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Ride-hailing and transit accessibility considering the trade-off between time and money

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ABSTRACT

Ride-hailing services can expand access to opportunities in urban areas, but out-of-pocket costs may limit its benefits for low-income individuals. This paper examines how ride-hailing shapes spatial and socioeconomic differences in access to opportunities while accounting for the trade-off between travel time and monetary costs. Using one year of aggregate Uber trip data for Rio de Janeiro in 2019 and a new multi-objective routing algorithm, we analyze the potential for ride-hailing services to improve employment accessibility when used as a standalone transportation mode and in conjunction with transit as a first-mile connection. We find that, compared to transit, standalone ride-hailing can significantly expand accessibility as a standalone mode for short trips, and as a first-mile feeder to transit in trips longer than 30 min. However, the accessibility benefits of ride-hailing accrue mostly to high-income groups due to affordability barriers. These findings suggest that policy efforts to integrate rideshare with transit are likely not going to benefit low-income communities without some form of subsidized fare discounts to alleviate affordability barriers. The paper also highlights how accounting for trade-offs between travel-time and monetary costs can importantly influence the results of transportation accessibility and equity studies.

1. Introduction

The emergence of ride-hailing services has been one of the most disruptive transportation innovations in recent decades (Chan & Shaheen, 2012; Dudley et al., 2017; Tirachini, 2020). Transportation network companies (TNCs), such as Uber and DiDi, can help people overcome transit network gaps and improve urban accessibility without the costs of car ownership (Brown et al., 2022; Jin et al., 2018; Young & Farber, 2019). Nonetheless, even though ride-hailing services are generally faster and more convenient than transit options, they are also more expensive for single riders and out-of-pocket costs are one of the biggest barriers to ride-hail for low-income people (Brown et al., 2022). This explains in part the growing number of studies trying to understand the circumstances under which ride-hailing could compete and complement public transit (Cats et al., 2022; Hall et al., 2018; Li et al., 2021; Yan et al., 2019; Young et al., 2020).

Various studies have shown how ride-hailing services can effectively expand mobility options (Alemi et al., 2018; Ceccato & Diana, 2021; Onono et al., 2019; Tirachini & del Río, 2019). However, few studies have examined the extent to which ride-hailing services improve access to opportunities, particularly when used in conjunction with transit, and how such accessibility benefits can vary across socioeconomic groups. Moreover, no studies have compared ride-hailing and transit accessibility considering the trade-off between travel time and monetary costs. Previous research on accessibility by ride-hailing has focused on either travel time (Barkley et al., 2018; Haddad et al., 2019) or out-of-pocket costs (Souza et al., 2021). Two exceptions are the works of Abdelwahab et al. (2021) and Cats et al. (2022). Nonetheless, these studies use generalized travel cost functions that combine time and monetary costs into a single cost value, which ignores the potential trade-offs between travel time and monetary costs (see Section 2). Being able to examine these trade-offs is particularly important for those investigating the potential competition and complementarity between ride-hailing and public transit because of how these transport modes provide markedly different levels of accessibility, though at significantly different costs (Schwieterman, 2019).

The aim of this paper is twofold. First, it examines how ride-hailing services can shape spatial and socioeconomic differences in access to opportunities while accounting for the trade-off between travel time and monetary costs. Second, the paper investigates the extent to which urban

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accessibility can be expanded by ride-hailing when these services are used either as a standalone transport mode or when used in conjunction with transit as a first-mile feeder to mass transit. The paper draws on material from one year of aggregate Uber trip data for Rio de Janeiro (Brazil) in 2019. Combining this data with multimodal transport routing, we calculate employment accessibility using cumulative opportunity measures that simultaneously account for both travel time and monetary costs. This is done using a new method recently developed by Conway and Stewart (2019) and implemented in the R package r5r (Pereira et al., 2021), which provides a multiobjective optimization routing method to account for cost constraints in public transit accessibility metrics. This work also combines custom travel matrices by Uber and transit designed to accommodate transfer times between these modes, which are used to calculate accessibility levels that result from the combined use of transit and Uber as a first-mile feeder.

This study advances the literature on transportation accessibility and equity by examining the trade-off between travel time and out-of-pocket monetary costs in accessibility. Our case study advances the state-of-the-practice in transportation equity analysis by showing how explicitly considering affordability of different modes affects transport accessibility and inequality estimates. Additionally, it expands upon previous research by analyzing the potential for ride-hailing services to improve accessibility when used in conjunction with transit as a first-mile feeder service. This is particularly relevant given the increasing number of transit agencies partnering with TNCs to improve accessibility for transportation-disadvantaged communities in low-density areas (Brown et al., 2021; Curtis et al., 2019; Zuniga-Garcia et al., 2022). Furthermore, this paper contributes to the growing empirical evidence on how ride-hailing services may shape transportation equity and accessibility conditions, providing new evidence in the context of the Global South.

The notion of transportation equity with regards to transport accessibility can be framed both in terms of egalitarian or sufficientarian perspectives, which focus respectively on issues of relative inequalities in access to opportunities, and on whether people have enough (absolute) level of access to opportunities (Lucas et al., 2016; Pereira et al., 2017). In this paper, we focus particularly on inequality issues, and take the predominant stance in the literature that a transport system is considered more equitable if it contributes to reducing inequalities of opportunities by prioritizing the accessibility of disadvantaged groups (Pereira et al., 2017; Zhang & Zhao, 2021).

The remainder of the paper is organized as follows. Section 2 presents a literature review on ride-hailing services and urban accessibility. Section 3 presents the study area analyzed in the paper. The data and methods used to calculate travel times and monetary costs and to estimate employment accessibility are presented in Sections 4 and 5. Section 6 presents the results, and Section 7 presents the conclusion of the study with reflections for future research and policy recommendations.

2. Literature review

Ride-hailing services are a relatively recent innovation in urban mobility, but they have been capturing a lot of attention from researchers and policy makers (Shaheen & Cohen, 2019). Several studies have analyzed the implications ride-hailing services can have for urban mobility systems in terms of public transit ridership (Diab et al., 2020; Erhardt et al., 2022; Lavieri & Bhat, 2019; Rayle et al., 2016) and transport externalities such as road congestion (Diao et al., 2021; Erhardt et al., 2019; Tirachini & Gomez-Lobo, 2020), air pollution (Barnes et al., 2020; Sui et al., 2019; Yu et al., 2017) and traffic crashes (Anderson & Davis, 2021; Barreto et al., 2021; Barrios et al., 2019; Conner et al., 2021; Kirk et al., 2020).

There is also a growing literature that examines how transportation network companies (TNCs), such as Uber, DiDi and Cabify, could have ambiguous effects as a complement and substitute to public transit (Hall et al., 2018; Yan et al., 2019; Young et al., 2020). While ride-hailing services can compete as a more convenient though more expensive transport alternative, these services can also increase the reach and flexibility of public transport by providing first mile-last mile connections (Cats et al., 2022; Shaheen & Chan, 2016; Wang et al., 2012). A few studies in this literature try to assess this potential complementarity and competition by looking at the overlap between the origins and destinations of trips conducted by ride-hailing versus transit (Jin et al., 2019; Kong et al., 2020; Liao, 2021). Other studies using travel surveys have shown that TNCs are increasingly used as first-last mile alternatives to integrate with transit (Bedoya-Maya et al., 2022; Brown et al., 2021; Sunitiyoso et al., 2022). Along these lines, there is also growing research on ride-hailing and transportation equity, looking at whether TNCs can effectively improve the mobility conditions of low-income and disadvantaged communities (Brown et al., 2022; Jiao & Wang, 2020; Jin et al., 2019) or whether ride-hailing services end up exacerbating the gap in the urban mobility and accessibility conditions of different socioeconomic groups (Abdelwahab et al., 2021; Barajas & Brown, 2021; Brown et al., 2021). There is also a growing literature looking at gender issues, and which examines the extent to which ride-hailing services benefit women's access given gendered particularities in travel behavior and safety concerns (Qiao et al., 2023; Sabogal-Cardona et al., 2021; Young & Farber, 2021).

Previous research has analyzed the wait times of passengers from TNCs as a surrogate to access to ride-hailing services (Hughes & MacKenzie, 2016; Insardi et al., 2019; Shokoohyar et al., 2020; Wang & Mu, 2018; Young & Farber, 2020). However, these studies provide only a limited account of accessibility, because they overlook travel time and land use patterns. By doing so, these studies focus on access to ride-hailing itself, and not on the level of access to opportunities that can be achieved by using these services.

Only a few studies have examined the extent to which ride-hailing can improve people's access to opportunities. One of these studies is the work conducted by Souza et al. (2021), who analyze four districts of Rio de Janeiro (Brazil). The authors compare the number of jobs that can be accessed by public transport and Uber given different monetary cost limits and number of passengers traveling together. The authors find that, overall, ride-hailing services provide substantially higher employment accessibility than transit, but they only become financially competitive once trip costs are shared between two or more passengers. Despite the contributions of the paper in analyzing transportation equity with ride-hailing, this study ignores how travel times are substantially different in the shaping of accessibility by ride-hailing and transit.

