Haglund, Nils; Mladenovic, Milos; Kujala, Rainer; Weckström, Christoffer; Saramäki, Jari

Where did Kutsuplus drive us? Ex post evaluation of on-demand micro-transit pilot in the Helsinki capital region

Published in:
Research in Transportation Business and Management

DOI:
10.1016/j.rtbm.2019.100390

Published: 01/09/2019

Document Version
Publisher's PDF, also known as Version of record

Research in Transportation Business & Management 32 (2019) 100390

Contents lists available at ScienceDirect

Research in Transportation Business & Management

journal homepage: www.elsevier.com/locate/rtbm

Where did Kutsuplus drive us? Ex post evaluation of on-demand micro-transit pilot in the Helsinki capital region

Nils Haglund[a], Miloš N. Mladenović[b,*], Rainer Kujala[a], Christoffer Weckström[b,1], Jari Saramäki[a]

[a] Department of Computer Science, Aalto University, Finland
[b] Department of Built Environment, Aalto University, Finland

ARTICLE INFO

Keywords:
Automated demand responsive transport
Paratransit
Ridesharing
Ridesourcing
Transportation network company
Multimodal integration
Mobility-as-a-service

ABSTRACT

As technical limitations are not anymore the main obstacle for successful urban micro-transit operation, further development has to focus on evaluating a range of potential challenges, providing lessons for policy and service development, including organisation of piloting activities. Contrastingly, few studies had employed detailed empirical data with trip and user properties to evaluate flexible micro-transit services in urban environments. This research focuses on evaluating the Kutsuplus, Helsinki Metropolitan Region (HMR) on-demand micro-transit pilot. Previous research on Kutsuplus has focused on evaluating financing and pricing policy, and users' and non-users' perceptions about the implemented service. This research develops a multidimensional evaluation framework, focused on the analysis of completed user journeys, accounting for Kutsuplus operating area, timing, and pricing scheme. Thus, this framework uses 82,290 completed Kutsuplus journeys, combined with routing, HMR travel demand data and pricing modelling. Results indicate that demand for Kutsuplus has been increasing over time, with low average vehicle occupancy, and low wait time after journey offer acceptance. Hourly demand pattern for Kutsuplus had a similar shape to the demand patter for fixed public transport, with small differences in peak time start and duration. Spatial demand had more orbital than radial direction, more versatile directional demand, focus on the western side of service area, and business-related locations in general. Most of the users were age 30 to 65, with younger or older users having also distinct trip characteristics. Kutsuplus was on par with private car for shorter journeys, but could also lead to undesired replacement of walking and cycling trips. Kutsuplus pricing was between public transport and UberPOP. With these and other results, the multidimensional evaluation framework provides a range of implications for user-centric service design, underpinned with an understanding of interdependencies between operating scheme, service pricing, and service level provided by other transport modes. Finally, we provide recommendations for further analysis of micro-transit journey data, raising implications for data collection practices in the future micro-transit pilots, and for further directions in developing our understanding of emerging mobility-on-demand services.

1. Introduction

Emerging mobility-on-demand services, in synergy with fixed public transport (FPT) systems, provide a range of opportunities for holistically addressing sustainability of the 21st century cities. Part of the wider societal paradigm shift, these new transport services are needed to respond to evolving user requirements (Davison, Enoch, Ryley, Quddus, & Wang, 2014; Finn, 2012; Liimatainen & Mladenović, 2018; Nelson, Wright, Masson, Ambrosino, & Naniopulous, 2010; Shaheen & Chan, 2016). In particular, user-centred development of mobility-on-demand services is a key component of successful urban mobility transition (Jin, Kong, Wu, & Sui, 2018; Mulley & Nelson, 2016). Previously, flexible micro-transit or demand responsive transport (DRT) services have commonly not been associated with urban areas, having high level of service of FPT. In fact, DRT was associated with areas of low demand, low FPT supply, and as services for people with differing abilities (Mageean & Nelson, 2003; Mulley & Nelson, 2009; Velaga, Nelson, Wright, & Farrington, 2012). Previously, DRT implementation challenges have largely been related to technical limitations in booking, routing and trip ordering technologies (Brake, Nelson, & Wright, 2004; Mulley & Nelson, 2009; Nelson et al., 2010). Nowadays, technical limitations are not anymore the main obstacle for successful service operation. For example, recent years have seen increasing availability of phones with GPS-enabled applications, overall advancements in digitalization of the transport sector, including cloud computing and data sharing, accompanied with advances in integrating multi-occupancy

* Corresponding author.
E-mail address: milos.mladenovic@aalto.fi (M.N. Mladenović).

https://doi.org/10.1016/j.rtbm.2019.100390
Received 30 April 2019; Received in revised form 7 November 2019; Accepted 8 November 2019
Available online 19 November 2019

vehicles with real-time booking and routing technologies (Ambrosino, Nelson, Boero, & Pettinelli, 2016; Davison, Enoch, Ryley, Quddus, & Wang, 2012; Furuhata et al., 2013; Mulley & Nelson, 2016; Shaheen & Cohen, 2018).

As technological development is enabling more rapid emergence and deployment of mobility-on-demand services, mechanisms for responding to diverse and evolving travel needs still have to account for integration with the existing spectrum of urban passenger transport modes. In fact, further service development still has to pay attention to a range of potential barriers, including fleet properties, institutional and regulative frameworks, financing schemes and operating costs, as well as operator and community culture. On the one hand, service integration with high-capacity FPT needs wider area network planning and cooperation between service providers (Brake, Mulley, Nelson, & Wright, 2007; Brake & Nelson, 2007; Finn, 2012; Mulley & Nelson, 2009; Mulley, Nelson, Teal, Wright, & Daniels, 2012). On the other hand, development of regulation and governance frameworks needs to account for distribution of undesired effects, including analysis of planning, financing, and operations responsibilities (Brake et al., 2004; Cetin & Deakin, 2019; Circella & Alemi, 2018; Cohen, 2018; Finn, 2012; Mageean & Nelson, 2003; Mulley et al., 2012; Mulley, Nelson, & Wright, 2018; Pangbourne, Mladenovic, Stead, & Milakis, 2019; Puche, 2019; Sharmeen & Meurs, 2019).

In addition to significant previous research efforts, the need to understand DRT implementation cases, and resulting user experiences, remains as one of the central research efforts. Previous research methods applied to evaluating DRT implementation have largely focused on user and travel surveys, with complementary qualitative or statistical modelling methods. For example, previous research efforts have focused on questionnaires for DRT and other mode users (Gehrke, Felix, & Reardon, 2019; Nelson & Phonphitakchai, 2012; Ryley, Stanley, Enoch, Zanni, & Quddus, 2014; Young & Farber, 2019). Such surveys are often complemented with other methods, such as focus groups (Deakin, Frick, & Shively, 2010; Mohamed, Rye, & Fonzone, 2019; Sihvola, Jokinen, & Sulonen, 2012), comparison to trip data (Rayle, Dai, Chan, Cervero, & Shaheen, 2016; Weckström et al., 2018), ethnographic studies (Henao & Marshall, 2018, 2019), or microeconomic analysis (Schwieterman, 2019). The use of these methods has brought about significant understanding of existing and potential user requirements, identifying development aspects for specific market segments. In addition to user surveys, there is a need for evaluating DRT case studies through quantitative analysis of citywide user travel patterns, in order to evaluate and further advance planning, financing, and operations principles (Ferreira, Charles, & Tether, 2007; Alonso-González, Liu, Cats, Van Oort, & Hoogendoorn, 2018, Hoffmann, Ipeirotis, & Sundararajan, 2016, Rayle et al., 2016). Despite the significant interest in evaluating success of micro-transit services, the major weakness is the lack of defined criteria and performance measures for evaluation, implemented in empirical cases. Such development of evaluation frameworks is underlined with the challenge of understanding complexities of travel behaviour change in a multimodal setting, as well as with challenges in empirical data access.

Having in mind the need to focus on empirical evaluation of DRT use patterns and comparison to other urban transport modes, this research focuses on ex post evaluation of the Kutsuplus pilot. Kutsuplus was a flexible micro-transit service using minibuses, operational from October 2012 to December 2015 in the Helsinki Metropolitan Region (HMR), Finland. Previous research efforts about Kutsuplus have evaluated financing and pricing policy, as well as users' and non-users' perceptions about the implemented service (Jokinen, Sihvola, & Mladenovic, 2019; Weckström, Kujala, et al., 2018). However, previous research about Kutsuplus has not included a detailed analysis of user journeys, especially having in mind various changes in the operating area, hours, or pricing scheme. Thus, this research focuses on developing an evaluation framework for analysing the actual Kutsuplus journey data. To this end, the following section will introduce background literature focused on the empirical trip analysis methods and details of the Kutsuplus pilot. The third section will describe the methodological framework developed in this research, while the fourth section presents evaluation results for each of the five performance evaluation dimensions. The paper concludes with a discussion of case study results, providing a set of lessons for policy and service development processes, as well as several recommendations for future urban piloting and research activities.

