengers and individual drivers, offering door-to-door rides using their private cars. The ride-sourcing business model, built upon the gig economy in which independent contractors supply the system, facilitates a dynamic response to market needs. This offers the demand side the flexibility to interact with the platform in real-time and gives the supply side the freedom to make decisions. Ride-sourcing drivers, as service suppliers, can make various choices ranging from strategic to operational. Daily system operations are primarily governed by drivers' tactical and operational decisions. The former refers to drivers' choices to select their working shift and area, and the latter is associated with their ride acceptance behaviour and relocation strategies. These decisions can disruptively impact system performance. For example, passengers' waiting time can significantly increase when drivers' acceptance rate is low. The unavailability of drivers potentially leads to a low match rate and thus lower level of service for passengers.

To this end, it is crucial to acquire a profound empirical knowledge of drivers' behavioural dynamics and their impacts on the system performance, which have been largely unknown in the literature due to the scarcity of relevant data. A typical assumption on the supply side in the primary research stream pertains to the fleet operation of automated vehicles/fully compliant drivers with no independent decision-making, which is not in line with current operations. The overarching aim of this thesis is to comprehensively investigate ride-sourcing drivers' behaviour with a focus on the operational decisions governing the within-day system operations, identify the key components affecting drivers' choices, and analyse their potential consequences for system performance. To this end, a bottom-up modelling approach was adopted using various methodologies ranging from qualitative to quantitative and behavioural to operational.

First, we conducted a focus group study with Uber drivers working in the Netherlands to gain an in-depth insight into drivers' perception of system operations, their interactions with the platform, and their concerns and expectations. Using the content analysis principle, we identified the relevant themes and categorised the findings into higher-order headings. We found that flexible working conditions facilitating independent decision-making is the fundamental motivation of drivers to join the platform. Given the constant development in the platform strategies, effective communication between the platform and drivers is vital in reducing the likelihood of misunderstanding and mistrust of drivers in the platform, resulting in adverse effects on the system. Although all drivers aim to maximise their profit, their strategies significantly vary, depending on their working characteristics such as employment

status and working experience. We proposed a conceptual framework characterising the relationship between drivers' tactical and operational decisions and the influential determinants. We found that various factors can affect drivers' behaviour depending on platform strategies, drivers' characteristics, riders' attributes, and external factors.

Second, using the findings of the focus group study and existing scientific and grey literature, we designed a cross-sectional stated preference survey to identify the key factors influencing drivers' ride acceptance behaviour based on the platform information sharing policy. The survey specifications were carefully designed to mimic the driver app when a ride request popped up. In addition to the current operations, we devised multiple hypothetical features in the app and revealed the relevant information to investigate drivers' responses to potential strategies. A unique dataset consisting of 576 valid responses from the ride-sourcing drivers in the US and 58 drivers in the Netherlands was collected. We adopted the random utility modelling approach to analyse the data. The results suggest that pickup time (i.e., the travel time between the driver's location and the rider's pickup spot) is the most crucial factor negatively affecting ride acceptance. It turns out that guaranteed tip (i.e., the minimum amount of tip indicated upfront by the prospective rider, a feature that is currently not available) and surge pricing are valued by drivers considerably higher than trip fare per monetary unit. Individual-specific determinants including employment status, experience level, and working shift, are found to be the critical determinants of drivers' ride acceptance. For instance, part-time and beginning drivers who work on midweek days have a higher acceptance probability.

Third, we delved into drivers' relocation strategies, referring to drivers' choices to find a ride while being idle. To this end, a stated choice experiment was designed to collect data from ride-sourcing drivers in the US. We considered four alternatives: staying around the drop-off location, driving to the surge area where surge pricing is applied, heading to the high-demand area in which higher demand is expected while the regular pricing is applicable, and cruising freely based on experience/intuition. We applied random utility maximisation modelling to our unique dataset to estimate the effects of the designated attributes. The results reveal that drivers' working characteristics are the key components governing their repositioning choices. Beginners, highly satisfied drivers, and drivers with more completed trips since the beginning of their shift are more likely to drive to surge and high-demand areas, depending on the surge value and the expected travel time between drivers' location and the surge/high-demand area. To gain more comprehensive insights, we investigated an alternative, not yet existing, novel repositioning guidance. Drivers' knowledge of pre-booked rides in the neighbourhood of the drop-off location impacts the likelihood of staying around the drop-off point, depending on the expected waiting time. Having a guaranteed bonus for driving to high-demand areas significantly incentivises drivers to drive towards those areas. Furthermore, providing drivers with real-time traffic information in the surrounding area may help reduce deadheading, especially when it is highly congested.