The work of Cats et al. (2022) analyzes ridehailing's dual role as a complement and substitute to public transit by comparing accessibility levels by both transport modes. Using Uber trip data in six cities in the United States and Europe, they found that Uber is used both in competing and complementary circumstances, even though the impact of ride-hailing on overall service accessibility varies greatly within and between cities. Despite a thorough comparison between accessibility by ride-hailing and transit, Cats et al. (2022) do not analyze how ride-hailing could expand transit accessibility when used as a first-mile service for transit. Nonetheless, this extended analysis was done by Abdelwahab et al. (2021), who used Uber trip data in Toronto to examine the extent to which ride-hailing helps advance transportation equity in terms of employment accessibility. The authors have found that, overall, ride-hailing outperforms transit in providing accessibility but integrating ride-hailing with public transit does little to improve access to jobs, particularly in deprived neighborhoods.

There is an important methodological characteristic in common in the works of Cats et al. (2022) and Abdelwahab et al. (2021). Both studies consider only the travel time of the fastest transit route between each origin-destination pair and then calculate the fare for those journeys sequentially, to later estimate accessibility using a generalized travel cost function that combines time and money into a single cost value. This is also how generalized travel costs have been previously used in several studies in the accessibility literature (Bocarejo & Oviedo, 2012; El-Geneidy et al., 2016; Geurs et al., 2010). However, this approach can be problematic for studies that try to account for out-of-pocket costs when analyzing accessibility by transit and ride-hailing for at least two reasons.

First, the generalized travel cost approach does not account for trade-offs between travel time and monetary costs. Oftentimes, multiple transit paths exist between a given origin-destination pair, and some path alternatives may involve longer travel times at cheaper costs, while others may be faster at a higher cost (for example with premium express services or trips that involve transfers between modes). There is no clear answer as to which path should be considered, given the variety of circumstances under which individuals have different preferences based on their monetary and time constraints. In fact, considering only one of the alternatives poses important implications for transportation equity analyses. On one hand, considering only the fastest paths may result in prohibitive costs for individuals with stricter financial constraints, as these paths may be more expensive due to transfers or faster modes. On the other hand, considering a single cheaper path may bias accessibility estimates by ignoring more efficient travel alternatives. In both cases, accessibility estimates may be biased and over or underestimated for individuals who are more money- or time-constrained in their travel choices, which often includes poorer and wealthier groups, respectively. Therefore, ignoring the trade-offs between travel time and financial costs can be particularly problematic for studies concerned with equity issues.

Secondly, calculating accessibility based on a generalized travel cost function poses several challenges. One issue is the conversion of money to time (or vice versa) by assigning a monetary value to time. This process involves several ad-hoc methodological decisions that may not be appropriate for studies that are concerned with transportation equity (Martens & Di Ciommo, 2017). Assigning a value of time (VOT) that varies according to people's income levels, for example, implies that the time of wealthier individuals is worth more than that of poorer citizens, which can perpetuate historical privilege (Börjesson & Eliasson, 2019; Goodwin, 1974). An alternative approach is to use a fixed VOT, which partially addresses this issue. However, it is not clear what value should be used, leading to ad-hoc decisions that compromise the comparability of different studies and may introduce other forms of bias. Additionally, converting an absolute amount of money to time with a fixed VOT is relatively straightforward, but doing so when looking at trip monetary cost as a share of one's total budget is much more complex and reduces the communicability and interpretability of results.

To date, the majority of research on public transit accessibility has primarily focused on travel time due to the limitations of routing engines, such as OpenTripPlanner and ArcGIS Network Analyst, which overlook the cost of transit fares. Only more recently, a new routing algorithm with a multiobjective optimization method has been developed that simultaneously accounts for time and cost constraints in public transit accessibility routing (Conway & Stewart, 2019). This method is utilized in the present study, allowing us to consider a large number of trip alternatives between the same origin-destination pair, ranging from faster though expensive itineraries to slower and cheaper routes. The method is further explained in the methods section.

3. Study area

Rio de Janeiro is the second largest city of Brazil and the fifth largest in Latin America with approximately 6.7 million inhabitants, making it one of the largest markets for ride-hailing in the continent. In Rio, ride-hailing services were used by approximately 6 % of the population that used some form of motorized transportation in 2018, twice as much as the national average of 3.1 % in all Brazilian cities (Warwar & Pereira, 2022). While there is no available data with information on the purpose of ride-hailing trips in Rio de Janeiro, the Uber trip data set used in this paper (see Section 4) indicates that approximately 12 % of all Uber trips in Rio are taken during the morning peak period, when most trips are often work-related or linked to other regular activities.

Ride-hailing users in the city make on average 8 trips per month, at an average cost of approximately 33 BRL per trip (Warwar & Pereira, 2022). Ride-hailing users in Brazil are largely made up of women (over 60 %), whites (approximately 48 %), as well as young (46 % are between 15 and 35 years old) and wealthier individuals (ibid.). In Rio, in particular, 60 % of ride-hailing users are among the 40 % wealthiest in the city, while only 23 % of users are among the city's poorest 40 %.

The spatial distributions of population, income and employment opportunities in Rio are presented in (Fig. 1). Wealthier population groups generally reside in the city's southern and southeastern regions (Fig. 1A), which are among the most densely populated areas in the city (Fig. 1B). High-income neighborhoods also tend to be relatively closer to the CBD, where the majority of jobs are located (Fig. 1C), thus facilitating the access to many urban facilities, which can be reached from such neighborhoods with a short ride. The poorest population, conversely, is mainly located in the northern and western regions of the city, which are less densely populated and very far from the city's main employment hubs, making ride-hailing more expensive and, thus, less affordable.

The public transportation network in Rio de Janeiro also tends to serve the population unequally (Fig. 1D). The subway system, usually regarded as having better quality than the other transit alternatives, serves mainly the wealthiest areas in the southeastern region and the CBD, although it also stretches to some neighborhoods in the northern region of the city. Rail and BRT services, which are generally slower and more prone to service disruptions than the subway, provide transportation over longer distances to the poorest areas located in the western- and northern-most ends of the city. The city also counts on a light rail system that runs mainly through the CBD and its vicinities, a ferry system that connects Rio to adjacent cities and a widespread municipal bus system that shares right-of-way with automobiles, thus leading to slower operational speeds. The buses are highly used by low-income people because they are less expensive than higher-order transit alternatives in Rio (more details in Section 4). The transit system's spatial configuration coupled with the co-distribution of people and jobs in the city leads to a scenario where those who depend on public transport the most, often face the longest commuting times. As per Rio's latest travel survey, 17 % of the transit trips conducted in the city were longer than 90 min, with an average commuting time of 57 min (Central, 2016).

4. Data

We combine data from many different sources. Socioeconomic and population data come from the 2010 Population Census (IBGE, 2011), the latest census available in Brazil. Data on job locations come from the 2019 RAIS, an administrative records product developed by the Ministry of Economy with information on all formal workers in the country.[1] These datasets are spatially aggregated to a hexagonal grid based on Uber's H3 index (Brodsky, 2018) at resolution 8, in which each cell has a radius of approximately 461 m and area of 0.74 Km^2. Income data were adjusted based on the inflation from 2010 to 2019 using the official IPCA index (Broad Consumer Price Index, in Portuguese).

The street network and the pedestrian infrastructure were extracted from OpenStreetMap in August 2019. To factor in street slopes when

[1] Although there is no recent data available on the location of informal jobs, these jobs are relatively more accessible with shorter commute times and distances than formal jobs (Motte-Baumvol et al., 2016). Moreover, the 2003 household travel survey of Rio suggests a very similar spatial distribution of both types of jobs in Rio. These data indicates that the number of formal and informal jobs in the same zone is highly correlated (0.78 Pearson correlation statistically significant at 0.001), and that the number of formal jobs in one zone is moderately correlated with the number of informal jobs in neighboring zones (Global Bivariate Moran's I of 0.30 statistically significant at 0.001).