2. Background

2.1. Previous research using empirical trip data analysis of flexible micro-transit services

In general, few studies had employed empirical data to examine the unique travel patterns of DRT service trips in urban settings, while also focusing mostly on a particular set of performance measures based on a limited data sources. Focused on ridesourcing order data extracted from the on-demand ride service platform DiDi Chuxing, one set of previous research analysed changes in vehicle-kilometres and vehicle-hours travelled, including shift from other vehicles (Chen, Liu, & Wei, 2019; Chen, Zheng, Wang, & Chen, 2018). Similarly, research focused on ridesourcing services provided by the transportation network company RideAustin in Austin, US, analysed vehicle miles travelled and related energy use (Wenzel, Rames, Kontou, & Henao, 2019), important for understanding aggregate effects. More disaggregate aspects have been accounted through deadheading ratio in relation to driver shifts and in comparison to average vehicles registered in the area (Komanduri, Wafa, Proussaloglou, & Jacobs, 2018; Li, Pu, Li, & Ban, 2019). Moreover, vehicle-based performance analysis can be useful for determining different driver types, based on the frequency and directionality of their shifts (Dong, Wang, Li, & Zhang, 2018; Wenzel et al., 2019). For example, trip data can help uncover if drivers are behaving as conventional ride-sharing drivers or as converted taxi vehicle drivers who drive even during mid-day working hours.

Another set of previous research has included a varying degree of geospatial dynamics analysis of empirical trip data (Dong et al., 2018, Komanduri, et al., 2018Li et al., 2019, Su, Fang, Luo, & Zhu, 2018, Wenzel et al., 2019). For example, a very common analysis of empirical trip data are averages and distributions of trip distance, often related to trip origins and destinations (Dong et al., 2018; Li et al., 2019; Wenzel et al., 2019). Similarly, studies using randomly sampled and anonymized ride-sharing trip records provided by DiDi company, are analysing pick-up and drop-off locations spatially and temporally, often classified to shared rides and single rides, or based on similar OD pairs (Dong et al., 2018; Li et al., 2019). Furthermore, same data sources have been used for analysing temporal traffic distributions in a day, as well as reliability of travel times per OD pairs (Dong et al., 2018; Li et al., 2019). Besides trip analysis, further research has provided limited evidence for influence of built environment factors to the service demand, such as density or diversity (Li et al., 2019; Yu & Peng, 2019). Only one effort, using DRT pilot "Breng flex" from the Arnhem-Nijmegen region in the Netherlands, has developed an evaluation framework to compare DRT and FPT based on computation and comparison of generalized travel cost (Alonso-González, Liu, et al., 2018). Moreover, this case study also included analysis of trips along spatial and temporal dimensions, while identifying suitability of the performed rides for walking and cycling, and underserved OD pairs. In summary, these previous evaluation frameworks had to rely on a constrained set of data in order to develop specific performance measures, often having to focus on a small set of measures and not explicitly account for comparison with other transport modes.

2.2. Kutsuplus pilot background and previous evaluation efforts

Considering the importance of sharing lessons from on-demand mobility service pilots, it is important to highlight certain aspects of the Kutsuplus service implementation. Helsinki Region Transport (HSL) established Kutsuplus as an automated urban DRT service, while operated by taxi companies. Kutsuplus relied upon state-of-the-art automated vehicle location, optimized trip pooling, vehicle routing, and travel time estimates (Häme, 2013; Jokinen, 2016; Jokinen et al., 2019; Rissanen, 2016; Weckström et al., 2018). Kutsuplus strategic objective was to support modal shift from car to public transport, as share of car travel is near 40% of all HMR trips (Rissanen, 2014, 2016). When submitting the trip request, the user defined origin and destination, number of needed seats, and earliest departure time possible (maximum 45 min before). After requesting a trip, the user would immediately receive one or more trip offers, including pick-up and drop-off stop and walking route. While boarding, the user was requested to provide a driver with a short alphanumeric verification code. Kutsuplus vehicle had capacity of nine seats, without standing. The professional taxi driver received real-time driving instructions, as stop-to-stop route was using the high-density HSL FPT network and smaller number of additional virtual stops added to some low-density urban areas. There were no specific strategies or infrastructural measures to integrate Kutsuplus with HMR FPT.

Kutsuplus was based on an advance payment, with user or company account having preloaded monetary value. During a part of the pilot, the user could also select a service class that was linked to the price category and travel time offer. In general, trip pricing was based on the fixed starting fee and the kilometre price calculated as the direct distance between origin and destination, as shown in the Table 1 below. The aim was to have a rather straightforward fare structure, easy to understand and apply. In addition, fare structure included group or time-of-day discounts. For the whole time the service has included a group discount of 20% for 2 passenger bookings, 30% for 3 passenger bookings, 40% for 4 passenger bookings and 50% for bookings with 5 passengers or more. Amounting to over 1000 stops, the service area was encircling the Helsinki downtown area in a semicircle, with roughly 9 km radius from the city centre (Fig. 1). Operating area for Kutsuplus has high quality infrastructure for FPT, cycling, and walking, including constant improvements to FPT trunk-line network. During the whole period of pilot, service offer area, operating hours, and pricing schemes have changed several times. At the end of the piloting period, Kutsuplus had 32,193 registered accounts.

There is a broader set of work related to Kutsuplus. However, most of this previous work has been before the service was launched, while being focused on qualitative methods for developing the service scheme (Jokinen, 2016; Sihvola et al., 2012), and using simulation framework for service development and ex ante evaluation (Häme, 2013; Hyytiä, Aalto, Penttinen, & Sulonen, 2010; Hyytiä, Penttinen, & Sulonen, 2012; Jokinen, 2016; Jokinen, Sihvola, Hyytiä, & Sulonen, 2011; Sihvola, Häme, & Sulonen, 2010). In addition, there has been one effort in evaluating service during its mid-operational stage, until spring 2014 (Rissanen, 2014). Thus, most of the research did not include empirical basis for understanding the actual service as implemented. In contrast, there has been only a couple of efforts to evaluate Kutsuplus service as implemented. The ex post evaluation provided by HSL (Rissanen, 2016) has included an annual trend analysis of trip count, trip-kilometres, vehicle-hours, vehicle-kilometres, trip price, as well as cost and financing distribution during the whole pilot. Moreover, this ex post evaluation report includes a summary of the Kutsuplus user survey conducted in May 2015. Another research effort focused on the ex post analysis of financing and pricing policy, and policy process itself (Jokinen et al., 2019). Overall, the analysis of fare structure and experienced service level indicates that Kutsuplus was attractive for the users, especially having in mind that target-pricing level was between public transport and taxi service. In addition, this research highlighted the relationships between acceptable fare and sustainable funding structure, relating this to heavy subsidy for Kutsuplus service through HSL. The only other ex-post evaluation used a questionnaire for users' and non-users' perceptions about the service (Weckström, Kujala, et al., 2018). This analysis highlighted diverse socio-economic background and travel behaviour patterns that Kutsuplus users had, exemplified by a wide variety of users' trip purposes. Users have highlighted good complementarity between Kutsuplus and HMR public transport, in addition to a range of other positive aspects (e.g., no need to search for parking, travelling with luggage, sending children, riding comfort, etc.). Moreover, this ex post evaluation highlighted the need to develop aspects of marketing strategy and branding in relation to societal learning of emerging mobility-on-demand niches. Overall, none of the previous research efforts in evaluating Kutsuplus service have used detailed disaggregate trip data or deployed a multidimensional evaluation framework.

3. Evaluation framework

Based on the experiences from a handful of previous empirical trip analyses, the evaluation framework will account for (dis)aggregate and spatio-temporal measures of service performance. Moreover, the evaluation framework is developed to avoid significant overlap with methods used in previous studies of the Kutsuplus pilot. Such a combination of evaluation measures is expected to build upon verified measures used in the previous research, while adding several complementary aspects for understanding the specific micro-transit pilot case from both efficiency and distributional effects standpoint. As a result, this evaluation framework has to following five performance evaluation dimensions, each having several performance measures (Fig. 2).