Fourth, the behavioural findings regarding drivers' ride-acceptance decisions are incorporated into a simulation model of system operations of a ride-sourcing platform where all parties interact with each other to analyse the corresponding implications on system operation. We adapted and adopted a discrete-event agent-based simulation framework enabling the platform agent to apply regular and surge pricing, the rider agent to submit a ride request, revoke it, and decline the received offer in case surge pricing is applicable, and the driver agent to make ride acceptance decisions based on the developed models in the previous studies. We found that the system operation is primarily affected by the supply-demand intensity divided into three states: undersupply (more requests than available drivers in a particular time and zone), balanced, and oversupply (more available drivers than the number of requests). We observe a distinctive pattern of system performance in terms of passenger waiting time, drivers' income, and the platform revenue in each state, depending on the extent of the misbalance between supply and demand. We compare the performance of a centralised fleet (i.e., mandatory acceptance on each ride request) and a decentralised fleet (i.e., ride acceptance decision by each driver). We found that the fleet characteristics concerning drivers' ride acceptance behaviour are crucial in system operations. For example, passengers' waiting time and drivers' income inequality are higher in a decentralised fleet. Surge pricing is found to be asymmetrically beneficial for all parties. Nonetheless, a higher trip fare caused by surge pricing has marginal negative impacts on the demand side.

Overall, we developed novel theories on the ride-sourcing supply-side behavioural dynamics and integrated them into the modelling of system operation to comprehensively analyse their consequences on system performance. In summary, the collective choices of drivers as service suppliers significantly determine ride-sourcing system operations. Therefore, ride-sourcing platforms must devise various measures to manage the fleet efficiently which account for drivers' behaviour. We argue that neglecting drivers' behaviour in system operations of a two-sided ride-sourcing platform possibly results in a misrepresentation of the system and thereby potentially leads to misled conclusions.

Samenvatting

Dankzij recente technologische ontwikkelingen zijn platforms voor ritbemiddeling inmiddels de vervoersmarkt binnengedrongen. Ritbemiddeling verloopt via een tweezijdig digitaal platform, dat als mediator fungeert tussen enerzijds individuele passagiers en anderzijds individuele chauffeurs die vervoer van deur tot deur aanbieden met hun eigen auto. Het bedrijfsmodel van ritbemiddeling, dat is gebaseerd op de kluseconomie, waarin onafhankelijke opdrachtnemers diensten leveren aan het systeem, maakt het mogelijk dynamisch te reageren op de vraag vanuit de markt. Hierdoor kan de vraagkant flexibel en in realtime in contact komen met het platform en heeft de aanbodkant de vrijheid om zelf te beslissen. Chauffeurs die via ritbemiddeling werken, kunnen als verleners van hun diensten allerlei keuzes maken, variërend van strategisch tot operationeel. De dagelijkse gang van zaken is met name afhankelijk van de tactische en operationele beslissingen van chauffeurs. Het eerste soort beslissingen heeft betrekking op de keuze van chauffeurs wat betreft werkuren en -gebied, en het tweede op hun gedrag wat betreft de ritten die ze accepteren en hun relocatiestrategie. Deze beslissingen kunnen een verstorende werking hebben op het functioneren van het systeem. Zo kan de wachttijd voor passagiers fors oplopen als de chauffeurs weinig ritten accepteren. Wanneer er geen chauffeurs beschikbaar zijn, kan dit ertoe leiden dat er weinig matches tot stand komen, waardoor het serviceniveau voor passagiers laag is.

Daarom is het van groot belang om diepgaande kennis te verkrijgen in de gedragsdynamiek van chauffeurs en de gevolgen daarvan voor het functioneren van het systeem. Omdat er nauwelijks relevante data beschikbaar zijn, is hier echter weinig literatuur over. In de meeste onderzoeken wordt met betrekking tot de aanbodzijde vaak aangenomen dat de vloot bestaat uit robotvoertuigen/volledig aan de vraag aangepaste chauffeurs die zelf geen onafhankelijke beslissingen nemen. Dit komt niet overeen met de huidige situatie. De overkoepelende doelstelling van deze scriptie is om een diepgaand onderzoek te doen naar het gedrag van chauffeurs die aan ritbemiddeling doen, met een focus op operationele beslissingen die van invloed zijn op de dagelijkse werking van het systeem, om de belangrijkste factoren voor de keuzes van chauffeurs te achterhalen en te analyseren wat de mogelijke gevolgen van die keuzes zijn voor het functioneren van het systeem. Hiervoor werd een bottom-upmodel toegepast gebaseerd op verschillende onderzoeksmethodes, variërend van kwalitatief tot kwantitatief onderzoek en van gedrags- tot operationeel onderzoek.

