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Ride-pooling adoption, efficiency and level of service under alternative demand, behavioural and pricing settings

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ABSTRACT

Previous studies into the potential benefits of ride pooling failed to account for the trade-off that users likely make when considering a shared ride. We address this shortcoming by formulating user net benefit stemming from pooling as a compensatory function where the additional travel time and on-board discomfort need to be compensated by the price discount for a traveller to choose a pooled ride over a private ride. The proposed formulation is embedded in a method for matching travel requests and vehicles. We conduct a series of experiments investigating how the potential of ride-pooling services depends on demand characteristics, user preferences and the pricing policy adopted by the service provider. Our results suggest that the total vehicle mileage savings found by previous studies is only attainable when users are very willing to share their ride (i.e. attach low premium to private rides) and are offered a 50% discount for doing so.

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Ride-pooling; willingness to share; delay tolerance; demand distribution; pricing

1. Introduction

Recent developments in communication and information technologies have led to the rise of real-time and on-demand ride-pooling services like UberX Share (formerly Uber-Pool) and ViaVan. Users of those platforms consent to sharing a vehicle with travellers heading in a similar direction, even incurring small route deviations to pick-up and drop-off co-riders, in exchange for a cheaper fare. By utilising vehicle capacity more efficiently, ride-pooling services can potentially lead to reduced vehicle fleets as well as reduced vehicle mileage. Potential societal benefits associated with ride-pooling thereby include decreased congestion levels (Martinez and Viegas, 2017, Engelhardt et al., 2019, Ke, Yang, and Zheng, 2020), noise (Zwick et al., 2021) and air pollution (Ward, Michalek, and Samaras, 2021), greenhouse gas emissions (Greenblatt and Saxena, 2015, Martinez and Viegas, 2017, Dandl et al., 2021, Bilali, Fastenrath, and Bogenberger, 2022, Pengyu Zhu and Mo, 2022), traffic incidents, road and parking space consumption (Martinez

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and Viegas, 2017), and resource and energy usage in the vehicle manufacturing process. At the same time, ride-pooling can induce additional car traffic through deadheading, by substituting public transport or active modes, or through induced travel demand (Perneštāl and Kristoffersson, 2019, Schaller, 2021).

The majority of the literature investigating the prospects of substituting private rides by pooled rides has concluded that it has major potential with respect to reducing traffic volumes and fleet size (Wang and Yang, 2019). A study by Ma, Zheng, and Wolfson (2013) for example stated that if the fleet of taxis in Beijing had allowed for shared rides in 2011, with users assumed to accept a maximum extra travel time of 5 min for their ride, 25% more users could have been served and 13% of the total vehicle mileage could have been avoided. Cici et al. (2013) concluded that a 67% reduction in vehicle mileage is possible if travellers are willing to incur a detour of up to 600 m. Another study analysed ride-pooling for up to three pooled requests using a graph representation that is denominated as a shareability graph and concluded that the total vehicle distance of taxis in New York could have been reduced by 32% (Santi et al., 2014). Concurring evidence is offered by Qian et al. (2017), who show that with appropriate incentives total taxi vehicle mileage in New York can be reduced by 47%, while a 46% and 29% mileage reduction is feasible in central areas of Wuhan and Shenzhen, respectively. When ride-pooling is offered with high-capacity vehicles of up to 10 seats, less than one-fifth of the size of the current taxi fleet of New York City can serve 98% of the original requests with a maximum delay of 3.5 min per passenger (Alonso-Mora et al., 2017). While the previously mentioned studies focused on ride-pooling in high-density metropolitan areas, Tachet et al. (2017) assert that also cities with lower densities have the potential to obtain substantial efficiency gains by substituting private taxi rides with ride-pooling.

Nevertheless, thus far, the promising potential of ride-pooling in substituting less efficient private rides presented in scientific literature is not observed in reality. In New York for instance, prior to shutting down in the wake of the COVID-19 pandemic, only 7% of Uber's rides and 25% of Lyft's rides were pooled (Schneider, 2022b). The low penetration rates of shared services have been exacerbated by the COVID pandemic. Since their redesign in 2022, limiting pooling to two passengers at a time, ride-pooling adoption in New York has been even more marginal. In Chicago, just 4% of all ride-hailing users requested a pooled ride in October 2022, compared to 17% before the pandemic (Schneider, 2022a).

One of the important deterrents for potential users that may hinder a wide-scale adoption of ride-pooling services is inconvenience associated with sharing a vehicle with strangers. We refer to this behavioural deterrence as the (un)willingness to share. User inconvenience may arise from a lack of privacy (Dueker, Bair, and Levin, 1977, Teal, 1987), a feeling of dependence and a fear of having negative social interactions with other users (Correia and Viegas, 2011, Morales Sarriera et al., 2017). During the recent pandemic, virus exposure has emerged as an additional concern for shared mobility (Hensher, 2020, Kucharski, Cats, and Sienkiewicz, 2021). It may explain the decreased market shares of UberX Share and Lyft Share in New York, the permanent termination of Via's ride-pooling services in New York and Washington D.C. (ViaVan, 2022), and the on-going suspension of ViaVan operations in Amsterdam.

A low propensity for sharing is especially problematic given that ride-pooling matching efficiency depends on mutual compatibility of trip requests. With few users, detours for picking up co-riders are likely to be relatively long, further hampering the attractiveness, feasibility and potential distance savings associated with pooled rides. In Chicago for instance, only 38% of ride-pooling trip requests in October 2022 were actually pooled, whereas in Toronto just 18% of individuals opting for pooling in September 2018 – which in itself accounted for just 26% of ride-hailing trip requests – were successfully matched to another rider (City of Toronto, 2019). That ride-pooling services may require a critical mass (Engelhardt et al., 2019, de Ruijter, Cats, and van Lint, 2022) resonates with the absence of ride-pooling from many cities around the world.

A possible explanation for the large discrepancy between the societal benefits of ride-pooling in theory and what has so far been observed in reality, is that previous ride-pooling studies fail to account for the complex trade-off that users are likely to make when considering a shared ride. In all of the aforementioned studies, users are assumed to opt for the ride-pooling service as long as the expected delay, i.e. later pick-up time and en-route detour, does not exceed a certain pre-specified threshold. Hence, no inherent deterrence from using ride-pooling was assumed, everything else being the same (*ceteris paribus*). In other words, in those studies travellers were assumed to be intrinsically motivated to share a ride, without requiring any form of compensation and while accepting a delay.

In this study, we instead explicitly account for the trade-off users can make between the discount offered for sharing their ride and the travel impedance that it induces. We formulate user net benefit due to sharing as a compensatory function where the additional travel time and on-board discomfort must be compensated by the shared ride discount for a traveller to choose a shared ride over a private one. This allows us to assess the potential adoption of ride-pooling by considering the two key barriers for adoption (Lavieri and Bhat, 2019). To assess service performance and level of service, we embed our user benefit formulation in the method for matching travel requests and vehicles introduced by Alonso-Mora et al. (2017).

The potential of ride-pooling services is expected to greatly vary across markets, depending on travel demand characteristics, road network properties and user preferences. Previous studies have analysed specifically how ride-pooling performance in a city is affected by the density of travel demand (Tachet et al., 2017, Engelhardt et al., 2019, Ke, Yang, and Zheng, 2020, Gurusurthy and Kockelman, 2020, Young, Farber, and Palm, 2020, Maricic, Kucharski, and Cats, 2022), the average ride length (Young, Farber, and Palm, 2020, Dean and Kockelman, 2021, Kucharski and Cats, 2022, Soza-Parra, Kucharski, and Cats, 2022) and the average network traffic speed (Tachet et al., 2017). Less attention has been devoted to studying the effect of the spatial distribution of travel demand on ride-pooling potential. Limited preliminary evidence for this relationship suggests that ride-pooling potential may increase with concentration of travel destinations (Narayan et al., 2022, Soza-Parra, Kucharski, and Cats, 2022). Research on the effect of behavioural preferences when accounting for costs and benefits associated with a choice for ride-pooling is also scarce, limited to the works of Kucharski and Cats (2020, 2022).

In addition to context-related attributes, service design may be a key factor influencing ride-pooling performance indicators. Studies on ride-pooling service design have

concentrated on the effect of pooling discount (Yang Liu et al., 2019, Ke et al., 2020, Zheng Zhu et al., 2020, Kucharski and Cats, 2020, Maricic, Kucharski, and Cats, 2022, Kenan Zhang and Nie, 2021), surge pricing (Yan et al., 2020), fleet size and capacity (Alonso-Mora et al., 2017, Yang Liu et al., 2019, Ke et al., 2020, Kucharski and Cats, 2020), design of pick-up and drop-off locations (Goel, Kulik, and Ramamohanarao, 2016, Yan et al., 2020, Gurumurthy and Kockelman, 2020, Fielbaum, Bai, and Alonso-Mora, 2021, Maricic, Kucharski, and Cats, 2022, Fielbaum, 2022), matching batch time (Kucharski and Cats, 2020, Ke, Yang, and Zheng, 2020, Pengyu Zhu and Mo, 2022) and allowable detours in pooled rides (Alonso-Mora et al., 2017, Ke et al., 2020, Zheng Zhu et al., 2020, Ke et al., 2021).