3.1. Kutsuplus service data

Methodology centres on the Kutsuplus journey dataset, which includes 82,290 journeys. These journeys are for January, March, June, July, August, October, and December throughout the operating period (1.10.2012–31.12.2015), amounting to approximately 45% of all Kutsuplus journeys during service pilot. Before analysis, data has been pre-processed for quality, while maintaining representativeness of different yearly periods (e.g., spring, summer, autumn). Thus, this data

Table 1
Kutsuplus service classes and pricing.

Starting date	Unnamed /"Kutsuplus"	"Normal"	"Economy"	"Fast"
01.10.2012	1.88 € + 0.19 €/km	–	–	–
08.02.2013	–	1.88 € + 0.19 €/km	1.50 € + 0.15 €/km	–
11.03.2013	–	1.88 € + 0.19 €/km	1.50 € + 0.15 €/km	2.63 € + 0.26 €/km
03.04.2013	–	3.50 € + 0.45 €/km	2.80 € + 0.36 €/km	4.90 € + 0.63 €/km
18.11.2013	–	3.50 € + 0.45 €/km	2.80 € + 0.36 €/km	–
12.01.2015	3.50 € + 0.45 €/km, 20% discount from 10 AM to 2 PM	–	–	–

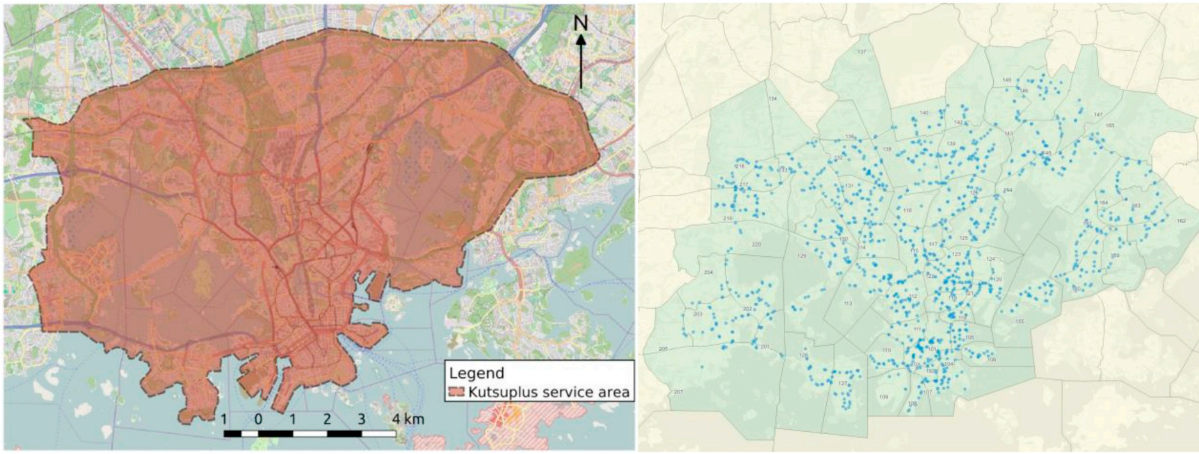

Fig. 1. Kustuplus service area and Kutsuplus stop distribution per HMR travel-demand prediction polygons.

sample is considered significant, covering representative months over operating years. Each Kutsuplus journeys has unique ID for pick-up and drop-off stop. The journeys dataset used for calculation and further modelling, includes the following columns per journey:

- Timestamp when user accepted journey offer (time);
- Pick-up time approximation sent to the user (time);
- Drop-off time approximation sent to the user (time);
- Number of passengers on journey (integer);
- User's age group (string);
- Total journey price in cents (integer);
- Pick-up stop ID (string);
- Drop-off stop ID (string);
- Order status (string);
- Service class (sting: Economy, Fast, Normal);
- Time stamp of actual user pick-up (time);
- Time stamp of actual user drop-off (time);

3.2. Spatio-temporal trip analysis and comparison of Kutsuplus to alternative modes

For formulating the analysis model, we used a complex network approach, relying on benefits of agent-based simulation recognized before, while avoiding extensive data processing and collection required from microsimulation methods (Chen et al., 2019; Narayan, Cats, van Oort, & Hoogendoorn, 2017; Ronald, Thompson, & Winter, 2017). For journey durations, we focus on in-vehicle time obtained directly from the Kutsuplus journey data, as difference between drop-off and pick-up time. Kutsuplus journey data is not suitable for doing out-of-vehicle time analysis due to lack of information on walking distances to PT stops. As part of Kutsuplus journey duration, we consider the amount of waiting from customer order and estimated pick up time against the time a FPT user would wait on average when departing spontaneously. Due to lacking routing data, which was a limitation of the dataset due to proprietary reasons, Kutsuplus journey distance has been calculated from stop to stop, as the Euclidean value, similar to (Dong et al., 2018). For comparison of Kutsuplus journeys, we also use travel demand data and zones from HMR travel-demand forecasting model HELMET (Ver. 2.1). FPT demand data is used to help characterize Kutsuplus demand. Overall, the HELMET model divides the full HMR to 500 prediction zones (ENN), while there are usually multiple placement zones (SIJ) within one prediction zone, available in GIS format. HELMET model journeys are starting during 06:00–08:59 for the Morning Rush (MR), 09:00–14:59 for Daytime Traffic (DT), and 15:00–17:59 for the Evening Rush (ER), available in CSV-format. During the MPH, city centre and several business locations are clearly highlighted as journey destinations, while MPH journey origins are mainly in the periphery (Fig. 3a). During EPH, the trend is largely reversed, with journeys having the direction out of the city centre, while they are more spread out spatially due to after work activities (Fig. 3c). For DH, journeys are a combination of MPH and EPH directional bias, with some cross-traffic patterns (Fig. 3b).

For calculating routes for all transport modes besides FPT, we used Google Distance Matrix API, with journey origins and destinations based on geographic coordinates of Kutsuplus stop locations provided by HSL. For taxi, we consider the unweighted private car routing, because taxi in HMR can use dedicated bus/tram lanes, enabling shorter duration journeys. However, at the time of the Kutsuplus operation, Uber did not have the legal status equivalent to a taxi operator. Thus, as Uber vehicles were not able to use dedicated bus/tram lanes, Uber journeys have used congestion-weighted private car routing. FPT routing was based on the customized routing algorithm, using General Transit Feed Specification (GTFS) data (Kujala, Weckström, Darst, Mladenović, & Saramäki, 2018; Kujala, Weckström, Mladenović, & Saramäki, 2018; Weckström et al., 2019). Routing has been done for Friday, September 18, 2015, as the representative day in the last stage of Kutsuplus operation. Friday was selected as a day when FPT operates slightly longer hours, with schedules otherwise identical to other weekdays, thus providing most similar service level to the Kutsuplus.

In the routing, we consider FPT options for a departure time widow, so that departure may happen within 30 min before or after the Kutsuplus pick up time, while latest arrival can happen 120 min after the Kutsuplus pick up time. We consider only Pareto-optimal journeys in our computations. Pareto optimality for a journey means that there are no faster options available for a FPT user departing at a certain point in time. In addition to the minimum journey duration (τ_{min}), we also compute the least number of FPT vehicle boardings, i.e., transfers (b_{min}), which is also used for determining Pareto-optimal journey option within the departure window. The assumption behind Pareto-frontier is that the user prefers to reach her destination in a short time and with as little as transfers as possible. Thus, her rational choice alternatives correspond to the set of journey alternatives on the Pareto-frontier (Fig. 4). In particular, for each origin and destination pair, Pareto-frontier includes alternatives compared to which there is no alternative with better performance either in travel time or in number of transfers to reach the destination. From Fig. 4, one could see an example of suboptimal journey with one transfer and 70 min compared to an optimal journey alternative with also one transfer, but with lower travel time of 50 min.