Als eerste hebben we een onderzoek uitgevoerd naar een focusgroep van in Nederland werkende Uber-chauffeurs. Hierdoor kregen we diepgaand inzicht in de perceptie van de chauffeurs op de werking van het systeem, hoe ze met het platform omgaan, waar ze zich zorgen over maken en wat ze verwachten. Aan de hand van het principe van contentanalyse stelden we

de relevante thema's vast en categoriseerden we de uitkomsten in algemenere rubrieken. We ontdekten dat de flexibele werkomstandigheden, waardoor chauffeurs hun eigen afwegingen kunnen maken, voor hen de belangrijkste reden is om zich bij het platform aan te sluiten. Gezien de constante ontwikkeling van de platformstrategieën is effectieve communicatie tussen het platform en de chauffeurs van groot belang. Dit verkleint de kans op misverstanden en voorkomt dat chauffeurs het platform gaan wantrouwen, wat uiteindelijk een ongunstig effect heeft op het systeem. Hoewel alle chauffeurs erop uit zijn zoveel mogelijk te verdienen, is er een aanzienlijke variatie in hun strategieën, afhankelijk van kenmerken als arbeidssituatie en werkervaring. Wij doen een voorstel voor een conceptueel kader dat de relatie beschrijft tussen de tactische en operationele beslissingen van chauffeurs en de factoren die daarop van invloed zijn. We ontdekten dat verscheidene factoren van invloed zijn op het gedrag van chauffeurs, afhankelijk van platformstrategieën, eigenschappen van chauffeurs, kenmerken van passagiers en externe factoren.

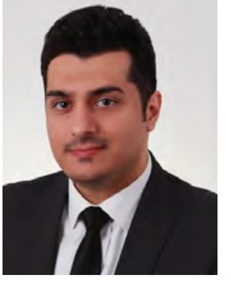
Ten tweede hebben we, op basis van de uitkomsten van het onderzoek naar de focusgroep en bestaande wetenschappelijke en grijze literatuur, een cross-sectionele stated preference-enquête ontwikkeld om te achterhalen wat de belangrijkste factoren zijn die van invloed zijn op het ritaanvaardingsgedrag van chauffeurs, gezien het informatiebeleid van het platform. Daarbij is erop gelet dat de gegevens in de enquête gelijk waren aan die uit de chauffeurs-app bij een ritaanvraag. We ontwierpen naast de bestaande functies verschillende hypothetische functies in de app, waarmee we relevante informatie kregen over de reacties van chauffeurs op mogelijke strategieën. Er werd een unieke dataset van 576 valide antwoorden verzameld van via ritbemiddeling werkende chauffeurs in Amerika en van 58 chauffeurs in Nederland. We hebben de gegevens geanalyseerd aan de hand van de benadering op basis van willekeurige nutsmodellen. Uit de resultaten blijkt dat de ophaaltijd (d.w.z. de reistijd tussen de plek waar de chauffeur zich bevindt en de plek waar de passagier moet worden opgehaald) de belangrijkste negatieve factor is voor het accepteren van ritten. Ook bleek dat een gegarandeerde fooi (d.w.z. de minimale fooi die van tevoren door een passagier wordt toegezegd, een functie die op dit moment niet beschikbaar is in het systeem) en prijstoeslagen door chauffeurs aanzienlijk meer worden gewaardeerd dan ritprijzen per munteenheid. Individueel-specifieke factoren als arbeidssituatie, niveau van ervaring en werktijden blijken een cruciale rol te spelen bij de acceptatie van ritten door chauffeurs. Zo is de kans dat chauffeurs een rit accepteren groter wanneer het gaat om parttime- en beginnende chauffeurs die doordeweeks werken.