The objective of this study is to analyse system performance of ride-hailing markets that allow for pooling under various in settings hitherto underexposed in scientific research. Specifically, we conduct a series of experiments that includes investigating the impact of behavioural settings in terms of (a) users' willingness to share their ride and (b) their delay aversion on service adoption and its operational efficiency. The proposed approach permits accounting for user preferences and their possible variation in the analysis. The incorporation of a cost-benefit trade-off at the individual passenger level allows us also to outline implications for the design of an effective discount structure – based on vehicle occupancy – to boost ride-pooling adoption and consequently reduce the total vehicle distance on the road. Finally, we demonstrate how the spatial distribution of demand may affect the performance of a ride-pooling system.

The remainder of this paper is structured into four sections. Section 2 provides a detailed description of our methodology. This is followed by details on the design of the numerical experiment in Section 3. The results for the experiments are presented and discussed in Section 4. This paper is concluded by stating the main conclusions that can be drawn in relation to the effect of users' behavioural preferences, the spatial distribution of demand and the pricing mechanism on the performance of a ride-pooling service (Section 5).

2. Methodology

The assignment of passenger requests to ride-pooling vehicles over a period of time enables the assessment of the total vehicle movement and service quality obtained by a ride-pooling service. There are several approaches for the real-time assignment of requests to vehicles. As a way of dealing with the large solution space in ride-pooling assignment, in early assignment approaches, such as the one developed by Ma, Zheng, and Wolfson (2013), incoming requests were individually allocated to vehicles using a greedy algorithm. Santi et al. (2014) introduced the concept of shareability graphs to systematically analyse the mutual compatibility of two requests using a graph representation so that assignment can be performed with traditional graph-solving optimisation methods. A follow-up study extended this graph-based approach by introducing additional graph representations to allow for bundling requests and therefore compose high-occupancy ride-pooling trips (Alonso-Mora et al., 2017). Their request-group-vehicle (RGV) graph constitutes the composition of request groups and the vehicle that may serve each request group, representing the assignment

problem as an Integer Linear Problem (ILP). A subsequent follow-up study by Simonetto, Monteil, and Gambella (2019) further reduced the complexity of graph-based assignment approaches, without a substantial loss of service performance. Agent-based models (ABM) have also been used to study ride-pooling, whereby users and vehicles are modelled as agents that dynamically interact (Fiedler et al., 2018, Winter et al., 2018).

In this study, we adopt the graph-based approach of Alonso-Mora et al. (2017), which offers the capability to model real-time ride-pooling with more than two passengers on-board the same vehicle. Contrary to a greedy approach, in which travellers are instantly assigned to an available vehicle when making a request, trip requests are being collected over a small period of time – in the order of seconds or minutes – and only assigned at the end of this interval. When given enough computation time, each assignment iteration will yield an optimal solution for the current set of requests, meaning that although the initial waiting time for travellers is longer, the approach can yield a shorter total travel time.

The approach contains a few implicit assumptions about ride-pooling operations. First, supply is assumed to be centrally controlled: drivers are fully compliant with central instructions regarding which requests to serve, the order of pick-ups and drop-offs in a pooled ride, and the route to follow. Private and pooled services use the same road infrastructure, i.e. there are no high-occupancy vehicle (HOV) lanes for ride-pooling vehicles. To limit computational complexity in the approach, it is assumed that ride-pooling operations has no effect on the traffic conditions in the network. Travel times in the network are fully predictable and can thus be precomputed. On the user side, the approach assumes that requests can be subject to assignment in consecutive iterations. Assigned travellers that have not yet been picked-up can be reassigned if it improves their level of service. Travellers with unsatisfied requests will be available for assignment until a certain time threshold is reached, i.e. when they run out of patience.

Before providing more details on our methodological contribution to the ride-pooling assignment procedure, we will first shed more light on the graph-based assignment process of Alonso-Mora et al. (2017), which forms the basis for our work and is subject to adaptations as highlighted in the subsequent sections.

2.1. Framework

In the graph-based approach of Alonso-Mora et al. (2017), which is visualised in Figure 1, requests are matched with other requests as well as with vehicles at fixed intervals. Each assignment iteration consists of the following nine steps:

- (1) Establish the status of vehicles as well as the pool of requests to be matched to a vehicle. The latter includes new trip requests and unassigned requests from the previous iteration. Pending requests are removed when assignment is no longer feasible.

Illustration in Figure 1: two empty vehicles, three requests.

- (2) Check which pairs of requests can be matched, assuming there is a vehicle located at the origin of one of the two requests.

Requests 1 and 2, and 2 and 3 form feasible request pairs.

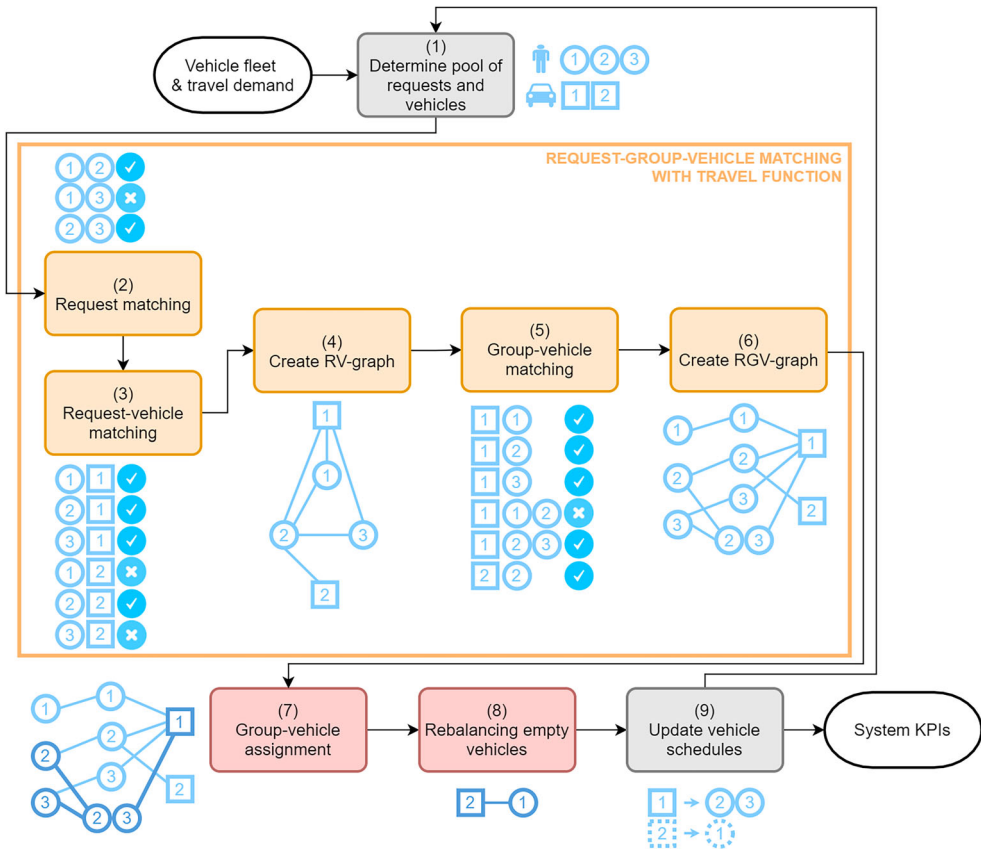


Figure 1. Overview of the methodology, including an example (in blue) with three requests and two (empty) vehicles.

- (3) Check which requests can be matched to which vehicles, considering vehicles' current location and on-board occupancy.

All requests can be served by vehicle 1, only request 2 can be served by vehicle 2.

- (4) Create a request-vehicle (RV) graph: a graph with request and vehicle nodes, where an edge indicates a feasible request pair match (as found in step 2) or a feasible request-vehicle match (step 3).

RV-graph as shown in Figure 1.

- (5) Check which groups of requests can be matched to which vehicles. To do so, first identify potentially feasible request group – vehicle matches based on cliques in the RV-graph, and then find whether there is a feasible route with which a vehicle can satisfy all requests in the group as well as passengers already on-board.

From the RV-graph it follows that a group consisting of requests 1 and 2, and a group consisting of requests 2 and 3 can potentially be served by vehicle 1. Besides, all 'groups' with only one request can potentially be served by vehicle 1. Finally, a 'group' consisting only of request 2 can potentially be served with vehicle 2. When checking the feasibility of these group-vehicle combinations, we find that there is no feasible route for vehicle 1 to satisfy the group consisting of requests 1 and 2.

- (6) Create a request-group-vehicle (RGV) graph: a graph with request, group and vehicle nodes, where an edge between a request and a group node indicates that a request is included in a request group, and an edge between a group and a vehicle node implying that a request group can be matched to a vehicle (as found in step 5). A label can be added to edges between group and vehicle nodes to represent the attractiveness or ‘value’ of the match.

RGV-graph as shown in Figure 1, with request (left), group (middle) and vehicle (right) nodes.

- (7) Decide which groups are assigned to which vehicles by translating the RGV-graph into an Integer Linear Problem. Multiple objective functions are possible, such as a maximisation of the number of assigned requests.

The group consisting of requests 2 and 3 is assigned to vehicle 1. Vehicle 2 cannot serve request 1 and is left unassigned.

- (8) Decide whether idle vehicles will rebalance, and if so, where to.

(Unassigned) vehicle 2 moves in the direction of (unassigned) request 1.

- (9) Update vehicle schedules according to the assignment (step 7) and rebalancing (step 8) result.