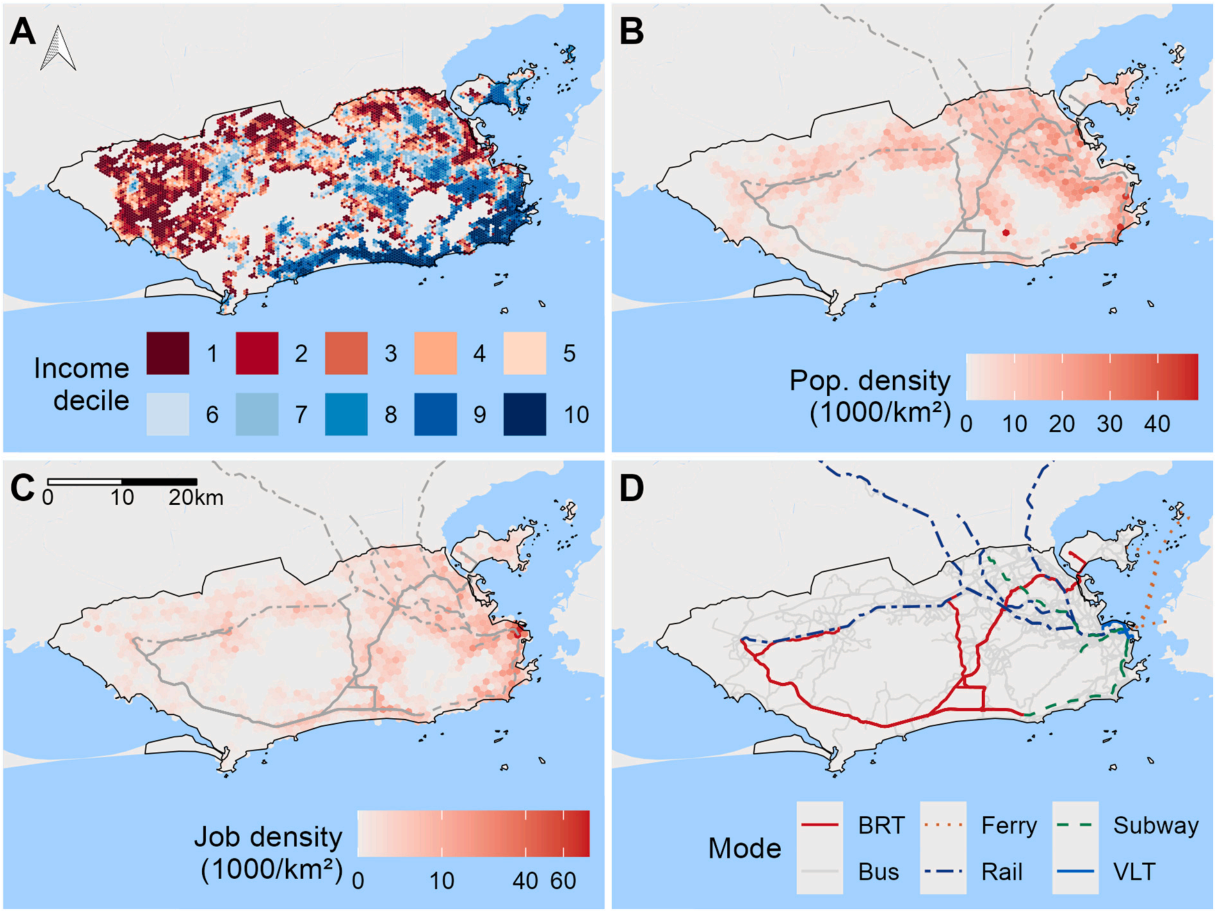

Fig. 1. Spatial distribution of (A) deciles of income per capita, (B) population density, (C) job density, and (D) main transit routes in Rio de Janeiro. Obs. Transit network from 2019, while population and income data are from 2010 adjusted by inflation between 2010 and 2019.

calculating walk travel times, we used elevation data with a spatial resolution of 30 m, produced by the Shuttle Radar Topography Mission (Farr et al., 2007). Data describing the public transport system in October 2019 was provided by Fetranspor (Rio state's federation of passenger transport companies) and SuperVia (train system operator) in the General Transit Feed Specification (GTFS) format. Intermunicipal buses were removed from the GTFS because we could not find reliable information on the fare costs of these services. Since we only analyze accessibility within the municipality of Rio de Janeiro, and because intermunicipal buses are more expensive than the other available transit modes in the city, removing these services does not significantly affect our results and conclusions.

Information of public transit fares were collected from Rio's transport authority website.[2] The fare prices in effect in 2019 are summarized in Table 1. Single mode fares are not dramatically different, a subway ticket is only 25 % more expensive than a municipal bus ride, for example. Nonetheless, the lack of fare integration between specific modes significantly affects the affordability of multimodal trips. In particular, the lack of integration between the municipal buses and the subway and the small discount in transfers between the buses and the rail makes faster transit options more expensive for low-income travelers who live far from rapid transit corridors and need to connect to them via buses.

To estimate accessibility by ride-hailing, we used two data sets provided by Uber under a non-disclosure agreement. The first data set is a travel matrix table that covers 152 million Uber trips taken from March 8th to December 20th, 2019. This data set consists of aggregate information on the total number of trips between origin-destination pairs, as well as their average distance, speed and fare. The data is spatially aggregated over a hexagonal grid based on the H3 index using resolution 8. This information is aggregated by day of the week (either weekdays or weekends) and by time blocks (morning peak 6 am - 9 am, day off-peak 9 am - 5 pm, evening peak 5 pm - 8 pm or night off-peak 8 pm - 6 am). In order to calculate employment accessibility considering the conditions most transit users would face when commuting to work, we used Uber trip data collected on weekdays during the morning peak. Due to privacy concerns, the travel matrix data provided by Uber only includes information for origin-destination pairs between which at least 10 trips were taken, after accounting for the aggregations listed above. To fill the data gaps between origins and destinations whose trip count was lower than

Table 1
Transit fares in effect in Rio de Janeiro in 2019.

Single mode		Trip integration	
Mode	Fare (BRL[a])	Integration	Fare (BRL)
Light-rail (VLT)	3.80	VLT + VLT	3.80
Municipal bus	4.05	Municipal bus + municipal bus	4.05
BRT	4.05	Municipal bus + VLT	4.05
Rail	4.7	Municipal bus + BRT	4.05
Subway	5.00	BRT + subway	7.10
Ferry	6.30	Rail + subway	8.55
		Bus/BRT + rail (no discounts)	8.75
		Bus + subway (no discounts)	9.05

[a] obs. As of October 2019, 1000 BRL (Brazilian reais) was worth approximately 241 USD.

[2] Available at https://www.cartaoriocard.com.br/rcc/institucional/tarifas.

10, we used Streetmap Premium, a commercial data set licensed by ESRI that brings historical traffic speed information based on GPS data collected multiple times of the day between the first quarters of 2018 and 2020.

The second data set provided by Uber presents information on the spatial distribution of pickup wait times (average, 25th, 50th and 75th percentiles) and number of pickups in Rio de Janeiro. The data set is spatially aggregated into hexagonal cells of different sizes (H3 index resolutions 8 and 9) to guarantee a minimum of 10 pickups per cell, for data fidelity and privacy concerns. This data set is also aggregated by day of the week and time blocks.

5. Methods

To investigate how ride-hailing services impact employment accessibility both as a standalone transport mode and when used in conjunction with public transport, we followed a method composed of four steps. The first involved calculating travel time and monetary cost matrices by public transit. The second step was to calculate a similar matrix, but for ride-hailing services. Next, we combined the matrices from the previous steps to generate a third travel matrix, in which ride-hailing is used as a first-mile feeder to rapid transit stations and the rest of the trip is completed by transit services. Finally, in the fourth step we calculated accessibility levels using each one of these matrices and compared how the accessibility conditions of each scenario are distributed in space and across different socioeconomic groups. Each methodological step is detailed below. In all of these steps, the spatial units of analysis are hexagonal cells from the H3 spatial grid (Brodsky, 2018) at resolution 8.

Data processing and visualization were conducted in R. The code used in this paper is publicly available in a GitHub repository,[3] and can be used as a reference when replicating the method of this paper in other contexts.

5.1. Travel time and cost matrices by public transit

Calculating the travel matrix between origins and destinations is a fundamental step to estimate accessibility levels in a given area. However, simultaneously accounting for both travel time and monetary cost in multimodal transport networks raises two challenges: the first is that the journey between a given origin-destination pair may be completed by multiple trip alternatives that may not be dominated by a supposedly "optimal" alternative. For example, the journey between one point to another might be completed with a fast but expensive subway trip (e.g. a 15-minute trip that costs 10 BRL) OR with a longer though cheaper bus trip (e.g. a 40-minute trip that costs 5 BRL). The first challenge is which path alternative should be considered when calculating accessibility estimates. Passengers looking to save time may prefer the first alternative, while those looking to save money might opt for the second. If we had omitted the first trip alternative from the travel matrix, we would have mistakenly concluded that the destination was inaccessible for trips that cost less than 10 BRL when, in fact, this is not the case. Similarly, if the second alternative had been omitted, we would have wrongly assumed that the destination was inaccessible for journeys of less than 40 min, which is also untrue. To overcome this issue, one needs to consider the full set of trip alternatives when calculating accessibility estimates, requiring the routing engine to output these alternatives in the first place - which takes us to the second challenge.