For transfers, we use a 3-minute margin as customary by the HMR journey planner. FPT routing computations are performed in a manner that allows a walk between two stops if they are at most 2 km apart. For

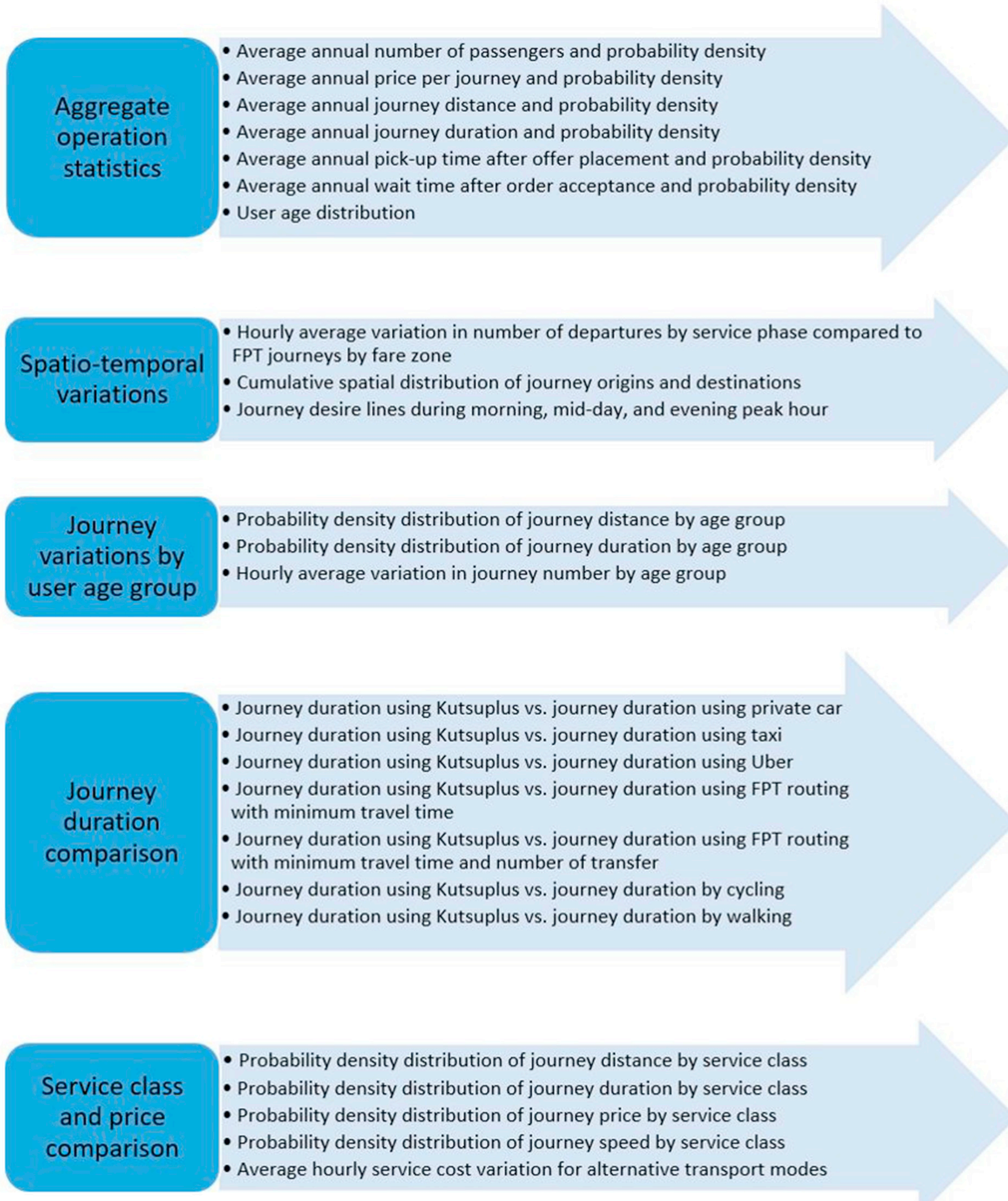

Fig. 2. Performance measures for the Kutsuplus evaluation framework.

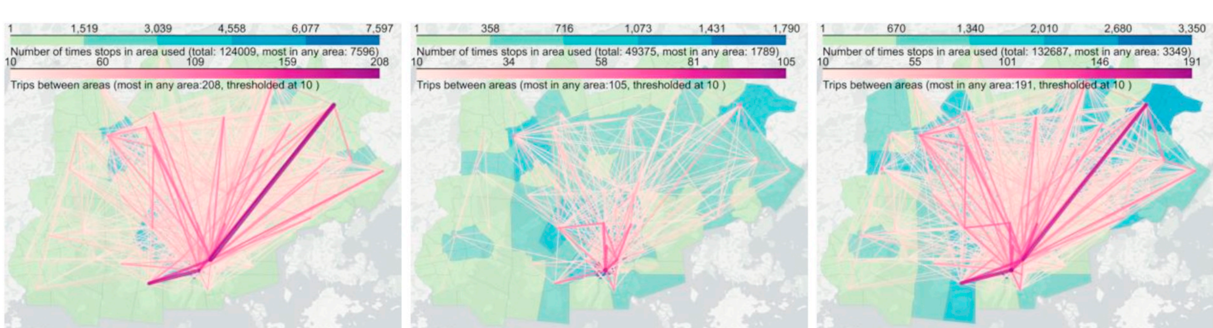

Fig. 3. HMR journey desire lines in the a) morning peak hour, b) mid-day peak hour, and c) evening peak hour.

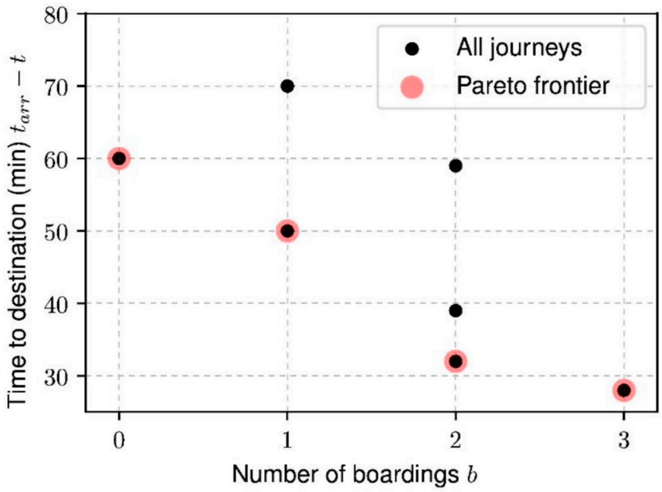

Fig. 4. An example set of Pareto-optimal journey alternatives for a certain departure time t.

sensitivity analysis and accessibility, especially with older age groups and special groups in mind, we also consider a walking cut-off of 0.5 km. Computation is done using gtfspy (https://github.com/CxAalto/gtfspy), an open source Python package for working with GTFS data and OpenStreetMap map data. For computational efficiency, the 82,290 Kutsuplus journeys are grouped by destination, resulting in 1314 routing runs, per number of unique destination stops. The routing algorithm is run for each destination stop only once per walking distance, and used during the analysis stage to inspect specific journeys with departure and arrival time constraints.

3.3. Service class analysis and price comparison with alternative transport modes

For service class analysis, we focus on distance, duration, price, and speed distributions. For service classes, we take into account that Kutsuplus pilot had Fast pricing during 11.3.2013–2.4.2013 and Economy pricing during 8.2.2013–2.4.2013. For cross-modal price comparison, we focus on the last stage of the Kutsuplus pilot. In cross-modal price comparison, prices are considered as total journey prices, enabling comparison to the Kutsuplus prices which are paid from one account. Only marginal costs are considered for alternative transport modes, so both walking and cycling are regarded as free, while car pricing considers only fuel costs. When Kutsuplus was active, regulation defined annual maximum taxi prices. Taxi used an increased pricing model during evenings, which accounts for the evening peak. Distance estimates given by Google Distance Matrix API routing are used for calculating total taxi price based on the time of day pricing during 01.07.2014–30.06.2016. Consequently, if a journey started outside of 6-20 h on a weekday, outside of 6-16 h on a Saturday (or corresponding Holiday Eve), or on Sundays, the increased base price was in effect. More specifically, regular base price was €5.36, increased base price was €8.18, with per kilometre pricing of €1.41 for 1–2, €1.70 for 3–4, €1.84 for 5–6, and €1.98 for over 6 passengers, respectively. For Uber, we use UberPOP pricing after November 2014, as UberBLACK was approximately 10 euros more expensive than taxis during daytime, and around 7 euros in the evenings, thus not being relevant for relative comparison to the Kutsuplus pricing. UberPOP has base price of €2.0, minute price of €0.2, kilometre price of €1.0, and minimum price of €4.0. Accurate data regarding Uber surge pricing is not readily available, so only default values have been used. FPT prices are based on single-journey value tickets purchased with the HSL travel card, where cross-zonal tickets are more expensive than internal tickets (e.g., Helsinki internal ticket, Espoo internal ticket). HSL zonal fare scheme

Table 2
Kutsuplus journey aggregate statistics.

Parameter	Year				Total
	2012	2013	2014	2015	
Average number of passengers	1.27	1.24	1.28	1.26	1.27
Average price (€)	3.31	5.86	6.40	7.15	6.74
Average distance (km)	5.43	5.23	5.02	4.90	4.98
Average duration (min)	20.45	17.36	16.84	16.98	16.98
Average pick-up time after offer (min)	0.76	0.20	0.42	0.62	0.51
Average wait from order acceptance (min)	22.44	21.70	19.87	21.44	20.87

before the change in 2019 relied on municipal boundaries for defining zone boundary, where public transport ticket price for one zone in 2015 is priced at €2.00, while cross-zonal ticket (e.g., Helsinki and Espoo) is priced at €3.88.