Vehicle 1 will pick-up requests 2 and 3, vehicle 2 will rebalance towards the origin of request 1.

The next two sections provide a more detailed description of the method, focusing on the steps where this study differs from previous work. In the following, we present our version of the request-group-vehicle (RGV) matching procedure for finding all feasible request group – vehicle combinations (Section 2.2, steps 2–6 in Figure 1), and the subsequent procedure of assigning vehicles optimally to requests (Section 2.3, steps 7 and 8 in Figure 1).

2.2. RGV matching

The matching procedure involves the creation of an RGV graph to identify which group-vehicle combinations are feasible, given vehicle capacity and travel cost constraints. The matching process of Alonso-Mora et al. (2017) is divided into three steps to ensure that not all group-vehicle combinations have to be enumerated and checked for feasibility, which considerably reduces the complexity of the matching algorithm. In this section, after we introduce the functionality of each of these three steps along with our modifications thereof, we provide a detailed formulation of the cost function and explain how it is used in the algorithm that checks the feasibility of group-vehicle pairs.

The first amongst the matching steps (step 2 in Figure 1) establishes whether two requests in the pool of available requests R can share a ride in the most fortunate scenario in which there is an empty vehicle readily available at the location of one of those requests. With this step, the set of potentially feasible request groups G can already be substantially reduced. The next step (step 3 in Figure 1) checks whether a vehicle v in the fleet of vehicles V can serve a single request $r \in R$ given its current location and residual capacity (i.e. the number of available seats). The result of both steps can be combined and stored in a RV-graph (step 4) where edges indicate that two requests, or a request and a vehicle, can be matched. Each clique in the RV-graph represents a

potentially feasible group-vehicle combination. Step 5 checks whether there exists a feasible sequence of stops S_ν for a vehicle ν to satisfy a group of requests $g \in G$, considering capacity and user level of service constraints. The RGV-graph consists of nodes representing the set of available requests R , the set of feasible request groups G and the set of vehicles V . Each edge between a request $r \in R$ and a request group $g \in G$ has a label a_{rg} indicating whether r is included in g ($a_{rg} = 1$) or not ($a_{rg} = 0$). Moreover, each edge connecting a request group $g \in G$ and a vehicle $\nu \in V$ has a label $b_{g\nu}$ indicating the sum of net sharing benefits of all requests in g and passengers in P_ν given the optimal sequence of stops S_ν^* . If a group-vehicle combination $g\nu$ is not feasible, $b_{g\nu}$ is assigned a very large penalty (a so-called big M), to ensure that this combination is not chosen during the assignment process.

Our approach differs from the original one by Alonso-Mora et al. (2017) in that group-vehicle edge labels in the RGV-graph contain sharing benefits instead of delay costs. Similarly, we substitute cost-based user constraints in the matching algorithm for benefit-based user constraints. In the remainder of this section, we describe our modifications to the original work by Alonso-Mora et al. (2017) in more detail.

2.2.1. Net sharing benefit

We formulate and quantify the individual benefits stemming from ride-pooling to represent the trade-off that travellers encounter when choosing between a private and a shared ride. In the following, we define the notion of net sharing benefits. Its purpose is threefold: (i) for identifying which pending requests need to be rejected by the ride-pooling provider (i.e. in determining the pool of unassigned requests), (ii) for identifying which requests and vehicles can be assigned to each other (i.e. in group generation and establishing group-vehicle pair feasibility) and (iii) in deciding which requests are to eventually be assigned to which vehicles (i.e. in assignment), as explained in this and subsequent sections.

We formulate the benefits and costs of ride-pooling relative to a private ride. The benefit associated with ride-pooling for a traveller with request r corresponds to the total fare discount offered by the service provider for shared rides and is thus dependent on the discount rate π_r that is applied to the ride fare c_r . π_r can be either set as a fixed rate or as a function of the level of service offered by the shared ride. We examine both cases in our experiments.

In contrast, the disbenefits of a shared ride relative to a private ride relate to extra travel time imposed by sharing and an additional discomfort associated with sharing a vehicle, all other things being equal. The total disbenefit of a ride thus depends on how users perceive both attributes when expressed in monetary terms. Sharing discomfort is described by reluctance to share γ_r , a ride-pooling alternative specific constant that represents the fare reduction users require for sharing a vehicle with other riders. To account for a different valuation of out-of-vehicle delay (i.e. waiting for pick-up) and in-vehicle delay (i.e. detouring), we introduce separate value of time parameters α_r (waiting time) and β_r (in-vehicle delay). The waiting time of a request is calculated as the difference between the pick-up time t_r^{pu} and time at which the request was made t_r^f . The in-vehicle delay is the difference between the actual and minimal travel time from pick-up to drop-off location. The latter is calculated for an immediate pick-up and the shortest route, with travel time τ_{o_r, d_r} .

between origin o_r and destination d_r . The actual in-vehicle time is the difference between the time of drop-off t_r^{do} and the time of pick-up t_r^{pu} . The total net benefit of r is thus formulated as

$$b_r = \pi_r \cdot c_r - (t_r^{\text{pu}} - t_r^r) \cdot \alpha_r - (t_r^{\text{do}} - t_r^{\text{pu}} - \tau_{o_r, d_r}) \cdot \beta_r - \gamma_r \quad (1)$$

2.2.2. Group-vehicle feasibility

The three main matching steps in the RGV approach (steps 2, 3 and 5 in [Figure 1](#)) involve applying the same algorithm for establishing whether a specific combination of requests and/or vehicles yields a feasible match. The steps differ only in their input:

- Pairwise request matching (step 2): two requests and a hypothetical vehicle located at the origin of one of the requests
- Request-vehicle matching (step 3): a single request and a specific vehicle
- Group-vehicle matching (step 5): a group of requests and a specific vehicle.

The algorithm can therefore be generalised by stating that it finds whether a vehicle v in fleet V , with passengers P_v on-board, can serve a group of unassigned requests U . The vehicle can be either virtual or specific, and the group of requests may consist of a single request or of multiple requests. Requests are removed from the queue when assigned or when so much time has passed that even immediate assignment to a request with the same origin and destination will not yield a (positive) benefit, in accordance with Equation (1). In other words, the upper bound of passenger's waiting time depends on the trade-off between all the components included in the total net benefit formulation and is therefore trip-specific rather than a constant uniform value.

In the first step of the algorithm, the complete set of stop sequences K_v is identified with which v can potentially satisfy U . Each stop sequence $S_v \in K_v$ is then checked for feasibility based on vehicle and user constraints. The vehicle constraint ensures that the vehicle capacity is not exceeded, i.e. v cannot serve U with stop sequence S_v if the vehicle capacity κ is exceeded by the vehicle occupancy O_s after each stop $s \in S_v$, similar to the approach of [Alonso-Mora et al. \(2017\)](#). As we assume that drivers strictly follow the shortest path between two nodes in a network with static travel times, for each stop sequence S_v we only need to check the feasibility constraints for a single route, i.e. the route made up of the shortest paths between the consecutive vehicle stops.

The user constraint proposed in this study is modelled with the net sharing benefit. Stop sequence S_v satisfies the user level of service constraint only if the net benefit b_r of each request in U and P_v is positive. This approach is based on three underlying assumptions. First, all ride-hailing users are open to pooling, but only if the benefit derived from lower fares (compared to a private ride) is larger than the costs of pooling. Second, the operator has perfect information regarding travellers' preferences of ride-pooling service attributes, and matches requests according to their interests. Third, reassignment of requests is possible, but only if a more desirable match is found for the user. In other words, all riders, whether already picked-up or not, must

prefer a shared ride provisioned with this specific route over a private ride, and if previously assigned, also over their current (pooled) ride.

If both types of constraints are satisfied, the benefit of the stop sequence b_{S_v} is computed by summing the net benefits of all individual requests in U and P_v . If there exists at least one feasible stop sequence $S_v \in K_v$ to serve U , then U and v form a feasible match. When there is more than a single feasible stop sequence, we will also need to determine which stop sequence is most optimal. Therefore, we search for the stop sequence in K_v with maximum benefit b_{S_v} , which we define as the total benefit of the particular group-vehicle combination b_{Uv} . However, if no feasible stop sequence exists, b_{Uv} is set to 'Invalid'. The complete procedure for checking the feasibility of group-vehicle combinations and finding the most optimal stop sequence for feasible combinations is specified in the pseudocode shown in Algorithm 1.