The second challenge is that performing multimodal transit routing with multiobjective optimization is a complex and computing-intensive task (Delling et al., 2015), specially because transit fares are often path-dependent; i.e. the fare cost of a ride can change depending on transfers that may have happened earlier in the journey, based on the fare system rules (Conway & Stewart, 2019; Lo et al., 2003). In a recent work, Conway and Stewart (2019) introduced a novel multiobjective optimization routing method to account for cost constraints in public transit accessibility metrics. Rather than finding only the fastest trip alternative regardless of monetary cost, the method is able to determine for a given origin-destination pair the multiple journey alternatives that are optimal in terms of both travel time and cost. As such, the method returns the set of alternative paths that form a frontier beyond which no journey is both faster and cheaper, ignoring trips that are simultaneously more expensive and slower than any existing alternatives. In other words, the model finds the fastest trip for each possible combination of fares in the transit network. The routing model proposed by the authors was implemented in the R5 routing engine developed by Conveyal.

In this paper, we used Conway & Stewart's (2019) routing model, available in R through the r5r package (Pereira et al., 2021), to generate the transit Pareto frontier for each OD pair. These frontiers include for each origin-destination pair both walk-only trips and trips in which transit is the main mode and the access to and egress from stations is done by foot. We have considered a walk speed of 3.6 km/h, a maximum walk time of 30 min to access/egress from transit stops and that a trip would consist of at most 4 transit legs. We have also considered trips departing every minute from 7 am to 8 am, and used the median travel time within this time window to calculate the accessibility levels. This strategy helps us mitigate the impact of statistical noises related to the variation of transit services availability within the morning peak (Conway et al., 2018). The travel time of a trip consists of the duration of a door-to-door journey, including the time it takes to walk from the origin to the departure stop, any wait and transfer time that occurs at stops, in-vehicle time and the time it takes to walk from the arrival stop to the destination. The monetary cost of a trip is the sum of the fares paid in each of its legs, including any fare integration discounts available when using the Riocard Mais smartcard as presented in Table 1.

5.2. Travel time and cost matrices by ride-hailing

A ride-hailing travel matrix covering all possible origin-destination pairs is essential to calculate the accessibility conditions that result from using ride-hailing services, both as a standalone mode and as a first-mile feeder to transit. However, the aggregate travel matrix data provided by Uber does not cover all possible combinations of origin-destination pairs. To fill in the data gaps, we used a multi-stage process.

First, we calculated travel times and distances by automobile during the morning peak for all possible origin-destination pairs using the Streetmap Premium data and the Network Analyst plugin in ArcGIS Pro. Using the origin-destination pairs for which we had Uber trip data, we used a linear regression model to predict Uber travel times and distances based on automobile travel times and distances calculated with Network Analyst (R^2 fit of 0.82 and 0.95, respectively). We used the coefficients derived from this model to estimate Uber's trips distances and travel times for pairs not covered in Uber's original data set. In a second stage, we used a similar regression to predict the cost of Uber trips based on travel time and distance (R^2 fit of 0.96), and used these coefficients to estimate Uber's trip costs for pairs not covered in Uber's data set. We manually imputed the value of 5 BRL for the cases where the predicted trip cost was below 5 BRL, which was the minimum Uber fare in Rio de Janeiro in 2019.

The travel times listed in Uber's data set and estimated through the linear regression include only in-vehicle time. To properly calculate the duration of a door-to-door journey we have to include the waiting time at the beginning of the trip (from the trip request to the vehicle arrival at the origin) to the total travel time. To do this, we summed the average waiting time at each origin, listed in the pickups data set provided by Uber, to the in-vehicle times between each origin-destination pair. This is a crucial step when estimating accessibility by ride-hailing, because areas under-supplied by drivers will have, on average, higher waiting times - thus potentially lower accessibility levels. For the sake of

[3] Available at <<https://github.com/ipeaGIT/access_uber>>.

simplicity, the calculation of total travel time assumes there is no walking before boarding and after arrival. For hexagons with missing data on waiting time due to privacy reasons, we estimated their waiting time as the average waiting time of their neighbors.

Finally, we have also included potential walk-only trips to the ride-hailing travel matrix, which is important to make sure we calculate accessibility levels correctly. For example, if we estimate accessibility with a monetary threshold that prevents any ride-hailing trips to be taken, but with a temporal threshold that allows some walking trips to be completed, we still have to consider the opportunities that can be accessed by foot from the origins, like one does when calculating transit accessibility. To do this, we have calculated a walk travel matrix with r5r and created a larger matrix between all combinations of origins and destinations which include both walking-only trips and Uber trips. The result is a Pareto frontier that considers walk-only and Uber-only trips.

5.3. Travel time and cost matrices considering first-mile by ride-hailing

The next step in our method was to calculate travel matrices considering a first-mile leg by ride-hailing and the remainder of the trip done by transit. To calculate the travel matrix by ride-hailing combined with transit we followed a four-step method. First, we calculated the time and cost by Uber from each origin to all hexagons containing rapid transit stations. We then merged this data set to the Pareto frontier composed of trips departing from each rapid transit station to all destinations in the city. Here, we had to consider multiple departure times by transit to accommodate the transfer between ride-hailing and transit. For example, if the ride-hailing trip arrived at the subway station at 7:15 am, we had to merge it with transit trips that departed from the same subway station after 7:15 am.

Next, we calculated the total travel time and monetary cost of each trip by adding the travel times and monetary costs of the first-mile leg by ride-hailing and the transit leg. In cases where multiple trip alternatives existed between an origin-destination pair (e.g. one could go from point A to B either via transit stations X or Y), we kept only the alternatives that were simultaneously more efficient both in terms of travel time and out-of-pocket cost than the other options. In other words, we calculated a Pareto frontier composed of trips whose first-mile was traveled by ride-hailing and the rest by rapid transit.

Finally, we merged both the Pareto frontier by ride-hailing combined with mass transit and the Pareto frontier by transit into a single larger frontier. As a result, the final Pareto frontier by ride-hailing combined with transit also includes transit trips whose access to stations was completed by foot, as long as these alternatives are not simultaneously slower and more expensive than the trips that include ride-hailing as a first-mile mode.

5.4. Accessibility estimates

To calculate accessibility levels, we used cumulative opportunity measures simultaneously considering travel time and monetary costs thresholds. Accessibility levels are then calculated in two distinct ways. First, we considered absolute monetary costs, as described in Eqs. (1), (1.1) and (1.2).

$$A_i = \sum_{j=1}^{n} O_j \times max_{k\in K}\left(f\left(t_{ijk}\right) \times g\left(c_{ijk}\right)\right) \quad (1)$$

$$f\left(t_{ijk}\right) = 1, iff\left(t_{ijk}\right) \le T; 0, iff\left(t_{ijk}\right) > T \quad (1.1)$$

$$g\left(c_{ijk}\right) = 1, ifg\left(c_{ijk}\right) \le C; 0, ifg\left(c_{ijk}\right) > C \quad (1.2)$$

where A_i is the accessibility to jobs at origin i, O_j is the number of jobs at destination j, K is the total set of paths between origin i and destination j, t_{ijk} is the travel time of path k between origin i and destination j, T is the travel time threshold, $f(t_{ijk})$ is a binary function which returns values 0 or 1 based on the travel time, c_{ijk} is the absolute monetary cost of path k between origin i and destination j, C is the absolute monetary cost threshold, and $g(c_{ijk})$ is a binary function which returns values 0 or 1 based on the absolute monetary cost between the origin i and destination j.

Because the burden of transportation costs can weigh differently for low- and high-income individuals, we also calculated accessibility considering monetary costs relative to the income per capita at the trip origin, as described in Eqs. (2), (2.1) and (2.2). This was done considering what would be the total monthly commute cost of an individual who uses the same path to commute to and from work every business day as a share of her/his monthly income, calculated as the income per capita before taxes of the trip origin hexagonal cell.[4] Assuming 22 business days in a month, the relative monthly cost of a trip is given by Eq. (2.2).

$$A_i = \sum_{j=1}^{n} O_j \times max_{k\in K}\left(f\left(t_{ijk}\right) \times h\left(b_{ijk}\right)\right) \quad (2)$$

$$h\left(b_{ijk}\right) = 1, ifh\left(b_{ijk}\right) \le B; 0, ifh\left(b_{ijk}\right) > B \quad (2.1)$$

$$b_{ijk} = \frac{c_{ijk} \times 2 \times 22}{I_i} \quad (2.2)$$

where $h(b_{ijk})$ is a binary function which returns values 0 or 1 based on the relative monthly cost, b_{ijk} is the relative monthly cost of a trip with path k between origin i and destination j in terms of one's monthly budget, B is the relative monthly cost threshold, and I_i is the monthly income per capita at origin i.

The main advantages of cumulative opportunities measures are that they are easy to communicate, operationalize and interpret (Geurs & van Wee, 2004). However, they are often criticized for the need to set arbitrary cost thresholds, for ignoring any activities outside these limits and for the fact that all activities within the thresholds are considered equally reachable (Geurs & van Wee, 2004; Pereira, 2019). In order to mitigate this issue, we have used several combinations of thresholds selected from three different distributions: travel times cutoffs range from 1 to 90 min, every 1 min (1, 2, 3, …, 88, 89, 90); absolute monetary costs cutoffs range from 0 BRL to 24 BRL, every 0.05 BRL (BRL 0, 0.05, 0.10, …, 23.90, 23.95, 24); relative monetary costs cutoffs range from 0 % to 40 %, every 1 % (0 %, 1 %, 2 %, …, 38 %, 39 %, 40 %).