Ten derde hebben we ons verdiept in de relocatiestrategieën van chauffeurs, d.w.z. de keuzes die chauffeurs tussen ritten door maken om een nieuwe rit te krijgen. Daarvoor werd een stated choice-experiment ontworpen, om data te verzamelen van chauffeurs die via ritbemiddeling werken in de VS. We keken naar vier alternatieven: in de buurt blijven van de locatie waar iemand was afgezet, rijden naar het gebied waar toeslagen van toepassing zijn, rijden naar een gebied waar naar verwachting veel vraag is maar waar normale prijzen gelden, en willekeurig rondrijden op basis van ervaring/intuïtie. We hebben modellen op basis van willekeurige nutsmaximalisatie op onze unieke dataset toegepast, om de effecten van de betreffende criteria te bepalen. Hieruit blijkt dat de arbeidskenmerken van chauffeurs bepalend zijn voor hun keuzes wat betreft relocatie. Beginners, zeer tevreden chauffeurs en chauffeurs met meer voltooide ritten sinds de start van hun werktijd rijden vaker naar gebieden waar een toeslag geldt of waar veel vraag is, afhankelijk van de hoogte van de toeslag en de verwachte reistijd tussen hun locatie en de plek waar de toeslag geldt of er veel vraag is. Om hier meer inzicht in te krijgen, onderzochten we een alternatieve, nog niet bestaande, nieuwe relocatierichtlijn. Wanneer chauffeurs weten dat er vooraf ritten zijn geboekt in de buurt van de plek waar ze een passagier afzetten, heeft dit invloed op de waarschijnlijkheid dat ze daar in de buurt blijven, afhankelijk van de verwachte wachttijd. Wanneer chauffeurs een gegarandeerde bonus krijgen als ze naar plekken met veel vraag rijden, vormt dat een aanzienlijke stimulans om naar die plekken te gaan. Bovendien kan het verstrekken van realtime verkeersinformatie in de nabije omgeving aan chauffeurs helpen om sluipverkeer te verminderen, vooral wanneer het erg druk is.

Ten vierde werden de gedragsresultaten over de beslissingen voor het accepteren van ritten door chauffeurs opgenomen in een simulatiemodel voor de werking van een ritbemiddelingsplatform waarop alle partijen met elkaar in contact staan, om de gevolgen daarvan op de werking van het systeem te analyseren. We stelden een discrete-event agent-based simulatiekader op, waarmee de platform-agent gewone prijzen en toeslagen kon instellen, de passagier-agent een ritverzoek kon indienen, deze kon intrekken en het ontvangen aanbod kon weigeren wanneer er een toeslag van toepassing was, en de chauffeur-agent beslissingen kon nemen over ritacceptatie op basis van de ontwikkelde modellen in de eerdere onderzoeken. We concludeerden dat het functioneren van het systeem vooral wordt beïnvloed door de vraag-aanbod-intensiteit, onder te verdelen in drie stadia: onderaanbod (meer aanvragen dan beschikbare chauffeurs op een specifiek moment en in een specifieke zone), balans en overaanbod (meer beschikbare chauffeurs dan het aantal aanvragen). We zien een duidelijk patroon in het functioneren van het systeem wat betreft de wachttijd van passagiers, het inkomen van chauffeurs en de omzet van het platform in elk van die stadia, afhankelijk van de mate waarin vraag en aanbod uit evenwicht zijn. We vergelijken het functioneren van een gecentraliseerde vloot (d.w.z. verplichte acceptatie van elke aanvraag voor een rit) met die van een gedecentraliseerde vloot (d.w.z. elke chauffeur beslist zelf over acceptatie van ritten). Onze conclusie was dat de kenmerken van de vloot wat betreft ritacceptatie van groot belang zijn voor hun functioneren van het systeem. Zo zijn de wachttijden voor passagiers langer en de inkomensongelijkheid van chauffeurs groter in een gedecentraliseerde vloot. Prijstoeslagen blijken voor alle partijen asymmetrisch voordelig te zijn. Wel heeft een hoger rittarief door het toepassen van een toeslag een marginale negatieve invloed op de vraagzijde.

Al met al hebben we nieuwe theorieën ontwikkeld over de gedragsdynamiek van de aanbodzijde van ritbemiddeling en hebben we die geïntegreerd in modellen voor de werking van het systeem, om de gevolgen daarvan voor het functioneren van het systeem diepgaand te kunnen analyseren. Samengevat bepalen de collectieve keuzes van chauffeurs als aanbieders van een dienst voor een groot deel de werking van systemen voor ritbemiddeling. Ritbemiddelingsplatforms moeten dan ook verschillende maatregelen nemen voor efficiënte vlootbeheersing, met oog voor het gedrag van chauffeurs. Wij stellen dat het negeren van het gedrag van chauffeurs in de werking van het systeem van een tweezijdig ritbemiddelingsplatform mogelijk leidt tot een verkeerde voorstelling van het systeem en daardoor mogelijk tot verkeerde conclusies.