Algorithm 1. Matching request group U to vehicle v : Establishing feasibility and optimality of potential stop sequences.

```

1. for  $S_v \in K_v$  do
2.   if  $\max_{s \in S_v} O_s \leq \kappa$  then ▷ Vehicle capacity constraint
3.     if  $b_r \geq 0, \forall r \in U \cup P_v$  then ▷ User net benefit constraint
4.        $b_{S_v} \leftarrow \sum_{r \in U \cup P_v} b_r$  ▷ Total benefit of feasible stop sequence  $S_v$ 
5.     else
6.        $b_{S_v} \leftarrow -1$ 
7.     end if
8.   else
9.      $b_{S_v} \leftarrow -1$ 
10.  end if
11. end for
12. if  $\exists S_v \in K_v$  such that  $b_{S_v} > 0$  then ▷ Stop sequence with maximum benefit
13.   $b_{Uv} \leftarrow \max_{S_v} b_{S_v}$ 
14. else
15.   $b_{Uv} \leftarrow \text{'Invalid'}$ 
16. end if

```

2.3. Assignment and rebalancing

In this part of the method, requests are assigned to vehicles based on the RGV-graph (corresponding to step 7 in Figure 1). The group-vehicle assignment is treated as an Integer Linear Problem (ILP) with binary decision variables x_{gv} indicating whether a group-vehicle combination with total net sharing benefit b_{gv} is chosen or not. The ILP is defined as follows:

$$\max \sum_{g \in G} \sum_{v \in V} \left(b_{gv} + \sqrt{M} \cdot \sum_{r \in R} a_{rg} \right) \cdot x_{gv} \quad (2)$$

$$\text{s.t.} \quad \sum_{g \in G} x_{gv} \leq 1, \quad \forall v \in V \quad (3)$$

$$\sum_{g \in G} \sum_{v \in V} a_{rg} \cdot x_{gv} \leq 1, \quad \forall r \in R \quad (4)$$

$$x_{gv} = [0, 1], \quad \forall g \in G, v \in V \quad (5)$$

The objective function (Equation 2) aims at maximising the total benefit for accepted requests and passengers, while prioritising the acceptance of a maximum number of requests by adding a very large reward for each request r in an assigned request group g . The sum of these rewards should however not overpass the big M penalty assigned to infeasible group-vehicle combinations in the objective function. Therefore, the reward per request group is set to \sqrt{M} . The total benefit associated with a group-vehicle combination $g-v$ thus consists of the summed net benefit for all requests and passengers in this group plus a large reward \sqrt{M} for each request that is a member of this group.

The Integer Linear Problem contains three types of constraints guaranteeing respectively a maximum assignment of one request group g to each vehicle v (Equation 3), that each request r is not part of multiple assigned request groups in G (Equation 4), and that each decision variable is binary (Equation 5).

Vehicles that are not assigned to a pick-up, can still be assigned to move in the direction of unassigned requests, in anticipation of new requests appearing in areas that currently are under-supplied (step 8 in Figure 1). In this study, the rebalancing procedure of Alonso-Mora et al. (2017) is adopted. Its objective is to minimise the total empty vehicle rebalancing distance while ensuring a maximum number of vehicles to be assigned to rebalance.

After vehicles are assigned to pick-up requests, rebalance or remain idle, vehicle schedules are updated and the simulation prepares for the next assignment phase (step 9 in Figure 1).

2.4. Key performance indicators

We measure the performance of the ride-pooling service using a series of Key Performance Indicators (KPIs) designed to capture the level of service (LoS) offered to users as well as its operational efficiency which is relevant for authorities and service providers. If ride-pooling services are assessed by examining the same aspects that public transport users consider to be most important (Bates et al., 2001, Edvardsson, 1998, Hensher, Stopher, and Bullock, 2003, König and Axhausen, 2002, Friman and Gärling, 2001), then the KPIs of shared rides LoS are reliability, comfort, travel time and fare level. Ride fares in this case are not considered as a KPI, since they are directly dependent on π_r and are thus endogenously defined as model input. The main LoS KPIs in this study include the acceptance rate (i.e. the percentage of fulfilled requests out of the total demand, thereby an indicator for coverage and reliability), the delay as a percentage of the direct travel time (indicating travel time), the average number of stops per passenger (pertaining to comfort) and the share of passenger time with a specific number of riders on-board (also related to comfort).

In addition to the quality of service delivered by the ride-pooling service, an authority is also interested in the share of the vehicle distance that can be reduced through ride-pooling. A suitable KPI to express distance efficiency is the gross effective vehicle transportation distance ratio, which is defined as the sum of the shortest OD-distance of accepted requests (= 'effective vehicle distance') divided by the total vehicle movement distance (Ehsani et al., 2018). The total vehicle movement distance (or vehicle mileage) consists of the transportation distance (the vehicle distance with at least one passenger on-board, including detouring) and the deadheading distance (the total

empty vehicle distance for accessing requests and rebalancing). Further, a net effective vehicle transportation distance ratio is defined. This ratio accounts for the fact that the summed shortest distance of accepted requests, which represents the distance needed when sharing is not allowed, excludes deadheading. For a more fair comparison, the deadheading distance is therefore subtracted from the total vehicle movement in the net effective vehicle transportation distance ratio. For operators, the average vehicle occupancy while a vehicle is transporting passengers is an important efficiency KPI.

3. Experimental design

A series of experiments is constructed to test the effect of users' behavioural preferences, the discounting policy and the spatial distribution of demand on ride-pooling performance in an urban context. Before specifying the scenarios that have been designed to test the effect of these variables (Section 3.2), we introduce the general set-up of the experiment in terms of road network, demand and vehicle fleet characteristics in Section 3.1. Section 3.3 concludes this section with a description of the model implementation.

3.1. Set-up

The assumed grid network consists of 121 nodes with a link distance of 500 m (Figure 2), thereby leading to a maximum trip distance of 10 km and a surface area of 25 km², comparable to the area inside the Ring Road of Amsterdam or the Inner Road Ring of Berlin (*Berliner Innenstadttring*). The intermediate stop distance approximates the optimal distance proposed by Gurusurthy and Kockelman (2020), whereby we implicitly assume

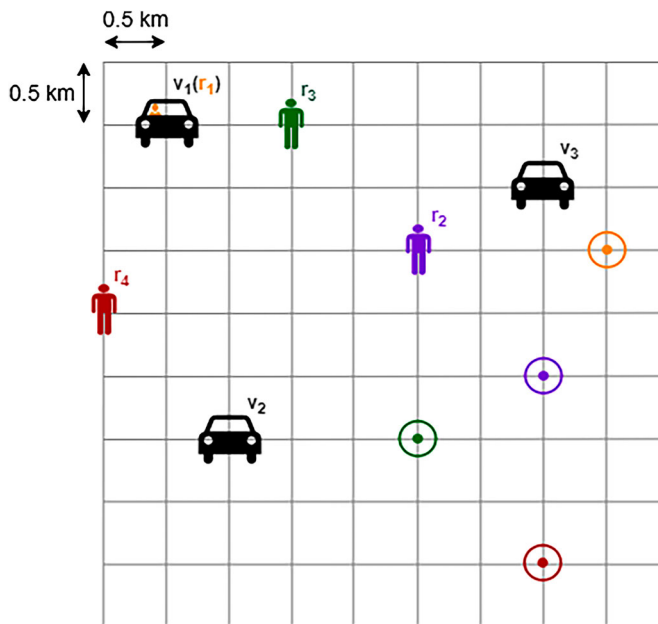


Figure 2. Assumed grid network, with three unassigned requests, one passenger and three vehicles as illustration.

that vehicles cannot stop at all road intersections and users are willing to walk to a pick-up location (and/or from a drop-off location) to minimise ride-pooling vehicle mileage (Gurumurthy and Kockelman, 2020, Maricic, Kucharski, and Cats, 2022, Fielbaum, Bai, and Alonso-Mora, 2021, Fielbaum, 2022). The assumed speed on the roads is slightly higher than in an average European city (Kfzteile24, 2019): 36 km/h. We assume that the time needed for pick-ups and drop-offs is negligible.

The total demand for trips is set to 1210 (single person) requests per hour, an average of 10 requests per hour per (demand) node. The way trips are distributed over the network is scenario specific, since we are explicitly interested in investigating the impact of demand distribution on system performance. In all cases trips with a ride distance of 2 km or shorter are excluded, as such rides are uncommon (T. L. K. Liu, Krishnakumari, and Cats, 2019) as well as undesirable in the context of a ride-pooling service. A gravity model (Erlander and Stewart, 1990) is applied to create a list of origin–destination pairs. Demand generation is assumed to follow a random process with Poisson distribution. Each request r is assigned with a request time t_r^f by sampling from an exponential distribution based on the expected interval λ between two successive requests with a specific OD-combination, which follows again from the (scenario-specific) demand distribution.

The fleet of the investigated ride-pooling service consists of 150 vehicles with a capacity of $\kappa = 3$, that of a normal car, initially evenly distributed over the network. Ride fares are set based on the regulated maximum taxi fares for the city of Amsterdam in 2019: a base fee of €3 and a kilometre fee of €2 (Gemeente Amsterdam, 2019).

For computational reasons, the total duration of the simulation is limited to 2 hours, with request groups being assigned to vehicles every minute (120 times in total). An additional warm-up period of 15 min is applied to minimise the impact of each of the starting conditions.

3.2. Scenarios

A total of 14 scenarios are constructed for investigating the effect of previously introduced behavioural attributes, the platform’s pricing policy and the spatial distribution of demand in the network. We limit the number of scenarios in the experiment by

Table 1. Scenario design ($\alpha_r = 0.5 \cdot \beta_r$), with scenario #1 as base scenario.

#	Demand distribution	β_r (€/h)	γ_r (€)	π_r (%)	Acronym
1	Uniform	30	3	50	U_30_3_50
2	Uniform	18	3	50	U_18_3_50
3	Uniform	24	3	50	U_24_3_50
4	Uniform	36	3	50	U_36_3_50
5	Uniform	42	3	50	U_42_3_50
6	Uniform	30	1	50	U_30_1_50
7	Uniform	30	2	50	U_30_2_50
8	Uniform	30	4	50	U_30_4_50
9	Uniform	30	5	50	U_30_5_50
10	Uniform	$\mathcal{N}(30,10)$	3	50	U_H_3_50
11	Uniform	30	$\mathcal{N}(3,2)$	50	U_30_H_50
12	Uniform	30	3	$50 + 7.5 \cdot \eta^{\text{pax}}$	U_30_3_D
13	Moderately directed	30	3	50	MD_30_3_50
14	Strongly directed	30	3	50	SD_30_3_50

designing scenarios that differ only in one variable at a time from a reference scenario. In this section, we provide the motivation for the specification of scenarios, summarised in [Table 1](#), based on the four experimental variables: delay aversion β_r , reluctance to share γ_r , sharing discount π_r and directionality in demand.