For the sake of brevity, some of the results presented in the paper are based on selected thresholds. When focusing on a single time threshold, we have chosen to use a travel time of 60 min, which captures the results for moderately long trips and which is close to the average transit commute time in Rio (57 min) as per the last travel survey (Central, 2016). The chosen absolute monetary costs threshold were 6 BRL, 12 BRL, 18 BRL and 24 BRL. These cutoffs cover potential transit and ride-hailing trips with distinct lengths and costs, ranging from just above the minimum Uber fare in Rio (5 BRL) to moderately expensive trips (24 BRL). Finally, the chosen relative monetary costs thresholds were 10 %, 20 %, 30 % and 40 %, highlighting the results when considering different affordability thresholds.

6. Results

Considering the Pareto frontier of travel time and monetary cost for all origin-destination pairs in Rio allows us to calculate the average

[4] Calculating relative monthly costs as a percentage of the income per capita at a given region means that we have assumed that the income is evenly shared by every member of a household. In practice, however, the total income of a household is not evenly shared by its individuals, with some household members requiring larger budgets to perform their activities, such as commuting. Data availability prevents us from calculating relative monthly costs considering household sizes and the number of economically active household members, which is why we opted to use the first method.

number of accessible jobs in the city given every possible combination of time and money thresholds. The result of this operation is a Pareto surface that represents the Pareto-optimal accessibility levels in the city - i.e. the number of accessible jobs calculated from the full set of trips that optimize for time and money combinations between each origin-destination pair (Fig. 2).

The transit-only panel shows that average accessibility levels by transit are largely influenced by travel time once the passenger is able to spend enough to afford a bus ticket, around 4 BRL. Above this value, though, average accessibility levels are almost unaffected by more expensive transit tickets, even though they would allow one to ride faster modes, such as the rail and the subway. The exception to this can be seen around the 8 and 9 BRL marks, values with which the passengers can make transfers between transport modes, such as the municipal buses, the subway and the rail. The dominance of travel time cutoffs over monetary cost cutoffs on shaping the accessibility levels happens largely because Rio uses a flat fare system, in which prices remain constant regardless of distance/time traveled. The ride-hailing-only panel, on the other hand, shows that money exerts a stronger influence than time on the accessibility levels by this transport mode: the more expensive the ride-hailing trip, the farther one can go with it. It also shows that the accessibility benefits from ride-hailing-only trips become more salient at higher costs, above 15 BRL, whereas transit-only accessibility benefits are significant even when considering cheap 5 BRL trips. Finally, the figure also shows how using ride-hailing as a first mile connection to transit can significantly expand employment accessibility for transit users. The marginal accessibility gains for every additional BRL becomes much more pronounced than on the transit-only scenario, while accessibility levels at low monetary thresholds remain much higher than when considering ride-hailing-only trips.

Although the Pareto surface can help us visualize the marginal impacts of time and money on average accessibility levels, it makes it hard to analyze and compare accessibility conditions at particular monetary and temporal thresholds. Thus, to facilitate the interpretation and comparison of results, in the rest of the paper we report our findings using selected combinations of travel time and monetary thresholds.

6.1. Spatial distribution of accessibility

Fig. 3 shows the spatial distribution of employment accessibility by transit-only, ride-hailing-only, and ride-hailing combined with transit in up to 60 min of travel and multiple absolute monetary cost thresholds. This figure presents the spatial context for the analyses in this paper, highlighting how accessibility conditions are distributed across the city in each transport mode scenario. Markedly, the maps show a sharp East-West divide in all three scenarios, in which residents of the east side of the city have higher accessibility levels. This pattern can be explained by the large concentration of jobs and public transit services near the city center, located in the East side of Rio (see Fig. 1).

The maps in Fig. 3 also show significant differences in the accessibility levels provided by the different transport mode alternatives. The transit system provides relatively high accessibility levels along mass transit corridors that run from the CBD towards the west, even at low monetary costs when compared to ride-hailing. A 6 BRL budget is enough to pay for a transit trip by bus (with transfers allowed between buses and BRTs), by train or by subway, without any travel time limit. Compared to the ride-hailing as a standalone mode, the transit system configuration results in higher accessibility in areas farther from the CBD, showing that, in Rio, mass transit can serve population groups that live in the outskirts of the city at relatively low costs. Nonetheless, very little additional accessibility is gained by spending more money on transit alone when compared to the other alternatives.

For ride-hailing services, on the other hand, accessibility is severely impacted by monetary costs restrictions. A 6 BRL budget only allows one to access the jobs in the immediate vicinity of the trip origin, resulting in very low accessibility levels on average. The number of accessible jobs consistently increases when taking more expensive trips into account. Nonetheless, the fact that accessibility is still largely concentrated near the city center, even at higher cost thresholds, indicates that ride-hailing as a standalone mode is very limited in providing access when costs are capped to 24 BRL.

The Fig. 3 also shows how the spatial distribution of accessibility levels are affected when allowing passengers to combine ride-hailing and public transit. Ride-hailing can extend the reach of the transit system far beyond the immediate vicinity of transit stations when used as an on-demand feeder service to the main transportation system. However, the accessibility gains that result from this combination are conditioned to higher monetary spending. Accessibility levels remain unchanged when allowing ride-hailing connections to public transport with a 6 BRL budget, but higher budgets result in accessibility gains in areas around the main transit corridors, from where ride-hailing services potentially substitute slow feeder transit trips to these corridors and long walks to the stations.

6.2. Average accessibility levels by transport mode and income group

The maps presented in Fig. 3 present a snapshot of the accessibility distribution when limiting trips to a given travel time threshold (60 min). The arbitrary choice of thresholds, however, may severely affect the results and conclusions of accessibility analyses (Pereira, 2019), an issue that we try to mitigate by considering several different travel time cut-offs in our accessibility analyses. Fig. 4 shows how average accessibility levels vary by transport mode with different combinations of absolute monetary cost and travel time thresholds.

The figure reasserts that a 6 BRL budget is not enough to generate accessibility gains from ride-hailing, neither as a standalone mode nor as a first-mile mode to transit. When using it as a standalone transport mode, only very short distances can be traveled when spending that amount of money. At the same time, it is virtually impossible to use ride-hailing as a first-mile mode to transit spending only 6 BRL. This is because the minimum Uber fare in Rio (5 BRL) plus the cheapest rapid transit fare (4.05 BRL) entails trips that are more expensive than the selected threshold. As a result, the curve for ride-hailing only barely rises above 0 % average accessibility, while the transit-only and the ride-hailing combined with transit curves overlap each other (only the latter is shown in the figure).

The advantage of ride-hailing becomes clearer with higher budgets (12 BRL onwards). In such cases, the ride-hailing as a standalone mode is able to provide much higher accessibility levels than the public transport system when considering relatively short trips, as a result of its higher speeds and lower access times. For example, considering a travel time threshold of 30 min and monetary cost thresholds of 18 and 24 BRL, the average accessibility by ride-hailing was 5 and 7 times higher than by transit, respectively. It is in these relatively short trips where ride-hailing has higher competitive advantage over transit. This advantage is limited to shorter trips due to cost constraints: the cost of ride-hailing trips, as opposed to the cost of transit trips in Rio, increases with its distance, making long trips more expensive than the monetary thresholds considered in the analysis. Consequently, the accessibility that results from using ride-hailing as a standalone mode reaches a ceiling at relatively low temporal thresholds, whereas the transit accessibility keeps growing for long travel times.