4. Results

4.1. Aggregate Kutsuplus operation statistics

Table 2 below shows aggregate Kutsuplus journey statistics per year, at the journey level. Based on the results, multiple passengers on a journey did not often use Kutsuplus at the same time. Compared to vehicle seating capacity of nine people, we can see that average occupancy was 14.1%. In addition, the journey price for Kutsuplus journeys increased over the years, while the average journey distance and duration decreased. Looking at journey data distributions (Figs. 5 and 6), most Kutsuplus journeys were less than 10 km long, lasted less than 30 min, cost under €10, and in over 90% of cases had only one or two passengers inside. Average pick-up time after offer, meaning difference between realized and offered pick-up times, was very low, indicating good service predictability. Times from order to pick-up were relatively short, implying Kutsuplus could often be ordered with a quite short notice. However, there has been a minor journey set with substantially long wait time after acceptance. Moreover, there seem to be no notable differences in the distributions if considering more specific pilot phases. The distribution of user age varies, with under age of seventeen being 0.3%, 18 to 29 being 11.8%, 30 to 44 being 49.9%, 45 to 64 being 23.1%, and over 65 years being 2.4%. Age information was not available for 12.5% of users.

4.2. Kutsuplus journey spatio-temporal distribution

The Fig. 7 below shows average number of Kutsuplus journey departures in a day for different service phases, in comparison to FPT journeys during the day per zone. While during the first two service phases demand was very low, it has increased in latter phases. There seems to be a FPT typical peak structure especially during the third and fourth service phases. The most active service phases of Kutsuplus clearly demonstrate a FPT typical peak structure, with a narrow morning peak and a broader afternoon peak. During the fourth phase, a clear midday peak is also visible, during which pricing was 20% off. However, Kutsuplus peak hours have been timed later than general peaks for FPT, while FPT has slightly wider peak time in the afternoon.

As a common feature for FPT and Kutsuplus demand, both feature high demand for the city centre (Fig. 8). While HSL FPT demand has directional bias from and to the city centre during MPH and EPH, the journeys made with Kutsuplus appear to follow a more cross-regional distribution (Fig. 9). However, whereas the FPT demand has a very clear directional bias, Kutsuplus does not. The DH demand of Kutsuplus resembles FPT demand pattern. Kutsuplus demand is largely centred to the west side of the service area, whereas FPT demand is focused in the northern and eastern parts.

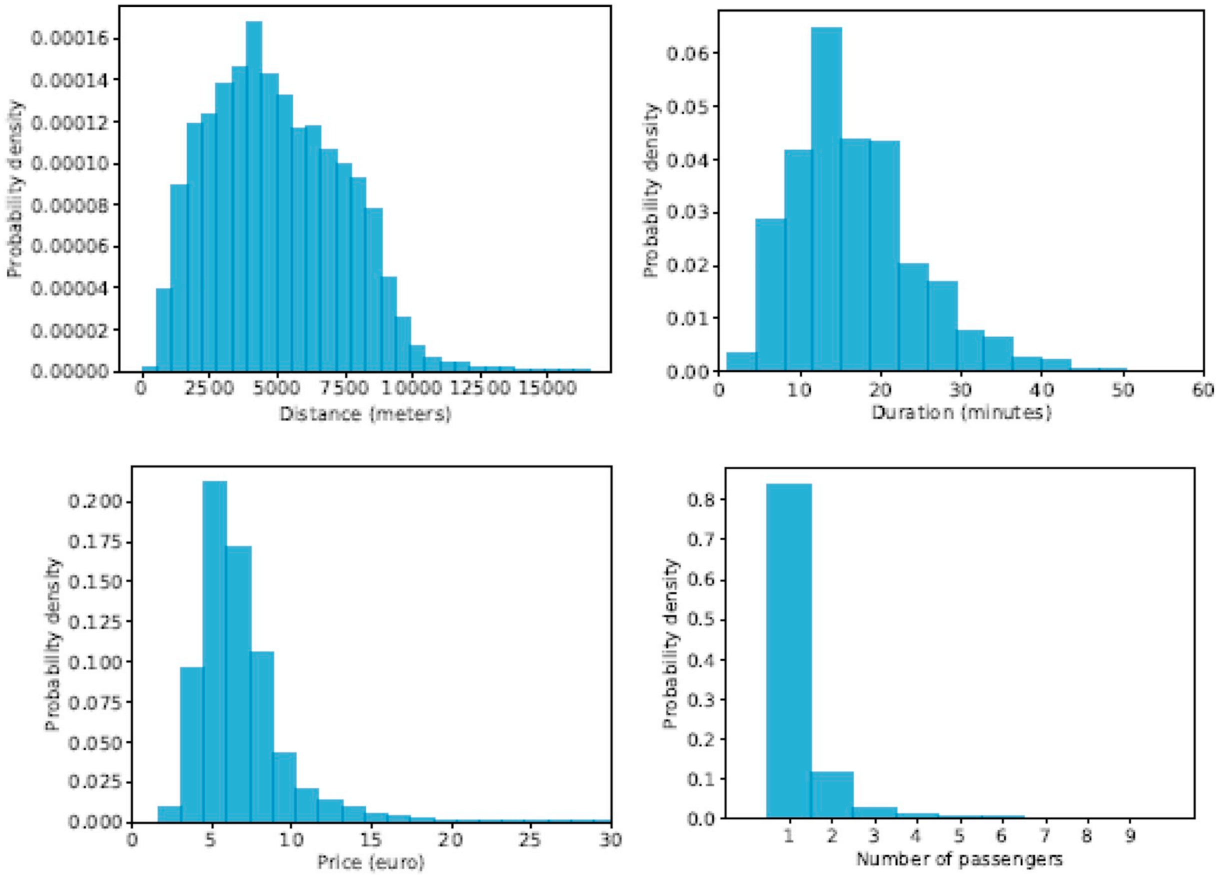

Fig. 5. Probability densities for a) journey distance, b) journey duration, c) journey price, d) number of passengers on a journey.

4.3. Kutsuplus journeys per age group

Distributions for journey distance and duration, in which age groups have been considered separately, is shown on the Fig. 10. Notable deviations cannot be observed when we account for the low number of journeys of the age groups '0–6', '7–17', and 'over 65'. The daily number of journeys by age group as a function of time has been visualized in the Fig. 11, for the most common age groups. There do not seem to be any notable deviations from the general peak structure. During MPH, it is more prominent that 18–29 olds used Kutsuplus for regional journeys relatively often. For MPH, EPH and DH, over 65-year-olds used Kutsuplus almost exclusively for journeys inside Helsinki. For uncommon age groups, where there was not sufficient data to pinpoint trends.

4.4. Journey duration comparison

Journey durations of travel mode alternatives are compared to Kutsuplus in the Fig. 12, with Kutsuplus journey duration on the x-axis and alternative mode journey duration on the y-axis. Kutsuplus journey duration was comparable to car usage when journeys lasted up to 20 min, after which car journeys were generally faster (part a and b). Converting journey durations to taxi and Uber, taxi is faster 53.5% of the time, while Uber is faster 46% of the time. FPT was slower than Kutsuplus (part c and d), but this does not account for time spent ordering and waiting. If FPT routing is accounting only for travel time,

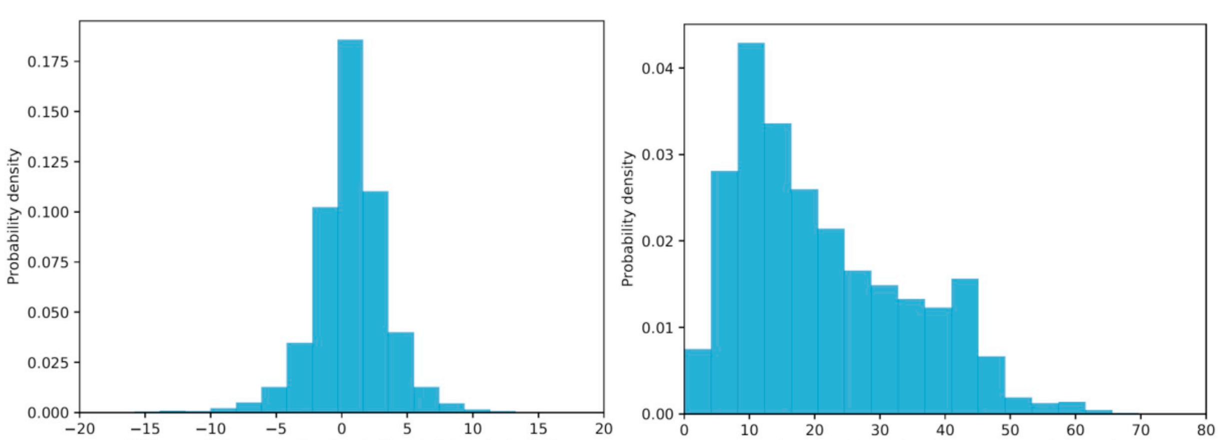

Fig. 6. Probability density for a) differences between realized and offered pick-up times and b) time to pick-up after order acceptance.