3.2.1. Delay aversion

Detours for picking up or dropping off additional travellers induce a cost for travellers already on-board the vehicle. Thus a potentially crucial behavioural factor for the potential to pool rides is the amount of disbenefit that travellers allocate to a single unit of delay, which is represented in this work by delay aversion β_r (Equation 1). Several recent studies (Krueger, Rashidi, and Rose, 2016, Lavieri and Bhat, 2019, Yang Liu et al., 2019, Alonso-González et al. “Value of Time and Reliability,” 2020) have estimated the value of in-vehicle time for ride-pooling, providing empirical indications for the range of travellers’ delay aversion values. Their estimates vary considerably, ranging from 8 to 23 €/h, which implies that the value of in-vehicle time for ride-pooling may be highly context-specific, depending on factors like the type of vehicle (autonomous or humanly-driven, interior configuration, etc.) and socio-economic characteristics. Since the specification of delay aversion in ride-pooling is not yet well established, we decide to test a relatively wide range of values to get a more complete picture of how travellers’ perception of delays can possibly affect ride-pooling potential. For the base scenario, we assume a delay aversion β_r of €30/h, while alternative scenarios test values of 18, 24, 36 and 42 €/h (scenarios 1–5 in [Table 1](#)).

At the same time, taste variations may play an important role in determining the scalability and efficiency of ride-pooling systems when users are able to choose between private and shared rides, as modelled in this study. Alonso-González et al. “Value of Time and Reliability,” (2020) found a substantial heterogeneity in the value of in-vehicle time of potential ride-pooling users. We therefore introduce a scenario with taste heterogeneity in delay aversion β_r . Since there is limited empirical knowledge on the variation of delay aversion amongst the population, we need to make an assumption about the shape of this distribution. We specify heterogeneity in delay aversion (scenario 10 in [Table 1](#)) as a normal distribution with a mean value of €30/h (the base value from scenario 1) and a standard deviation of €10/h: $\mathcal{N}(30, 10)$.

In all of the experiments, the value of α_r , representing the extent to which waiting time is perceived more negatively than in-vehicle time, is set to half of β_r , which is in line with the waiting time multiplier found in stated preference studies on potential ride-pooling users (Yang Liu et al., 2019, Alonso-González et al. “Value of Time and Reliability,” 2020) and a revealed preference study in urban public transit (Yap, Cats, and van Arem, 2018).

3.2.2. Reluctance to share

Recently, the concept of willingness to share, also referred to as the reluctance to share or the willingness to pay to not have to share a ride with other travellers, has started to gain more attention in the literature. Lavieri and Bhat (2019) concluded that travellers’ reluctance to share represents a fixed cost, independent on the duration of the ride. Alonso-González et al. “What are the Determinants,” (2020) confirm this principle, yet with the notation that it applies only to ride-pooling with one or two co-riders, and not for all

travellers in the population. When travelling with more than two co-riders, which represents microtransit rather than ride-pooling, they find a travel time dependent willingness to share. For small-scale ride-pooling however, both studies find a relatively small fixed average reluctance to share, in the range of €0.50–€1. Alonso-González et al. “What are the Determinants,” (2020) also observe that the willingness to share is highly context-specific, depending on for example geographical characteristics and familiarity with ride-pooling services.

All in all, empirical research on travellers’ reluctance to share is still scarce, especially when considering different contexts. With a first indication that the reluctance to share a vehicle with one or two co-riders is represented by a fixed cost, we decide to test a relatively large range of fixed values for reluctance to share γ_r in our numerical experiments: from €1 to €5 (scenarios 1 and 6–9 in Table 1). In all of the other scenarios, we assume a median value of $\gamma_r = €3$. Again, when lacking full understanding of the specification of behavioural attributes related to sharing, covering a large range of values allows examining the implications of these attributes for the potential of ride-pooling.

As mentioned earlier, Alonso-González et al. “What are the Determinants,” (2020) state that different classes of potential ride-pooling users have a different specification of their reluctance to share. In fact, preferences related to fellow passengers in ride-pooling are found to exercise more pronounced heterogeneity than preferences towards travel time (Hongmou Zhang and Zhao, 2018). A possible explanation for this is that some users enjoy the social interactions that come along with sharing a ride while others are reluctant to share their ride with strangers. This implies that for some users in fact the willingness to share γ_r might be positive, or in other words that the fact that a vehicle is shared induces an additional benefit next to a reduced ride fare. Again, lacking empirical evidence on the distribution of preferences across the population, a normal distribution is assumed to capture heterogeneity. Since heterogeneity in reluctance to share γ_r was found to be (likely) larger than heterogeneity in delay aversion β_r (with its assumed standard deviation of one third of the mean), the standard deviation relative to the mean to describe heterogeneity in the reluctance to share γ_r is therefore set higher than for the delay aversion β_r in scenario 10. We specify a mean reluctance to share of €3 and a standard deviation of €2: $\mathcal{N}(3, 2)$ (scenario 11).

3.2.3. Sharing discount

An additional scenario (scenario 12 in Table 1) has been devised to test the effect of a ride-pooling providers’ pricing mechanism. All scenarios except scenario 12 assume a fixed 50% discount for all ride-pooling rides, independent of whether sharing actually occurs throughout the ride. This is in line with services offered by ride-pooling platforms, e.g. UberPool, that typically offer discounts between 25 and 60% of the fare of a private ride (Shaheen and Cohen, 2019). We are interested in examining the impacts of an alternative pricing mechanism that reflects the actual extent of sharing experienced by the user. We therefore specify an alternative scenario where a similar discount of 50% is given to the user even if he or she ends up being served privately (same as for all other scenarios, whereby the discount is basically a compensation for the risk of having to share), while an additional 7.5% discount is given for each co-rider n^{pax} on-board the vehicle during the part of the ride with highest vehicle occupancy. The aim of this additional scenario is to explore whether occupancy-dependent discounts in

ride-pooling can be effective in reducing vehicle mileage by facilitating the matching process, as well as at what user cost. It is not meant to give a specification of the (socially) optimal pricing strategy, which, depending on the results of this study, may however be an interesting topic for future research.

3.2.4. Demand distribution

The effect of directionality in demand on the performance of ride-pooling is tested using three different scenarios. In the base scenario (1 in Table 1) demand is perfectly uniform, with equal production and attraction in each of the nodes. In two additional scenarios (scenarios 13 and 14 in Table 1), we specify a demand distribution that represents an increasingly concentrated demand pattern, with more production in the outer nodes of the network and more attraction in the central nodes, intended to mimic a morning peak pattern.

3.3. Implementation

The simulation model is implemented in Python from scratch, using the open-source library Numpy to enable efficient operations of large data structures in the model, such as creating and storing the edges of RGV-graphs when many requests and vehicles are considered. The Networkx package is used to compute the shortest path between a pair of locations in the road network, after which the corresponding travel time is stored in a look-up table.

We compute the complete RV- and RGV-graphs without imposing a time budget or limits on the number of edges. An exhaustive search is performed to find the optimal stop sequence with which a vehicle can serve one or more requests (Algorithm 1). The optimisation problems that are part of the group-vehicle assignment and rebalancing procedure are, for all experiments, solved to optimality using the MOSEK Optimiser API. Consequently, each assignment iteration is guaranteed to yield an optimal result.

With these settings, the majority of scenarios could be run within 30 min on a single-core 2.30 GHz processor. Two noticeable exceptions are the scenarios with the lowest delay aversion β_r and lowest reluctance to share γ_r with run times of approximately 5 hours. In these scenarios, as a result of more favourable preferences towards sharing, larger request groups are potentially feasible, hence increasing the solution space. Consequently, it requires considerable computational time to test those as the set of possible stop sequences to satisfy such groups is considerably (i.e. more than exponentially) larger than for small request groups. Also the scenario with an occupancy-dependent additional discount ($U_{30_3_D}$) enlarges the solution space and consequently the computational complexity of this scenario is also relatively high compared to most other scenarios (i.e. a run time of nearly 1h with the same processor).

Even though we investigate real-time ride-pooling, given the offline evaluation nature of this work we do not focus on the computational efficiency of the algorithm in this study. Notwithstanding, the approach adopted in this study is in principle suited for simulation in real-time, as long as we manage to limit the computational load of each assignment iteration. We can think of several changes to the current implementation to do so, including a timeout or a constraint on the number of edges in the development of RV- and RGV-graphs, a timeout when seeking the optimal stop sequence for a group-vehicle combination and a timeout in the ILP assignment of vehicles to requests. As these

implementation directly touch upon the core of the work by Alonso-Mora et al. (2017), we refer to their work for more details.