The advantages of combining ride-hailing with transit, on the other hand, become more evident as the time threshold increases. From the 30 min mark onward, approximately, the accessibility curve of ride-hailing combined with transit curve (Fig. 4) detaches from, and remains consistently higher than, the transit-only curve. The accessibility benefits of using ride-hailing as a first-mile feeder to transit also become more prominent when taking into account more expensive trips, as shown by the wider gap between the ride-hailing combined with transit and the transit-only curves. Considering a temporal threshold of 60 min, for example, the use of ride-hailing as a first-mile feeder to transit expands

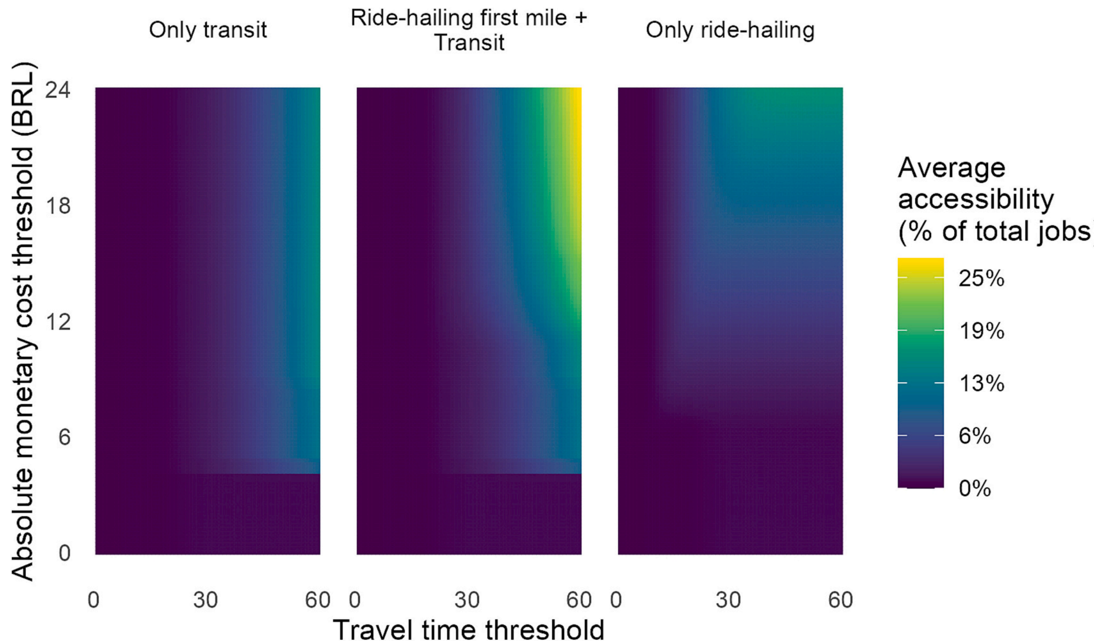

Fig. 2. Pareto-optimal accessibility with the average number of jobs accessible for each combination of travel time and monetary costs.

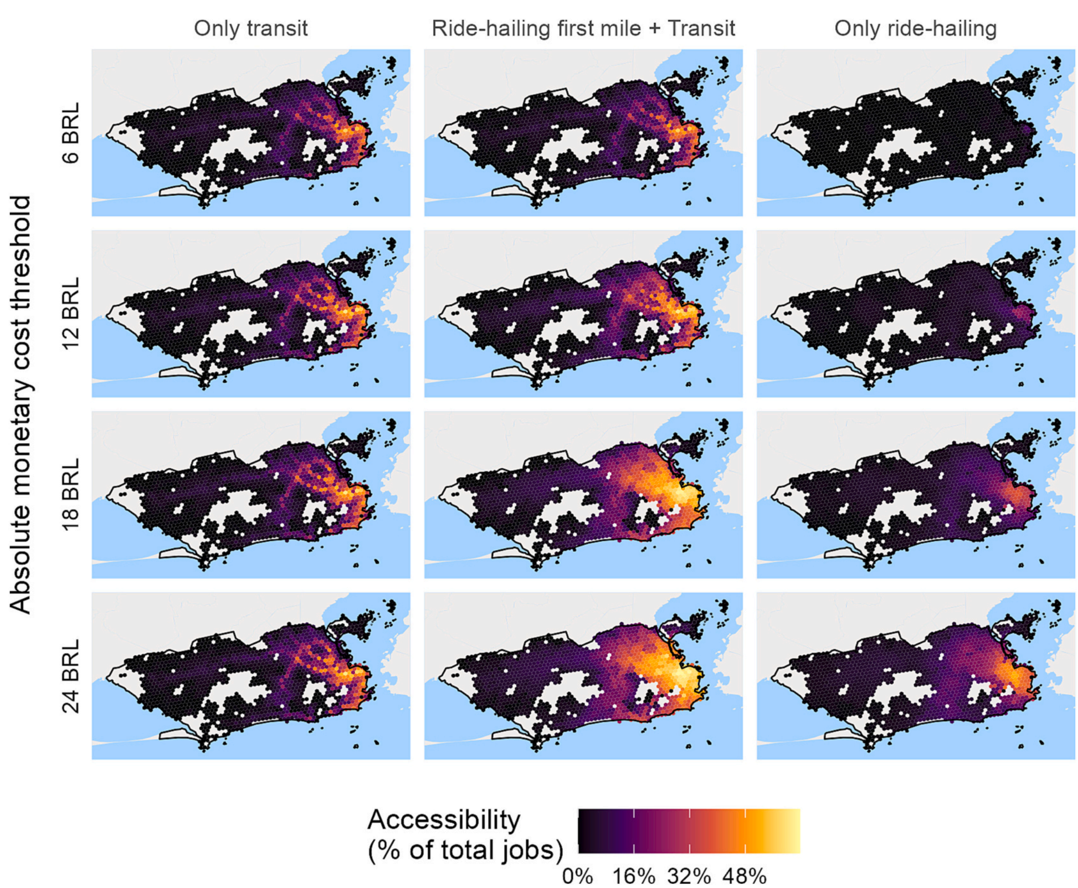

Fig. 3. Spatial distribution of employment accessibility by different transport mode alternatives in under 60 min of total travel time and multiple monetary cost thresholds. Rio de Janeiro, 2019.

the average employment accessibility of transit riders by approximately 61 % and 75 % when taking into account trips of up to 18 BRL and 24 BRL, respectively.

The previous figures show how absolute monetary costs impact potential employment accessibility levels, but they do not account for the affordability of these costs according to travelers' incomes. The costs of daily trips, however, may impose significant financial burdens on commuters' budget, especially in a city like Rio, with high poverty levels:

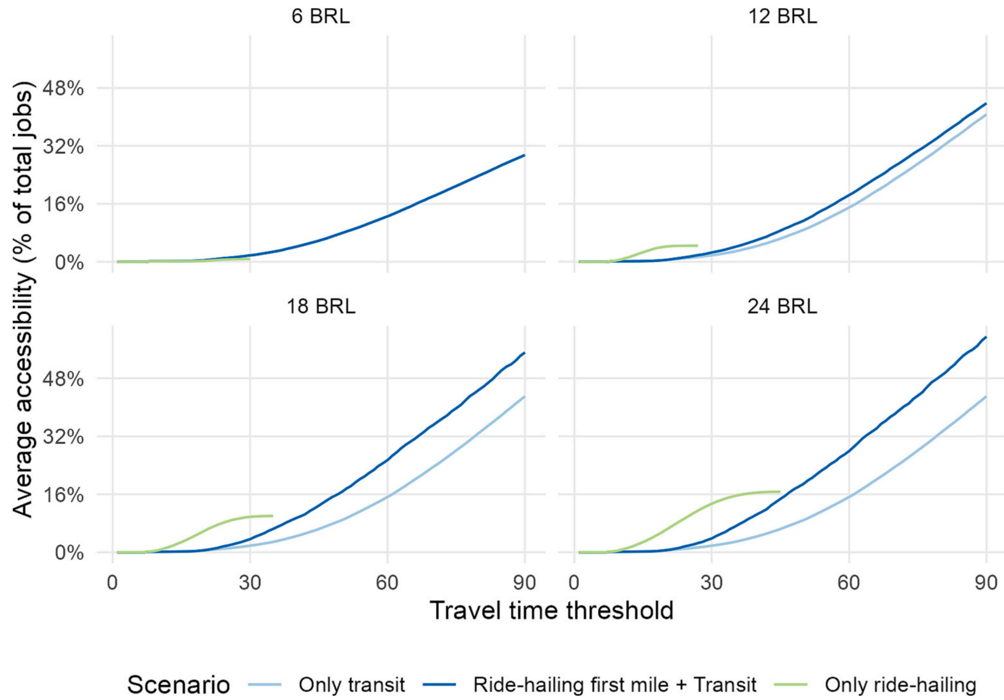

Fig. 4. Average employment accessibility for different combinations of travel time and absolute monetary cost thresholds by transport mode. Rio de Janeiro, 2019.

wealthy and poor passengers may pay the same to travel from one place to another, but the former spends a much smaller share of their budget than the latter. Therefore, using ride-hailing to commute to and from work, be it as a standalone mode or as a first-mile feeder to public transport, may not be viable for a large part of the population due to financial constraints. This makes it particularly important to assess the accessibility conditions considering monetary restrictions not only in absolute terms, but also as a share of one's income.

Fig. 5 shows how the average accessibility levels in Rio de Janeiro vary by transport mode with different combinations of relative monthly cost and travel time thresholds. Because aggregate analyses may mask significant differences among population groups, the figure exhibits the

Fig. 5. Average employment accessibility for high- and low-income groups for different combinations of travel time and monetary costs relative to income by transport mode. Rio de Janeiro, 2019.

average accessibility levels of the wealthiest 10 % and the poorest 40 % of the population separately.[5] The different scenarios of transport mode are indicated by the color of each curve, while the line type (whether solid or dashed) indicates the population group that each curve refers to.