About the Author



Peyman Ashkrof was born in Tehran, Iran. He developed a passion for mathematics and physics during his high school years which ignited his interest in pursuing a degree in engineering. In 2008, he began his undergraduate studies in Civil Engineering at the University of Science and Culture in Tehran, where he performed well in both academics and extracurricular activities. Notably, Peyman participated in a national competition focused on designing and implementing a small-scale steel bridge, which his team won the first place for technical design.

After completing his undergraduate degree in September 2013, Peyman pursued a master's degree in Road and Transportation Engineering at K. N. Toosi University of Technology in Tehran. He earned the highest grade for his thesis titled "The Impact of ICT (Information and Communication Technology) on travel behaviour," which he completed in September 2015.

Throughout his education, Peyman worked part-time at a road construction company, gaining practical experience in the field while continuing his academic pursuits. Following the completion of his master's degree, he secured a full-time role at the same company as a construction supervisor, later progressing to the position of project manager. Remarkably, he maintained an active presence in academia, collaborating with fellow researchers and participating in scientific events.

In November 2017, Peyman embarked on an international academic journey as a researcher in the department of Transport and Planning at TU Delft, where he investigated the impact of fully-automated vehicles on travellers' mode choice. In June 2018, he joined a supranational project, "Electric Mobility Europe," which aimed to study electric vehicle users' route choice and charging behaviour.

In February 2019, Peyman commenced his PhD journey in the department of Transport and Planning at TU Delft as part of the CriticalMaaS project funded by the European Research Council (ERC) and the Amsterdam Institute for Advanced Metropolitan Solutions (AMS). He developed models and novel theories to explain the supply-side behavioural dynamics of ride-sourcing systems and investigated their possible consequences on system operations.

List of Journal Articles

- Ashkrof, P., de Almeida Correia, G. H., Cats, O., & van Arem, B. (2020). Understanding ride-sourcing drivers' behaviour and preferences: Insights from focus groups analysis. *Research in Transportation Business & Management*, *37*, 100516.
- Ashkrof, P., de Almeida Correia, G. H., Cats, O., & van Arem, B. (2022). Ride acceptance behaviour of ride-sourcing drivers. *Transportation Research Part C: Emerging Technologies*, *142*, 103783.
- Ashkrof, P., de Almeida Correia, G. H., Cats, O., & van Arem, B. (2023). On the Relocation Behaviour of Ride-sourcing drivers. *Transportation Letters.*
- Ashkrof, P., de Almeida Correia, G. H., Cats, O., & van Arem, B. (2023). The Implications of Drivers' Ride Acceptance Decisions on the Daily Operations of Ride-sourcing Platforms. *Under review.*

Peer-reviewed Conference papers

- Ashkrof, P., de Almeida Correia, G. H., Cats, O., & van Arem, B. (2020). Ride-sourcing drivers' behaviour and preferences. *Forum on Integrated and Sustainable Ttransportation Systems (ISTS2020) - online.*
- Ashkrof, P., de Almeida Correia, G. H., Cats, O., & van Arem, B. (2022). Ride acceptance behaviour of ride-sourcing drivers in the era of COVID-19. *The 17th International Conference Series on Competition and Ownership in Land Passenger Transport (Thredbo) in Sydney, Australia.*
- Ashkrof, P., de Almeida Correia, G. H., Cats, O., & van Arem, B. (2022). On the Supply-side of Ride-sourcing Digital Platforms: Drivers' Ride Acceptance Behavior. *The 16th International Network on European Communications and Transport Activities Research (NECTAR) conference in Toronto, Canada.*
- Ghasemi, F., Ashkrof, P., & Krucharski, R. (2022). Ride Acceptance Behaviour Investigation of Ride-sourcing Drivers Through Agent-based Simulation. *The 10th Sysposuim of the Eurpoean Assocaition for Research in Transportation (hEART) in Leuven, Belgium.*
- Ashkrof, P., de Almeida Correia, G. H., Cats, O., & van Arem, B. (2022). On the Relocation Behaviour of Ride-sourcing drivers. *The 10th Sysposuim of the Eurpoean Assocaition for Research in Transportation (hEART) in Leuven, Belgium.*
- Ashkrof, P., Ghasemi, F, Krucharski, R. de Almeida Correia, G. H., Cats, O., & van Arem, B. (2023). The Implications of Drivers' Ride Acceptance Decisions on the Daily Operations of Ride-sourcing Platforms. *Euro Working Group Transportation (EWGT) in Santander, Spain.*

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