4. Results

In this section, we report the results of the experiment and analyse the effect of users' preferences (Section 4.1), the variation thereof (Section 4.2), the applied discount structure (Section 4.3) and the demand distribution (Section 4.4) on the level of service and efficiency of a ride-pooling service. The complete set of KPI values is presented in Table 2 (level of service) and Table 3 (efficiency). In the following four sections, we discuss the effect of each of the above mentioned aspects in detail.

4.1. Effect of (homogeneous) behavioural preferences

As can be expected, the acceptance rate (Figure 3a) increases as the reluctance to share γ_r decreases. The acceptance rate rises from 25.4% when $\gamma_r = \text{€}5$ to nearly 100% when $\gamma_r =$

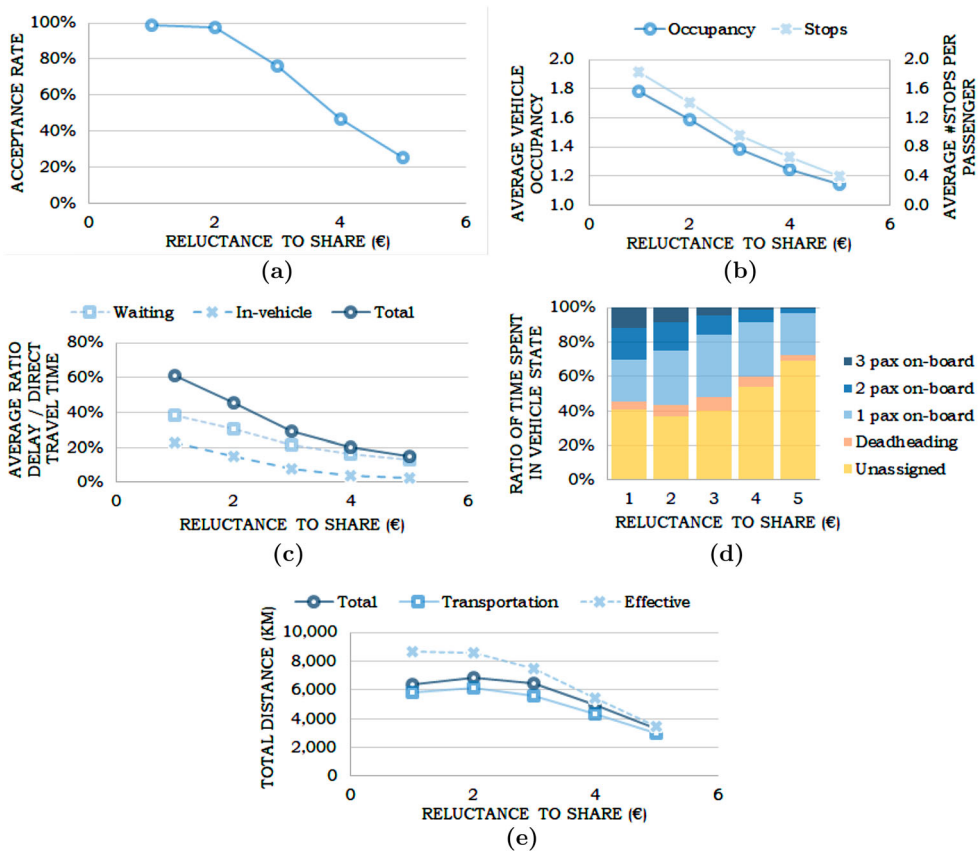


Figure 3. The effect of reluctance to share γ_r on (a) acceptance rate, (b) vehicle occupancy and number of intermediate stops, (c) average passenger delay, (d) vehicle time spent in different states and (e) total vehicle movement, total transportation distance and effective transportation distance.

Table 2. Level of service KPI values for each scenario.

Scenario	Acceptance rate	Average total delay per passenger (s)	Average waiting time per passenger (s)	Average in-vehicle delay per passenger (s)	Average passenger ratio delay/direct travel time	Average number of stops per passenger	Ratio of passenger time with 0 co-riders	Ratio of passenger time with 1 co-rider	Ratio of passenger time with 2 co-riders
U_30_3_50	76%	126.8	92.1	34.7	30%	0.95	50%	32%	18%
U_18_3_50	88%	200.5	122.4	78.1	49%	1.56	31%	33%	36%
U_24_3_50	81%	158.5	103.6	55.0	37%	1.24	40%	35%	25%
U_36_3_50	70%	106.2	84.8	21.4	25%	0.79	58%	31%	11%
U_42_3_50	64%	93.2	77.1	16.0	21%	0.67	63%	29%	8%
U_30_1_50	99%	219.5	138.2	81.3	61%	1.83	25%	38%	37%
U_30_2_50	98%	169.6	114.0	55.6	45%	1.40	35%	37%	28%
U_30_4_50	46%	102.7	82.9	19.8	21%	0.66	64%	27%	9%
U_30_5_50	25%	88.0	74.7	13.2	15%	0.39	76%	21%	3%
U_H_3_50	76%	154.2	103.5	50.8	36%	1.08	46%	32%	22%
U_30_H_50	67%	162.8	106.4	56.4	42%	1.19	45%	34%	21%
U_30_3_D	82%	221.7	118.7	103.0	54%	1.97	23%	32%	45%
MD_30_3_50	68%	117.7	92.5	25.1	29%	0.79	56%	30%	14%
SD_30_3_50	63%	130.7	106.5	24.2	32%	0.80	53%	33%	14%

Table 3. Efficiency KPI values for each scenario.

Scenario	Total vehicle movement distance (km)	Total vehicle transportation distance (km)	Total deadheading distance (km)	Total rebalancing distance (km)	Gross effective vehicle transportation distance ratio	Net effective vehicle transportation distance ratio	Empty vehicle rebalancing distance ratio	Average vehicle occupancy	Ratio of non-empty vehicle time with occupancy 1	Ratio of non-empty vehicle time with occupancy 2	Ratio of non-empty vehicle time with occupancy 3
U_30_3_50	6488	5588	900	156	1.15	1.34	0.173	1.38	70%	22%	8%
U_18_3_50	6357	5690	667	78	1.27	1.42	0.117	1.68	52%	28%	20%
U_24_3_50	6456	5657	799	133	1.21	1.38	0.166	1.52	61%	26%	13%
U_36_3_50	6350	5453	898	156	1.12	1.30	0.174	1.30	75%	20%	5%
U_42_3_50	6142	5218	925	187	1.09	1.28	0.202	1.24	79%	18%	3%
U_30_1_50	6389	5867	522	9	1.36	1.48	0.017	1.78	44%	34%	22%
U_30_2_50	6853	6133	720	56	1.26	1.41	0.077	1.59	56%	30%	15%
U_30_4_50	4966	4330	636	106	1.10	1.26	0.167	1.24	79%	17%	4%
U_30_5_50	3321	2958	364	37	1.05	1.18	0.102	1.14	87%	12%	1%
U_H_3_50	6389	5556	833	152	1.16	1.33	0.182	1.45	66%	23%	11%
U_30_H_50	5570	4949	621	84	1.17	1.32	0.135	1.45	65%	25%	10%
U_30_3_D	5687	5186	501	125	1.35	1.48	0.249	1.85	43%	29%	28%
MD_30_3_50	6000	4829	1171	393	1.06	1.31	0.335	1.32	74%	20%	6%
SD_30_3_50	6288	4552	1736	910	0.95	1.31	0.524	1.35	72%	22%	6%

€1. The increase is approximately linear until the great majority of requests is accepted. Interestingly, the average vehicle occupancy (Figure 3b) increases more than linearly when γ_r decreases, as well as passengers' waiting time and in-vehicle delay (Figure 3c). It is found that hardly any rides are shared (i.e. the average vehicle occupancy is 1.14, implying that not much sharing takes place) if users are highly sensitive to sharing with other passengers (Figure 3d), resulting in an average in-vehicle delay close to zero. In such a scenario, the operational efficiency in terms of the number of effective passenger kilometres per vehicle kilometre is as low as 1.05. This ratio is found to increase approximately linearly with an increase in the willingness to share. It can be explained by the finding that the total effective vehicle distance (due to more requests served) increases more than the total vehicle movement distance when users are more flexible (Figure 3e), as a result of a more efficient assignment of vehicles to requests. Also, deadheading is found to be relatively uncommon when users' sharing tolerance is high (Figure 3d), as new requests can be picked-up by vehicles on their way to drop off other passengers. If $\gamma_r = €1$ for example, the average effective passenger distance per total vehicle kilometre in the system (including transportation and deadheading) rises to 1.36 km.

When considering the effect of delay aversion β_r , instead of reluctance to share γ_r , similar, albeit less pronounced, results are found. The acceptance rate, for example, does not exceed 90% in any of the scenarios. Evidently, the level of service and operational efficiency are more sensitive to the tested values of the willingness to share, γ_r , than to those of the delay aversion, β_r .

4.2. Effect of taste heterogeneity

Substantially fewer requests are accepted when reluctance to share varies amongst the user population (with an unchanged mean): 66.8% versus 76.0% of all requests (Figure 4a). As can be seen in Figure 4b, the acceptance rate varies considerably amongst user groups that are characterised by different degrees of reluctance to share. Heterogeneity in the delay tolerance on the other hand barely has an impact on the acceptance rate: 75.9%. An explanation for this difference could be that users with a high delay aversion can often still be satisfied (Figure 4b) by serving them with the shortest or a relatively short path so that their delay costs are minimised. This happens at the cost of more flexible passengers that will get served with a delayed pick-up and/or a less direct route. In other words, a level of service is offered that discriminates amongst users based on their delay aversion. With the majority of accepted requests having an above average delay tolerance (since it is easier to find a ride for those requests), the average delay experienced by users in the system, 36.4% of the direct travel time, is higher than when the delay tolerance is assumed homogeneous (29.5%, Figure 4c).