The accessibility levels of the wealthiest, shown in solid lines, follow a similar pattern to the average accessibility levels of the entire population, but at much higher levels: with public transport trips of up to 90 min and that may compromise up to 40 % of their income, they can access approximately 76 % of all jobs in the city. As hypothesized before, using ride-hailing services, both as a standalone and as a first-mile mode, yields much larger accessibility benefits to the wealthiest citizens than to the population as a whole. The wealthiest residents can ride more expensive and longer ride-hailing trips than the rest of the population when compromising the same share of their income on transport, thus significantly increasing their capability to access jobs within a given time threshold.

The accessibility conditions of the poorest, shown in dashed lines, on the other hand, are remarkably different. Allowing transport expenditures of up to 20 % of their monthly income barely results in any accessibility benefits, which only become more noticeable when considering trips that compromise 30 % of their income on commuting costs. Another important difference is that the ride-hailing combined with transit and the transit-only curves never separate from each other, resulting in only the latter being visible in the chart. Thus, using a ride-hailing service as a first-mile mode to transit does not yield any employment accessibility gains to low-income people. In fact, Rio's poorest residents can barely afford public transport itself, making a ride-hailing leg to reach transit prohibitively expensive. Using ride-hailing as a standalone mode is also impractical since Uber's base fare is more expensive than most transit fares and trip costs increase too quickly with trips distances.

6.3. Accessibility gains from integrating ride-hailing and transit

Now we turn to the potential accessibility gains from using ride-hailing as a first-mile leg to mass transit and how such benefits are distributed both in space and across the population. Fig. 6 shows how many more jobs one could reach in 60 min from different areas of Rio by combining ride-hailing and transit compared to riding transit-only trips.

Considering absolute monetary costs (Fig. 6A), significant accessibility gains can be obtained throughout the city when considering trips that cost up to 12 BRL. These gains are more pronounced along train and BRT corridors, ranging from the north of the city towards the west, and very limited at the southern and southeastern regions of the city, where some of the wealthier neighborhoods are located. In these wealthier neighborhoods, the accessibility benefits that result from combining ride-hailing and transit only become more prominent when considering more expensive trips, of up to 18 and 24 BRL. This is explained by the fact that this area has relatively high accessibility levels even without considering ride-hailing services, as it is well served by public transport, especially the subway. The accessibility gains that result from using ride-hailing as a first-mile mode to rapid transit are, therefore, relatively well distributed across the city when calculated using absolute monetary cost thresholds. The locations that benefit the most are concentrated along rapid transit corridors, but significant gains can be seen both on poorer neighborhoods located towards the western and northern regions of the city and on wealthy areas located at the south and southeastern regions.

When transport affordability is considered (Fig. 6B), however, the spatial distribution of accessibility gains changes dramatically. Accessibility gains become largely concentrated in high-income neighborhoods in the south region and near the CBD, whereas low-income neighborhoods that could potentially gain large accessibility sums when calculating it with absolute cost thresholds show barely any gains when calculating it with relative thresholds. This discrepancy is a result of the low purchasing power of the residents of such regions, who cannot afford the costs of first-mile ride-hailing trips.

To demonstrate how accessibility differences across income groups are affected by these spatial distributions, Fig. 7 presents the distribution of accessibility gains among high- and low-income individuals (the wealthiest 10 % and the poorest 40 %, respectively). Fig. 7A shows that low-income communities could potentially get large accessibility benefits from ride-hailing services, even when compared to those accrued by high-income groups: on average, accessibility gains are higher for the poorest population than for the richest when limiting monetary costs to 12 BRL (with a median gain of 2 % versus 0 %), and very similar when limiting costs to 18 and 24 BRL (with median gains of 6 % and 8 %, respectively). However, because of affordability constraints, the accessibility gains of low-income individuals are nearly eliminated (Fig. 7B), as opposed to those of high-income groups, suggesting that on-demand rideshare or microtransit services with dynamic routing could largely benefit low-income neighborhoods if financial barriers were alleviated.

In summary, our findings illustrate how differences in accessibility between population groups in Rio de Janeiro are largely shaped by the high socioeconomic and spatial inequalities observed in the city. Even though there are significant accessibility gains to be obtained by integrating ride-hailing services to the transit system in Rio, there are important financial barriers that limit who can benefit from these services on a daily-basis. As a result, ride-hailing becomes a limited mobility solution to improve mass transit and reduce social exclusion - particularly in the Global South context where many cities face high poverty rates.

7. Conclusion

This study examined how ride-hailing shapes spatial and socioeconomic differences in employment accessibility in Rio de Janeiro while accounting for the trade-off between travel time and monetary costs, considering ride-hailing both as a standalone transportation mode and when combined with transit as a first-mile feeder. Our results indicate that ride-hailing provides higher employment accessibility than public transit when considering trips of up to 40 min, and that the use of ride-hailing as a first-mile feeder to transit can significantly expand employment accessibility when considering trips that take at least 30 min. In both cases, though, the accessibility gains from ride-hailing come at relatively high out-of-pocket costs. These gains become more pronounced when considering trip costs of 12 BRL or more, which are expensive when compared to transit fares. As a result, when we account for different affordability thresholds where a person could only allocate between 10 % and 40 % of their monthly income on commuting costs, the accessibility benefits of ride-hailing services accrue mostly to high-income individuals. Because transit fare prices in Rio de Janeiro are fixed regardless of traveled distances, transit becomes substantially cheaper than ride-hailing and thus better able to cater to the needs of low-income populations, most of whom live in urban peripheries and engage in long commutes.

These results show that ride-hailing services can importantly shape access to opportunities in cities. However, our findings suggest that these services do not provide an equitable alternative to public transit systems - neither as a standalone mode nor when combined with transit. While Transport Network Companies (TNCs) can potentially overcome existing transit network gaps, the potential accessibility benefits from TNCs to transit-dependent populations are rather limited, since these are mostly composed of low-income individuals for whom monetary costs are a critical barrier. This suggests that the growth of market-priced TNCs is likely to increase levels of transport inequalities within Rio.

This paper also shows how accessibility estimates can vary greatly

[5] The cut-offs of the wealthiest 10 % and poorest 40 % is inspired by the Palma ratio, an inequality measure commonly used in transport studies to compare average accessibility conditions of the most well-off and disadvantaged population groups (Guzman & Oviedo, 2018; Herszenhut et al., 2022).

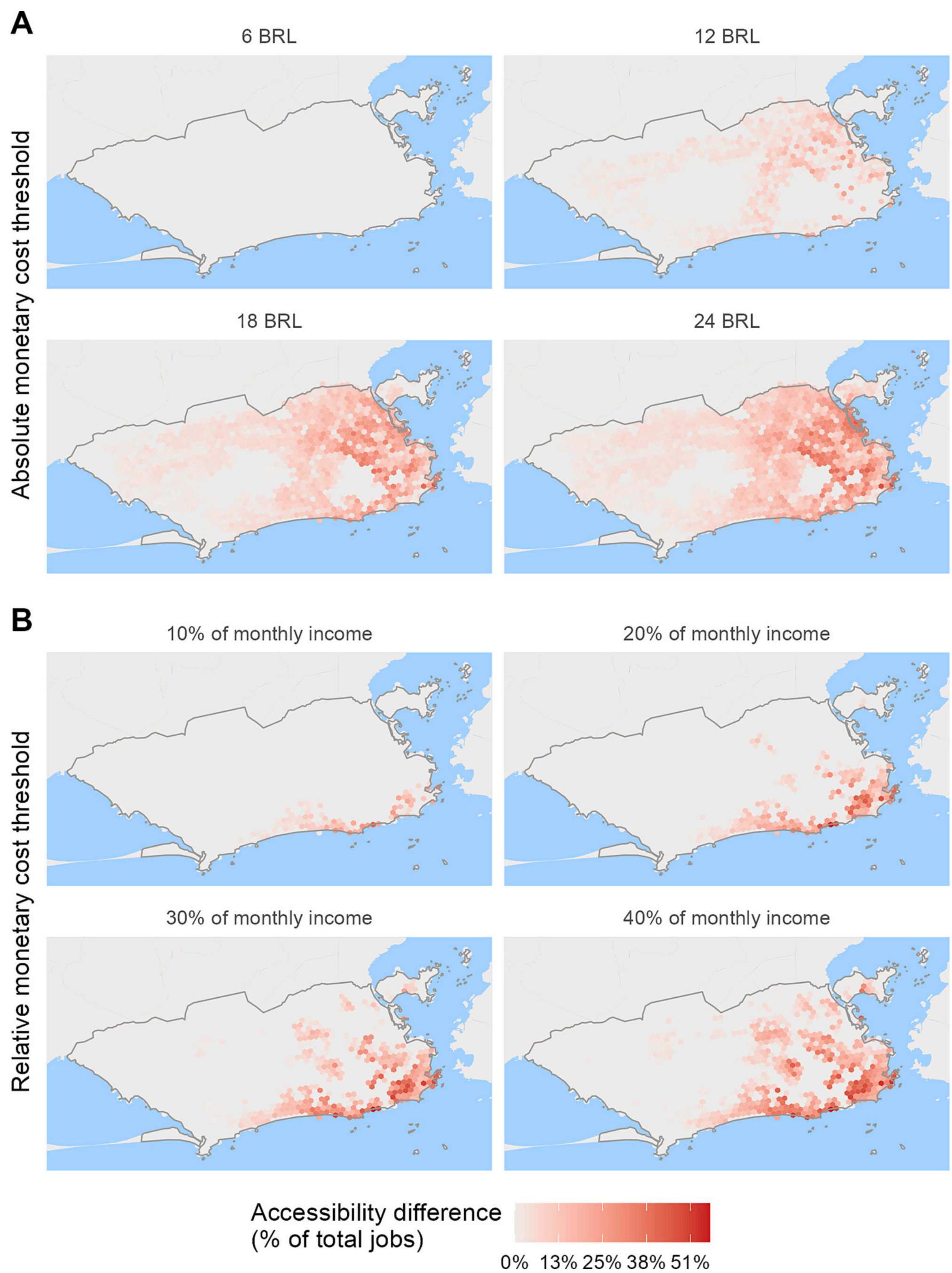

Fig. 6. Employment accessibility gains by ride-hailing combined with transit compared to transit-only accessibility considering a 60-minute travel time threshold and multiple monetary cutoff values in terms of absolute costs (A) and cost relative to income (B). Rio de Janeiro, 2019.