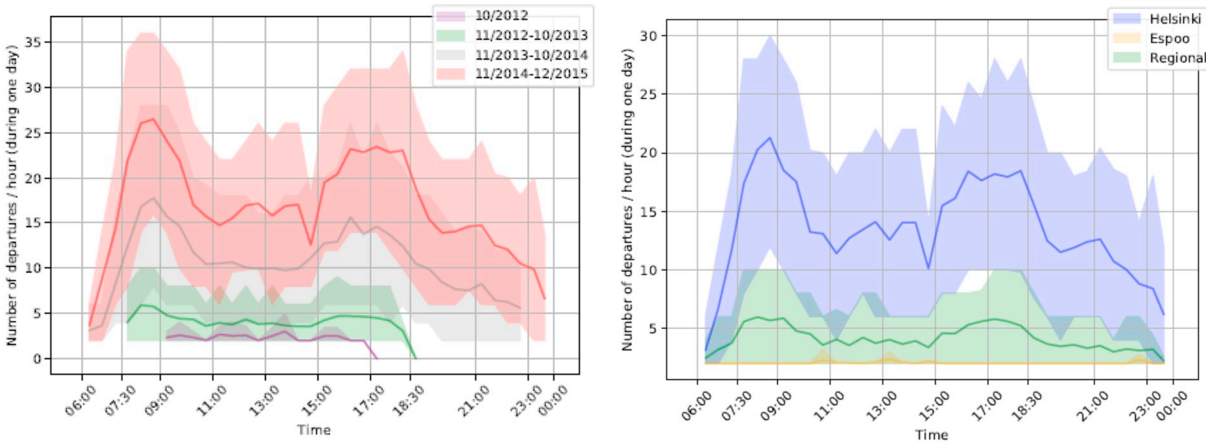

Fig. 7. Hourly average variation (with 10th and 90th percentile area as background) of a) Kutsuplus journeys by service phase b) PT journeys by fare zone.

FPT is faster 7.8% of the time, while if FPT routing is accounting also for minimizing number of transfers, then FPT is faster only 5.4% of the time. Walking was much slower than Kutsuplus (part e), being faster only 0.2% of the time. Walking was not a feasible option for replacing Kutsuplus travel, but when testing for walk distances up to 2 km, every twentieth Kutsuplus journey could have been completed by walking. In contrast, cycling could have been used as a faster travel option for almost a fifth of all Kutsuplus journeys (part f), being faster 18.6% of time.

4.5. Service class and price comparison

Fig. 13 shows service class distributions for journey distance, duration, price and travel speed. While Kutsuplus Fast journeys were more expensive (part c) they do not seem to have significant differences in terms of distance or duration to normal journeys (part a and b). We show an approximation for journey speed in part d of the Fig. 13, which further implies that neither Kutsuplus Fast nor Economy journeys were more efficient than the default service class provided.

Journey price as a function of time of day is visualized in the Fig. 14 below. From this figure, one can conclude that Kutsuplus has been priced between FPT and Uber Pop, respectively. Pricing for all modes except for FPT correlate with journey distance and there are no other significant variations by the time of day. Because municipality borders are the only cause of pricing differences for FPT we consider regional fare zones separately. Kutsuplus was used mostly in Helsinki FPT zone with about two thirds of the journeys.

5. Discussion and conclusions

First, the ex post pilot evaluation provides details of Kutsuplus number of passengers, journey distances and duration, journey price, and user age. These results confirm general trends observed in the previous research that demand for Kutsuplus has been increasing over time, while being confined to the limits of the service area in the HMR centre (Jokinen et al., 2019). Thus, Kutsuplus could have been used for further distances if the operating area and number of vehicles was significantly increased, as this was the case in previous mobility-on-demand services (Dong et al., 2018). In addition, despite the vehicle capacity of nine seats, the average occupancy was just over one user (1.27), which is an important indicator of system operation. This is a similar finding to previous research of shared rides, indicating that percentage of journeys with more than two passengers was very small (Li et al., 2019). Such a small number of passengers per journey can be considered an important weakness in the system operation. In addition, the estimate of pick-up accuracy was good, even during peak hours. However, one has to note that "time-to pick up after journey acceptance" consists of three elements. First, user may have specified a particular time for the earliest possible pickup time. Second, the offered pickup time is bounded by this estimate, which could have caused further delay from the algorithm constraints itself. Third, there is the actual potential delay due to traffic flow conditions. As this detailed data on the users service ordering process is missing, these detailed use cases cannot be identified with certainty, and should be an important lesson for defining data collection in the future pilots. Although wait time after journey acceptance was reasonable in most of the cases, there has been a minor set of journeys with a very long wait time, over 45 min. Such wait time could be a result of small system capacity in the

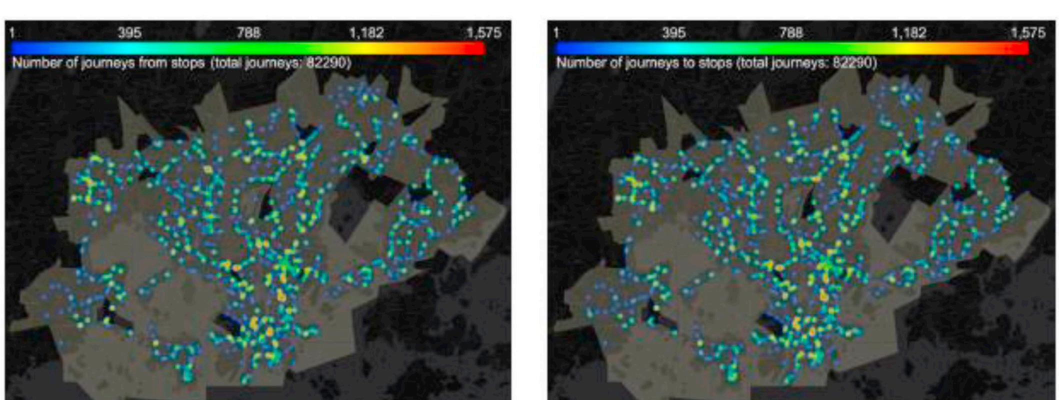

Fig. 8. Spatial distribution of all journey a) origins and b) destinations.

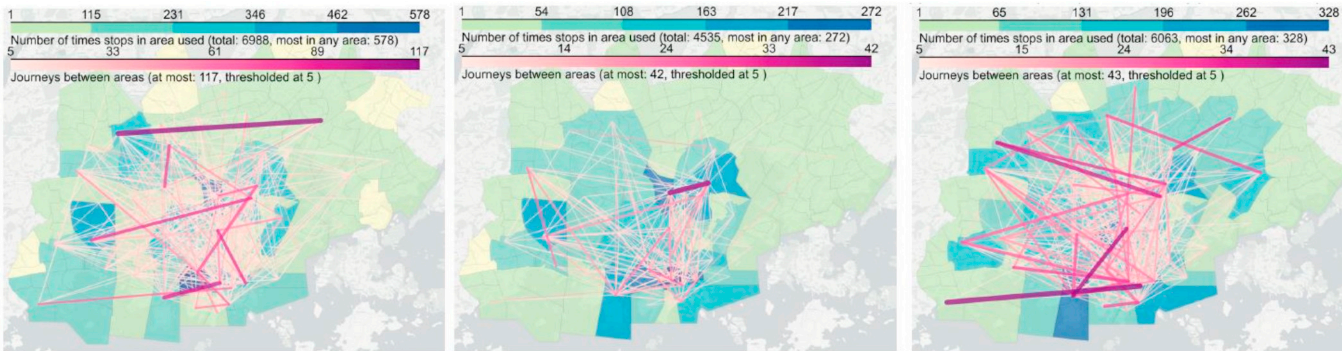

Fig. 9. Kutsuplus journey desire lines during phases 3 & 4 in the a) morning peak hour, b) mid-day peak hour, and c) evening peak hour.

peak hours, combined with high demand in low pricing conditions, or experimenting with the constraints in the dial-a-ride algorithm setup.