When considering a scenario with varying willingness to share, it is found that users with a below average willingness to share are much more likely to reject a ride-pooling service (Figure 4b) even when offered a direct ride, leading to a lower overall acceptance rate (Figure 4a). The total rebalancing distance is limited (Figure 4d) since there are relatively many requests around unassigned vehicles that cannot be served even with a direct route. The effective transportation distance ratio, an indicator for distance savings

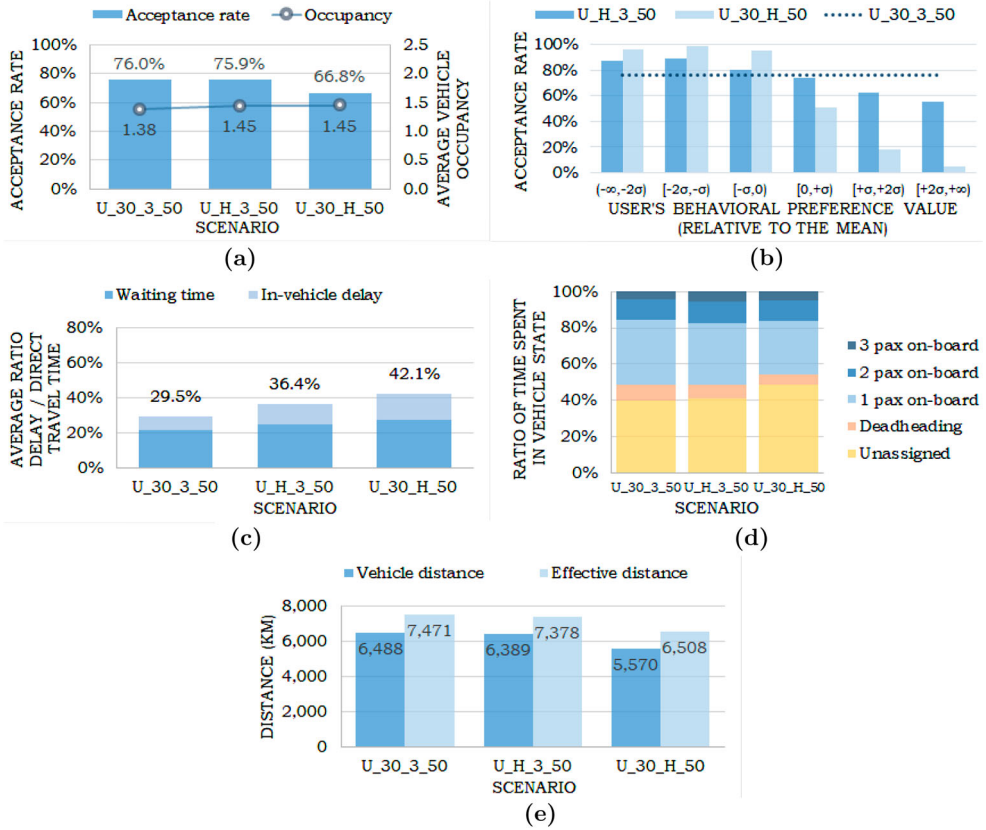


Figure 4. The effect of heterogeneity in delay aversion β_r and reluctance to share γ_r on (a) average vehicle occupancy, (b) acceptance rate, (c) average passenger delay, (d) vehicle time spent in different states and (e) total vehicle movement distance and effective transportation distance (the difference between those indicating distance savings).

(Figure 4e), ranges between 1.15 and 1.17 for the three scenarios in this set of experiments, and thus does not seem to be substantially dependent on whether heterogeneity in ride-pooling tolerances is considered. Based on this, we can say that the operational efficiency in terms of the vehicle-km travelled that a ride-pooling system can save is not very sensitive to the variation of sharing preferences over the population.

4.3. Effect of discount mechanism

As expected, when users receive an additional 7.5% discount per co-rider they share the highest occupancy part of their ride with, the average vehicle occupancy increases dramatically (from 1.38 to 1.85, as can be seen in Figure 5a), and a similar increase is found in the share of time passengers spend in a full vehicle (from 17.7% to 45.1% of the total passenger time). By utilising the available vehicle capacity more efficiently (Figure 5c), the acceptance rate (also Figure 5a) increases from 76.0% to 82.1%, although at the cost of a higher average delay (Figure 5b). A higher vehicle occupancy will burden passengers with longer detours and consequently an in-vehicle delay of more than three times as high as when no additional discount is offered (25.1% vs 8.1% of the direct travel

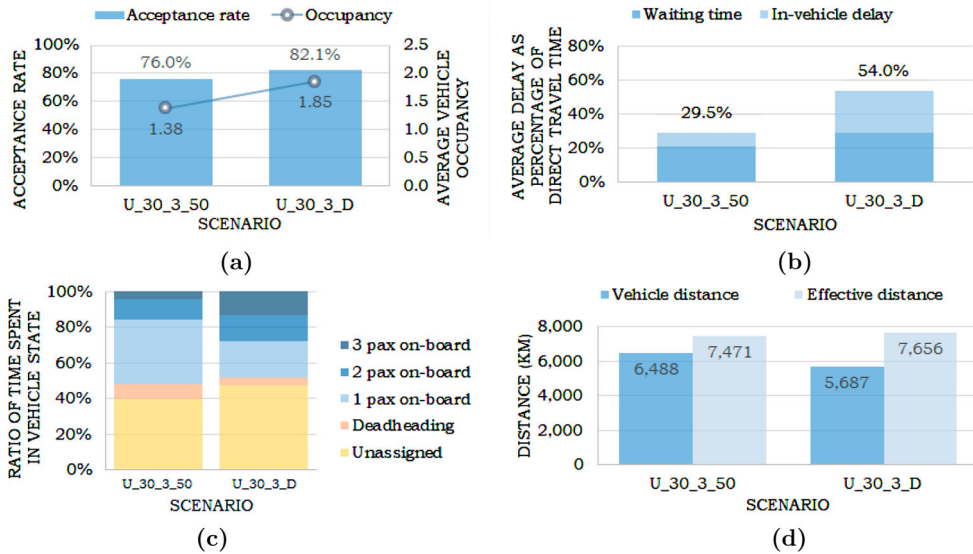


Figure 5. The effect of discount structure on (a) acceptance rate and average vehicle occupancy, (b) average passenger delay, (c) vehicle time spent in different states and (d) total vehicle movement distance and effective transportation distance (the difference between those indicating distance savings).

time). Also, the average waiting time for pick-up is marginally longer in the scenario with an occupancy-dependent discount, with pick-ups being complicated by the fact that many vehicles are driving around fully occupied.

The (gross) effective vehicle transportation distance ratio increases from 1.15 to 1.35 when an additional 7.5% discount is awarded per co-rider. In combination with a higher acceptance rate, relatively large distance savings (Figure 5d) are achieved with the introduction of an additional occupancy-dependent discount. Passengers, however, may be reluctant to choose a service for which they know the maximum cost but not the exact cost a-priori. The distance that a ride-pooling service can save (when compared to private rides) stems not only from the more efficient transportation of requests (the transportation distance drops from 5588 to 4829 km) but also from a reduction in the deadheading distance to access new requests (from 900 to 501 km), as requests are being picked-up by non-empty vehicles on their way to drop off other passengers.

4.4. Effect of demand distribution

More directionality in demand leads to more requests being rejected by the ride-pooling service, namely 37.1% when demand is strongly directed versus 24.0% when demand is perfectly uniform, as shown by Figure 6a. If demand is perfectly uniform, the average vehicle occupancy of vehicles in revenue mode (also Figure 6a) is 1.38 and the average passenger delay (Figure 6b) is 29.5% of the direct travel time. The drop in the number of accepted requests when there is a moderate level of direction in demand leads to a drop in the vehicle occupancy (1.32) and average delay (29.1% of direct travel time). Interestingly, when the level of direction increases further however, the vehicle