given different combinations of travel time and monetary cost thresholds. This result draws attention to a broader methodological question about the extent to which accessibility estimates and equity analyses might be sensitive to whether and how researchers incorporate both of these costs in accessibility calculations. Previous research has shown that by ignoring monetary costs researchers tend to overestimate the accessibility of low-income groups, which may lead to underestimated levels of accessibility poverty and inequality (Herszenhut et al., 2022; Liu & Kwan, 2020). However, even the use of travel cost functions that take monetary costs into account can generate biased results if one follows the commonly adopted practice of considering the fastest journeys and then calculating monetary costs sequentially (Conway & Stewart, 2019). This study illustrates how using multiobjective-optimization routing to calculate Pareto frontiers could be a promising way to account for trade-offs between time and money in accessibility research. From an equity perspective, taking this trade-off into account is particularly important, especially in contexts with great social inequalities. However, the use of Pareto frontiers to estimate accessibility is still very new, and more research is needed to investigate how trade-offs between time and monetary cost can be incorporated in other types of accessibility metrics such as gravity-based, utility and person-based measures. We hope the Pareto frontier function implemented into the R package r5r can unlock some of these research possibilities.

From a policy perspective, the findings of this study indicate that major accessibility gains could be achieved by policies that promote an integration between mass transit and some form of on-demand rideshare. Different transport agencies have been exploring partnerships with TNCs to understand the extent to which ridesharing and

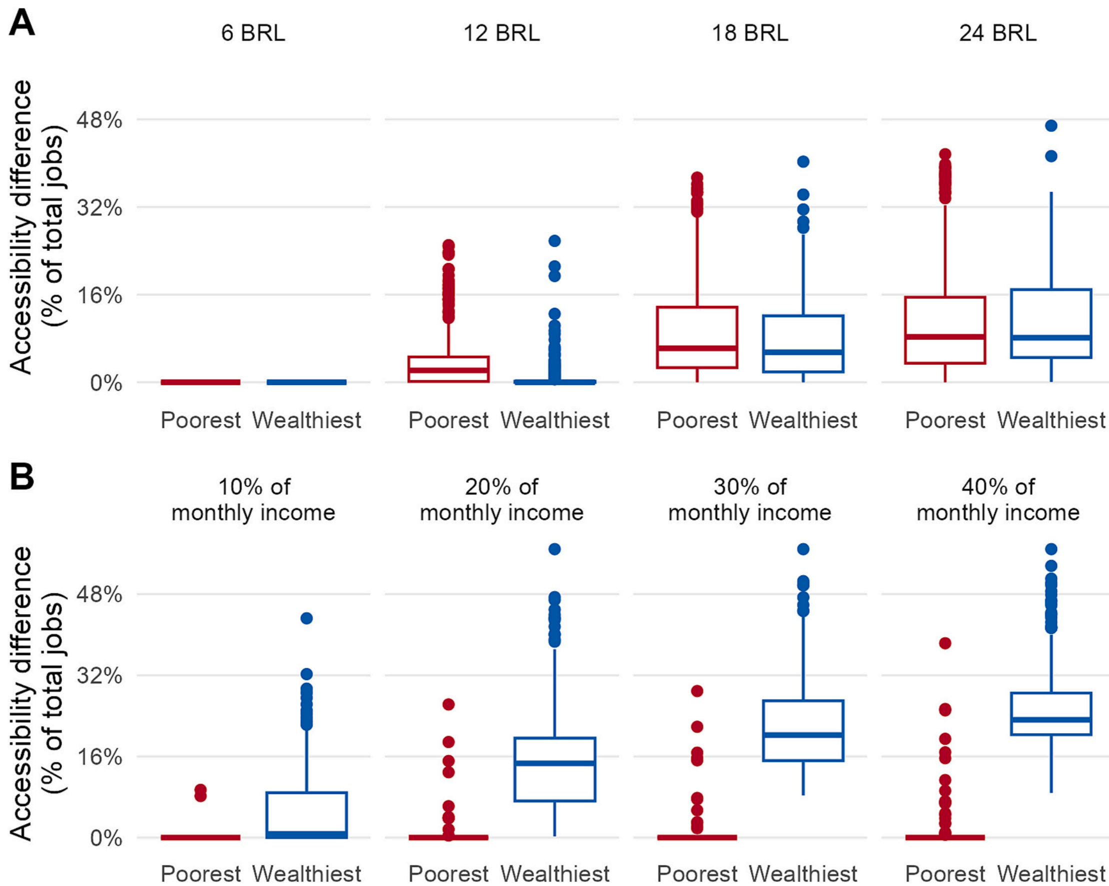

Fig. 7. Distribution of employment accessibility gains by ride-hailing combined with transit compared to transit-only accessibility for different income groups, considering a 60-minute travel time threshold and multiple monetary cutoff values in terms of absolute costs (A) and cost relative to income (B). Rio de Janeiro, 2019.
Obs. Wealthiest population was defined as those in the 10 % with the highest income, while the poorest were defined as those among the 40 % with the lowest income.

microtransit with dynamic routing could provide an efficient means to serve neighborhoods with lower population density as first- and last-mile connection and increase accessibility and ridership (Curtis et al., 2019; Schwieterman & Livingston, 2019). However, the findings are also aligned with the result of previous studies (Brown et al., 2021; Palm et al., 2021) that show that policy efforts on integrating rideshare with transit are likely not going to benefit low-income communities without some form of subsidy. This could be done, for example, by using an integrated payment system with fare discounts for transfers between a rideshare and transit trips at particular transit stations.

One limitation of this study is that it uses the latest census data available, which was collected over 10 years ago and which could generate some bias in the results. Nonetheless, we believe this bias should not be strong enough so that it would invalidate the study given that we have corrected income data for inflation in the period, and given that the spatial distribution of socioeconomic classes in Rio have remained fairly stable over the past few decades. This paper also considers only formal jobs. The lack of information on informal jobs is a common issue in low- and middle-income countries. Different data sources, such as point of interests from OpenStreetMap and social media or satellite imagery data could be explored in future research as a proxy for the spatial distribution of informal jobs. Another limitation is that we consider potential first-mile trips of any length. Even though our results did not significantly change when we capped these trips up to 30 min, future studies could arrive at more robust results if they could use travel behavior data to inform how far people are willing to travel the first-mile trip by ride-hailing. Additionally, it would be interesting to compare accessibility levels by ride-hailing and traditional taxis. This analysis was not possible due to the lack of data, but future studies should consider including a scenario of “transit & taxi” to be compared with the scenario of “transit & ride-hailing”.

Moreover, this study has only analyzed employment accessibility considering daily commuting costs for single-passenger trips. Given that the costs of ride-hailing could be shared among multiple passengers, analyzing scenarios in which two or more people ride the same trip together would likely yield more favorable results to TNCs. Future studies that focus on access to less frequent activities (such as healthcare or leisure) could also arrive at different results than the ones found in this paper. Further research should also investigate how accessibility by ride-hailing and transit compare in cities where the costs of transit fares depend on zone- or distance-based rules. Finally, future studies could use Pareto frontiers to investigate how travel mode choices are affected by accessibility levels when accounting for travel time and monetary cost trade-offs.

CRediT authorship contribution statement

Rafael H.M. Pereira: Conceptualization, Methodology, Software, Validation, Resources, Data curation, Writing – original draft, Writing – review & editing, Supervision, Project administration, Visualization. **Daniel Herszenhut:** Conceptualization, Methodology, Software, Formal analysis, Writing – original draft, Writing – review & editing, Visualization. **Marcus Saraiva:** Conceptualization, Methodology, Software, Data curation, Writing – original draft. **Steve Farber:** Writing –

review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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