Looking at the temporal demand distribution of Kutsuplus journeys, one can conclude that morning demand shows a narrower peak than the afternoon demand, with some discrepancy when compared to FPT peak hours. As opposed to FPT morning peak that is starting at 6 am, Kutsuplus morning peak seems to be starting around 8 am. Similarly, afternoon Kutsuplus peak is later than FPT peak, starting around 16:30 as opposed to 15 h, respectively. Comparatively, previous research finds that the peaks for shared rides occur later from single ride peaks (Li et al., 2019). This information, combined with the fact that Kutsuplus users were mostly not very young or very old people, could imply that Kutsuplus has been used in a more flexible manner than FPT, and often for business journey or social purposes (Weckström, Kujala, et al., 2018). However, the overall daily Kutsuplus demand pattern, especially in the later pilot stages, resembles FPT demand pattern shape. This is contrary to some patterns in the previous research about ridesharing, where the noon peak is much higher than the morning and evening peaks (Li et al., 2019). Moreover, the Kutsuplus service demand on Fridays does not differ from other weekdays. This is important to note as FPT services typically have extended operations on Fridays and weekend nights, due to potential demand surges in the evening.

The spatial demand characteristics obtained in (Weckström, Kujala, et al., 2018) seem to roughly correspond to realized journeys, as does the distance distribution, though the role of the city centre seems slightly exaggerated in this previous research. Such a change in the desire line distribution is resulting from a difference in journey zone sizes and corresponding boundary locations in relation to Kutsuplus stops. When compared to FPT demand, Kutsuplus spatial demand has more orbital than radial direction, more versatile directional demand, and focus on the western side of the service area. Moreover, Kutsuplus journeys were geographically spread out over the whole area. However, most frequent journey origins and destinations centred on several, mostly business-related, locations. This finding is somewhat contradicting previous findings where mobility-on-demand services have been used for commuting (Dong et al., 2018), while it is more in line with the findings that the journeys occur between commercial locations and towards city centre (Wenzel et al., 2019). Looking into details, demand by the east metro branches seems to have been quite low for Kutsuplus. In practice, there are none or very few journeys between stops on the metro line, while the demand in areas in the east where there was no trunk line seems proportionally quite large. This might be explained by

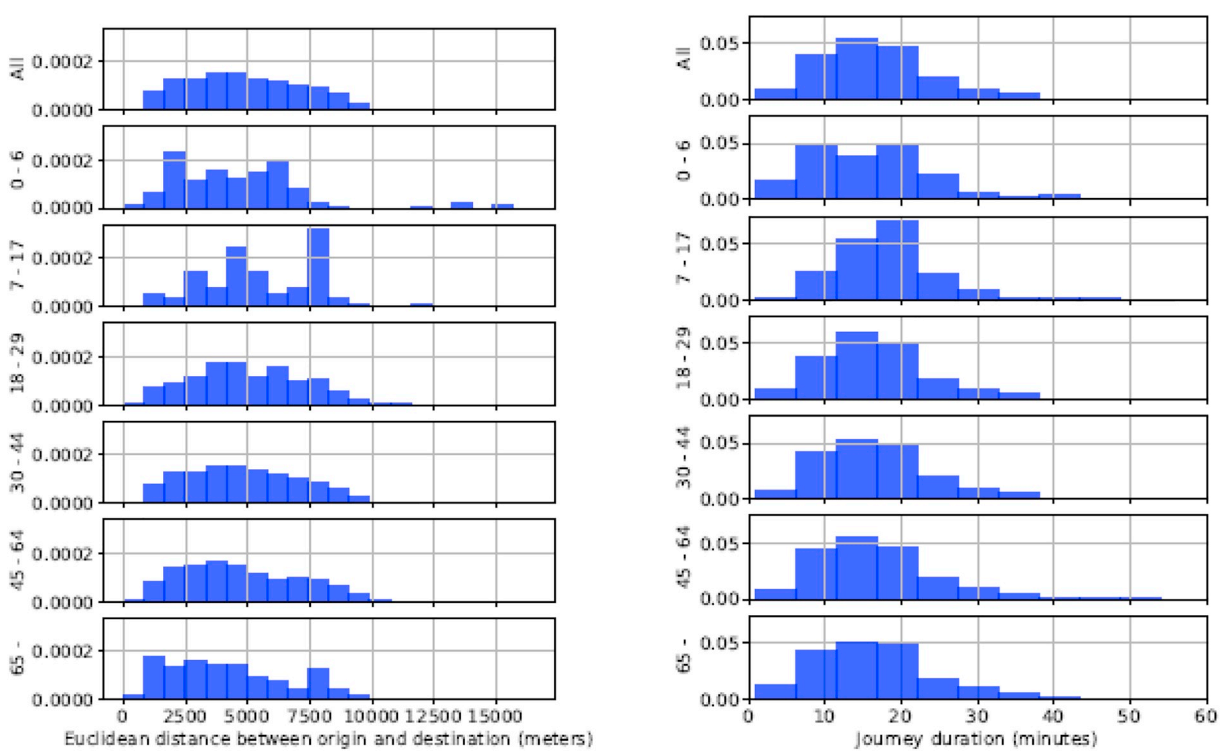

Fig. 10. Probability density distribution for Kutsuplus journeys by age of a) journey distance and b) journey duration.

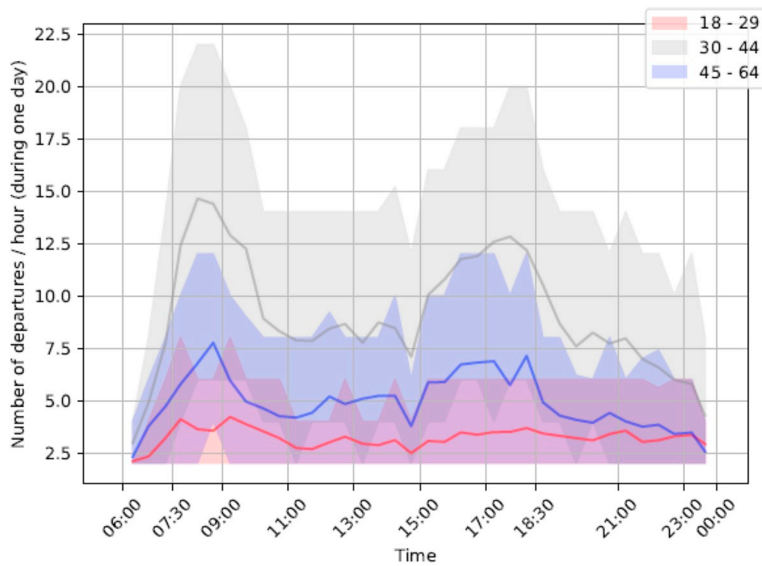

Fig. 11. Kutsuplus hourly journeys per age group in the fourth service phase (with 10th and 90th percentile area as background).

socioeconomic differences or the need for a transfer at a hub terminal in the city centre. Moreover, journeys inside Espoo (i.e., western part of Kutsuplus operating area) were not popular, even though are relatively present in the HELMET model. This is likely due to the bus trunk line 550 with short headways and longer operating hours than Kutsuplus, effectively operating for orbital journeys close to the edges of the Kutsuplus service area. As opposed to previous research where the airport is the single largest journey destination (Wenzel et al., 2019), Kutsuplus service area did not include the HMR airport due to agreement with taxi companies when formulating the pilot plan. Finally, previous research informs us that there is a strong relationship between journey demand and built environment factors, such as density or diversity (Li et al., 2019; Yu & Peng, 2019). As HMR has quite high values of density and diversity around FPT trunk lines, these aspects should be taken into account when interpreting the OD data. However, further research is needed for testing this hypothesis.

Results also provide variations and distributions of journey parameters based on the classification into several user age groups. In contrast to the previous research, which states that higher shares of young groups have more demand for ridesourcing (Yu & Peng, 2019), groups between 30 and 65 years have mostly used Kutsuplus. There are some differences in the demand patterns based on users' age. For example, the age group of 18–29 seems to have used Kutsuplus relatively often for morning peak hour regional journeys. This group could have consisted from university students and staff, which could have used Kutsuplus as the flexible form of travel between different Aalto University campuses (i.e., Otaniemi in Espoo, and Arabia and Töölö in Helsinki). On the contrary, the age group of over 65-year-olds had a strong trend to use Kutsuplus within downtown Helsinki, although a smaller number of frequent users could cause these trends. Considering that journey analysis could not be complemented with additional background or preferences data, there could be further reasons in relation to FPT fare system, as indicated in (Jokinen et al., 2019).