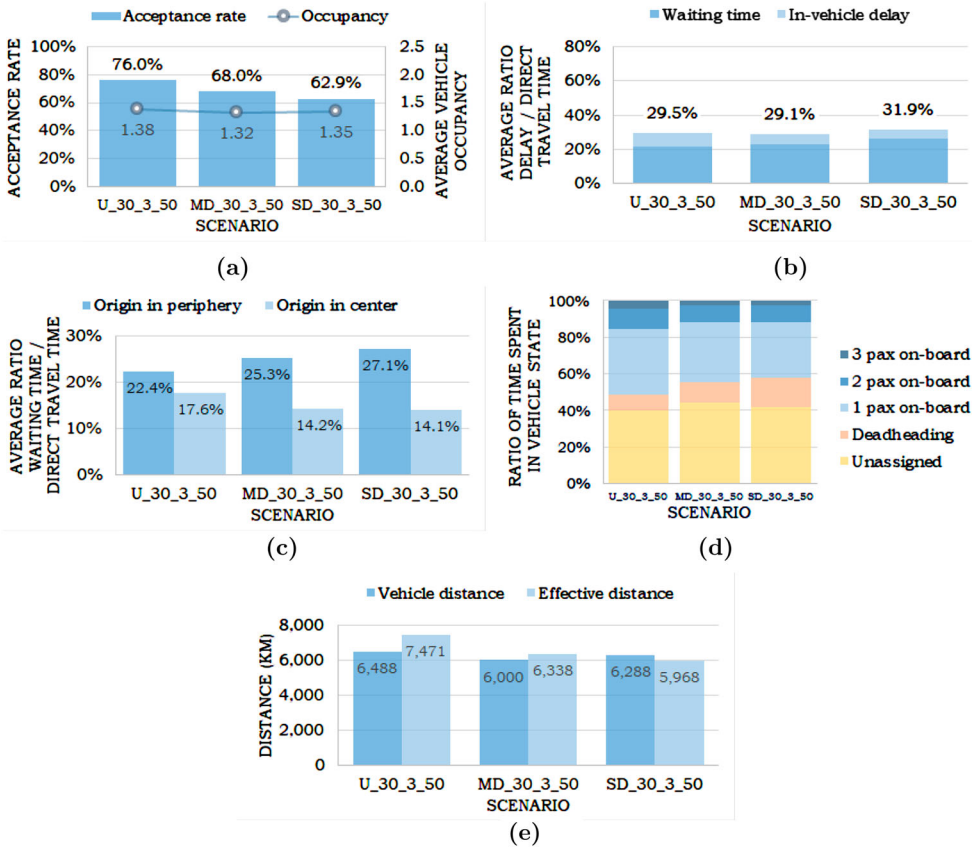


Figure 6. The effect of directionality in demand on (a) acceptance rate and average vehicle occupancy, (b) average passenger delay, (c) location-based average waiting time, (d) vehicle time spent in different states and (e) total vehicle movement distance and effective transportation distance (the difference between those indicating distance savings).

occupancy (1.35) and the average delay (31.9% of the direct travel time) bounce back. With a larger spatial inequality in pick-ups and drop-offs, average waiting times are relatively short in the center, where attraction exceeds production (Figure 6c), compared to the nodes in the periphery of the network. Since only the minority of requests originates in the center in this case, the average waiting time is mainly determined by requests originating outside of the centre, where production exceeds attraction. In these nodes, the average waiting time is nearly twice as high (27.1% vs 14.1%).

The effective passenger kilometres per ride-pooling vehicle kilometre is 0.95 when there is strong directionality in demand. This alarming result suggests that the total vehicle distance can be longer than the effective transportation distance even for ride-pooling services (Figure 6e). In addition, contrary to what might be expected, it shows that directionality in demand may jeopardise ride-pooling efficiency. Our results point to two explanations. First, directed demand (towards the centre) requires considerable deadheading from centre to periphery to solve supply deficits in the periphery (Figure 6d). Deadheading for instance accounts for 27.6% of all vehicle kilometres in a scenario in which demand is strongly directed, compared to only 13.9% of the mileage when

demand is uniform. Second, directionality in demand does not induce a considerable increase in vehicle sharing, as shown by [Figure 6\(a,d\)](#). Likely, incompatibility in trip origins – which are distributed across the periphery – compensates for clustering in trip destinations. When demand is uniform, it is more likely that a passenger can be picked up along the way of serving another passenger.

5. Discussion and conclusion

This work is the first study to consider ride-pooling potential while accounting for the trade-off that users encounter when presented with the option of ride-pooling. Previous studies, such as [Santi et al. \(2014\)](#) and [Alonso-Mora et al. \(2017\)](#), assumed that all users are potentially willing to ride-share as long as their waiting time and total delay do not exceed a certain non-compensatory threshold. This is not very realistic as taxi users have no reason to share their ride (and accept a delay) unless attaining a benefit in return. Therefore, in this study we formulate a compensatory user cost formulation where the disbenefits associated with sharing one's ride need to be at least compensated by the fare reduction offered for the user to substitute a private ride with ride-pooling. Hence, the assumption is that users will only switch to a ride-pooling service if such a choice yields a net positive benefit over a conventional taxi or ride-hailing service. Also, this work accounts for the fact that sharing a vehicle with strangers, which in the literature is considered to be one of the main potential barriers for a successful implementation of ride-pooling services, induces a disutility.

Our compensatory formulation is embedded in the matching framework proposed in [Alonso-Mora et al. \(2017\)](#). A group of requests is considered feasible only if all the individuals included in the shared ride evaluate it as superior to the private ride alternative, as well as satisfying vehicle-related constraints.

When representing the choice whether to ride-share or not as a compensatory function between travel attributes (travel time, ride fare and the presence of co-riders), we find that the distance savings from ride-pooling reported by previous studies are only attainable when users have favourable preferences to sharing rides. For example, when users have a relatively high willingness to share, or more specifically when they are willing to pay no more than 1 euro to upgrade a shared ride to an individual one, assuming no change in travel time, 32% of the transportation vehicle kilometres in the network can be removed. This compares to a 40% reduction found by [Santi et al. \(2014\)](#) in their study on ride-pooling in New York. However, our work shows that if users are found to be less willing to share – or in other words, users are willing to pay high premium (i.e. a higher fare) for a private ride – we can expect distance savings that are considerably lower than reported in previous work. We find for example that, in the scenario where travellers are least willing to share, the total vehicle transportation distance can be reduced by just 15% when allowing for shared rides. This scenario assumes that ride-pooling users demand a compensation of 5 euro for the fact that they have to share their vehicle with other passengers. Furthermore, it should be noted that in this scenario, and in most others, ride-pooling users get rewarded with a discount rate of 50%, relatively high compared to discounts currently offered by ride-pooling services. It is thus plausible that ride-pooling distance savings in reality are even lower than those found in our analysis.

In addition, our results show that besides the expected distance savings also the level of service that a ride-pooling system offers depends considerably on users' tolerance to delays and willingness to share a vehicle with co-riders. When we vary both attributes, we find the acceptance rate of a ride-pooling service to range between 25% and 99% of all incoming requests, and the average delay of accepted requests to range between 15% and 61% of the direct travel time. In conclusion, our results highlight that any comparison of ride-pooling model outputs has to carefully account for the behavioural specifications.

Although heterogeneity in user preferences seems to have only a limited impact on potential distance savings, it is found to have negative consequences for the level of service with more rejected requests and a larger average delay. Moreover, this results in striving to serve few users with a below average sharing tolerance at the expense that many of the accepted requests with an above average tolerance get assigned a less efficient ride. This calls for the development of discriminative pricing or service provision mechanisms, including the possibility for the service provider to choose to decline travel requests.

Furthermore, this study has shown that the design of a ride-pooling service, such as its pricing structure, may substantially affect the expected societal benefits and service quality. A relatively small additional discount of 7.5% per co-rider with whom a user shares their ride at maximum occupancy, on top of the standard 50% discount assumed in all experiments, can for example more than double the total reduction in vehicle kilometres. At the same time, the percentage of rejected requests drops from 24% to 18% if such a discount policy is implemented. Instead of offering a flat subsidy per pooled ride or charging a tax on private rides, policy makers looking to minimise road traffic externalities may thus be better off subsidising ride-pooling based on vehicle occupancy.

This study also shows that the potential of a ride-pooling system can be greatly dependent on external variables, such as the spatial distribution of demand. Demand patterns are likely to be at least somewhat concentrated due to spatial clustering of activities like work, leisure, residence and shopping. Notably, our results demonstrate that when most requests are directed towards the center of the network, typical for a morning peak, a ride-pooling system performs worse than when demand is uniform, both in terms of level of service and efficiency. This is a direct result of (i) the spatial imbalance in demand and supply, which requires vehicles to deadhead from drop-off locations in low demand areas to pick-up locations in high demand areas, leading to increased vehicle mileage and longer waiting times for pick-up and (ii) limited pooling due to dispersion of trip origins over the periphery. To be specific, the (gross) effective vehicle transportation distance ratio can even drop below 1 when the directionality of demand is high, while the average user delay can amount to 32% of the direct travel time in such a scenario. In summary, we found that directionality in demand negatively affects both level of service and operational efficiency of ride-pooling services.

Our results highlight the importance of gaining more empirical underpinning for the willingness to pool to facilitate demand forecasts concerning the future role of ride-pooling in our cities. In addition, future research can investigate the impact of additional aspects on ride-pooling performance. This includes exploration of more complex discounting mechanisms and demand distributions (both spatially and temporally) than

the one assumed here. Also, it might be interesting to find whether ride-pooling efficiency can be improved by strategic rejection of requests that negatively affect ride-pooling performance on a system level, even when assignment is feasible, such as requests that are destined for a location far away from where new demand is expected. Moreover, the validity of ride-pooling studies can be improved by accounting for vehicle idle time at stops, as well as by the incorporation of mode choice, such as in Zheng Zhu et al. (2020), whereby passengers can choose travel modes other than private ride-hailing and ride-pooling. Furthermore, adopting a probabilistic choice modelling framework will enable the consideration of link travel time variability and thereby the associated passenger in-vehicle time uncertainty. Finally, future research can address the equity aspects of a ride-pooling system, including the spatial disparity of service accessibility.

Contribution

The authors confirm contribution to the paper as follows: study conception and design; de Ruijter, Cats; analysis and interpretation of results: de Ruijter, Cats; draft manuscript preparation: de Ruijter, Cats. All authors reviewed the results and approved the final version of the manuscript.

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