When considering journey alternatives for Kutsuplus journeys, after a successful pick up, Kutsuplus was indeed a fast choice compared to FPT for the same journeys. While using FPT requires pre-trip planning according to the schedule, and was not generally faster than Kutsuplus, the mean wait time at the stop on spontaneous departures was relatively short, when compared to the amount of waiting Kutsuplus sometimes required after the initial departure estimate. In practice, both Kutsuplus vehicles and Kutsuplus users often arrived at the stops before the target pick-up time. Partial explanation for this result can be found in the short pre-booking times and conservative travel time predictions. Although Kutsuplus was mostly faster than FPT, as in (Alonso-González, Liu, et al., 2018), it cannot be directly inferred that the relationship was one of complementing or competing, as highlighted before (Komanduri et al., 2018; Yu & Peng, 2019).

When comparing alternative transport modes, it was found that Kutsuplus was usually faster than FPT, biking, and walking, while on par with private cars for shorter journeys. However, we have to note that the lack of actual Kutsuplus routing data is a limitation of this research in the DRT context. Even in this context, there is an important question about potential replacement of walking and cycling journeys. As identified in previous research, Kutsuplus could replace similar percentage of walking and cycling journeys, i.e., 20–25% (Henao & Marshall, 2018; Rayle et al., 2016). Such an outcome from using DRT is not always desirable when taking into account the health and environmental effects. Alternatively, it is important to underline that when testing for walking distances of up to 2 km, every twentieth Kutsuplus journey could have been completed by walking. These findings underline important questions of the role of mobility-on-demand services for active mobility, and consequently users' wellbeing (Pangbourne et al., 2019; Pangbourne, Stead, Mladenović, & Milakis, 2018).

Finally, results include a comparison of Kutsuplus service per price class, and journey price with alternative transport modes. Overall, one can conclude that price per journey is mostly below €10, finding its pricing position between FPT and UberPOP, respectively. In relation, it might be tempting for FPT users to use Kutsuplus over regional borders, as regional FPT tickets are more expensive than single-region tickets. It is important to highlight that pricing has been used as a mechanism to flatten out the demand and push it out of peak periods, due to limited vehicle capacity available, while under pressure of constantly increasing demand. Importantly, despite the price changes during the course of the pilot, these changes do not seem to have been related to the actual differences in the service level. When Kutsuplus service classes were inspected, no significant differences to normal Kutsuplus operations were found in relation to the increased or decreased price. Similar results have been highlighted before, as (Jokinen et al., 2019) have noted that the classes should have been based on the real differences in service level aspects, such as in the journey duration. The relatively low number of available Fast journeys and the lack of identifiable users caused some limitations for the service class inspections. It might have also been that Fast customers had vehicles more readily available through the ordering interfaces, which would make strict journey duration comparisons undescriptive. Unfortunately, it is not

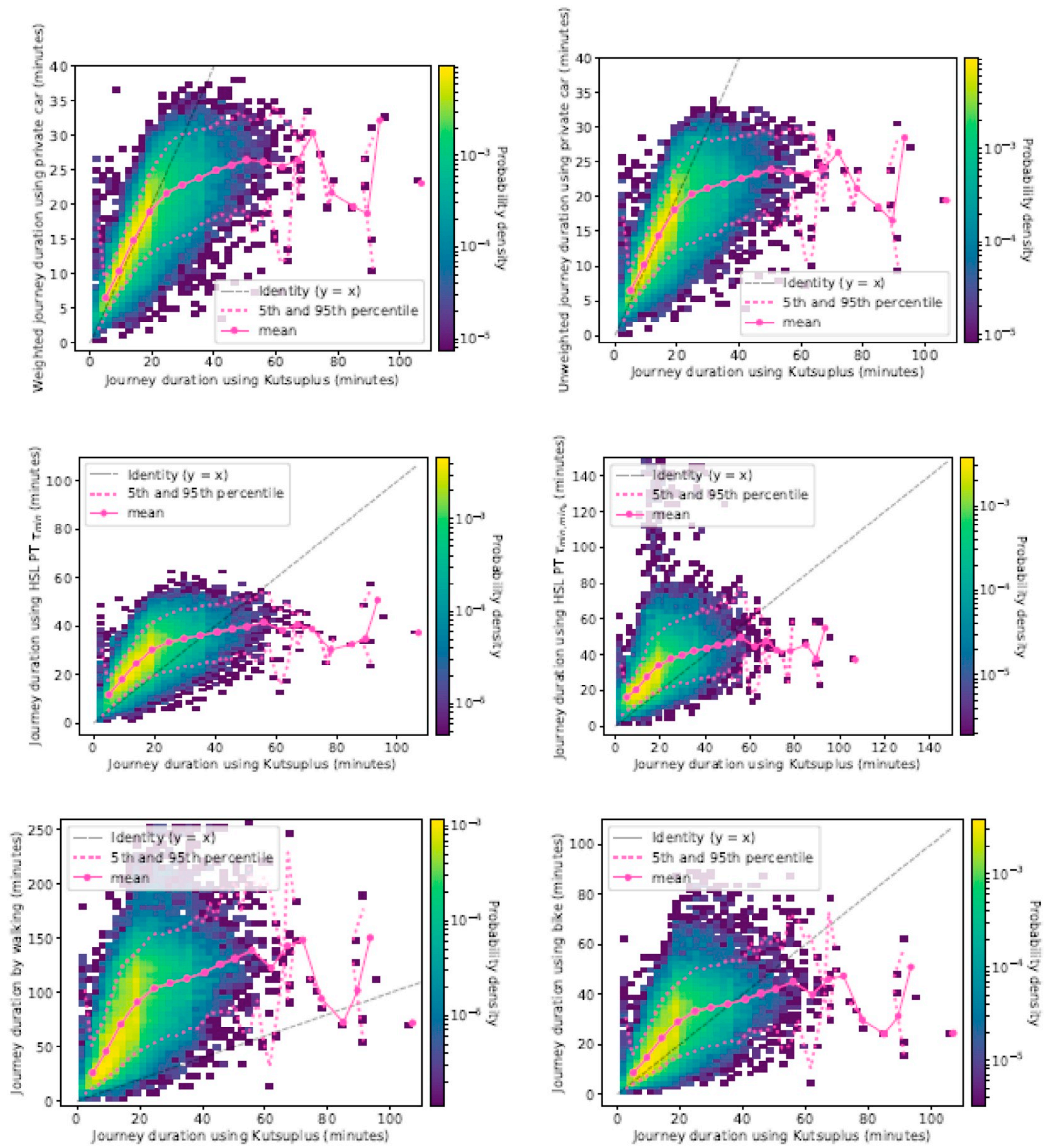

Fig. 12. Journey durations of all Kutsuplus journeys against alternative modes of travel, including a) Uber, b) taxi, c) PT with min travel time, d) PT with min travel time and transfers, e) walking, and f) cycling.

possible to quantify failed order attempts due to the missing data. Certainly, it is worth highlighting that results are bound to the experimenting pricing model used and the overall price level, as Kutsuplus was strongly subsidized, with total subsidy amounting to over three million euros in 2015.

5.1. Implications for managerial practice

The case study results provide basis for recommendations in developing future multimodal mobility services in urban areas. While the characterizations obtained are not directly expandable to a broader mobility-on-demand context, they provide unique insight to the realized journeys of a relatively long lasting on-demand micro-transit service pilot. Such lessons are especially relevant for other public-private DRT services, such as Breng flex, that was also stopped due to similar financial reasons to Kutsuplus. Evaluating the trends, we can certainly underline the previous DRT lesson that breaking out of car-dependent urban transport systems is not an easy and straightforward task. Data-driven foundation planning and evaluation of DRT services can help in better understanding the alternatives substituting and complementing capital-intensive FPT systems. In particular, a conclusion is that delivering integrated mobility systems will have to be underlined with a development of methods for integrated mobility system planning. In line with previous recommendations, a particular focus of planning processes should be on the definition of operating zones, hours, and pricing schemes for static versus on-demand mobility services. Here, developing procedures for advancing planning of stop locations from the users' perspective is one of the aspects that should be further considered. Moreover, planning practice has to reflect upon interdependencies between service demand, fare subsidizing, fleet utilization, operating revenue, service availability and pricing schemes.

Advancing the planning and governance structures will have to go hand in hand with building institutional capacity for piloting and experimentation. Future pilots of on-demand mobility services will have to pay special attention to identifying user profiles for the specific service. In the case of Kutsuplus, target audience was coming in and out of focus during the pilot, often leaving the user to individually innovate the use of the service. For example, the question users had to answer by themselves was whether Kutsuplus was cheap enough to compete with other forms of ordered transport while having significant positive travel

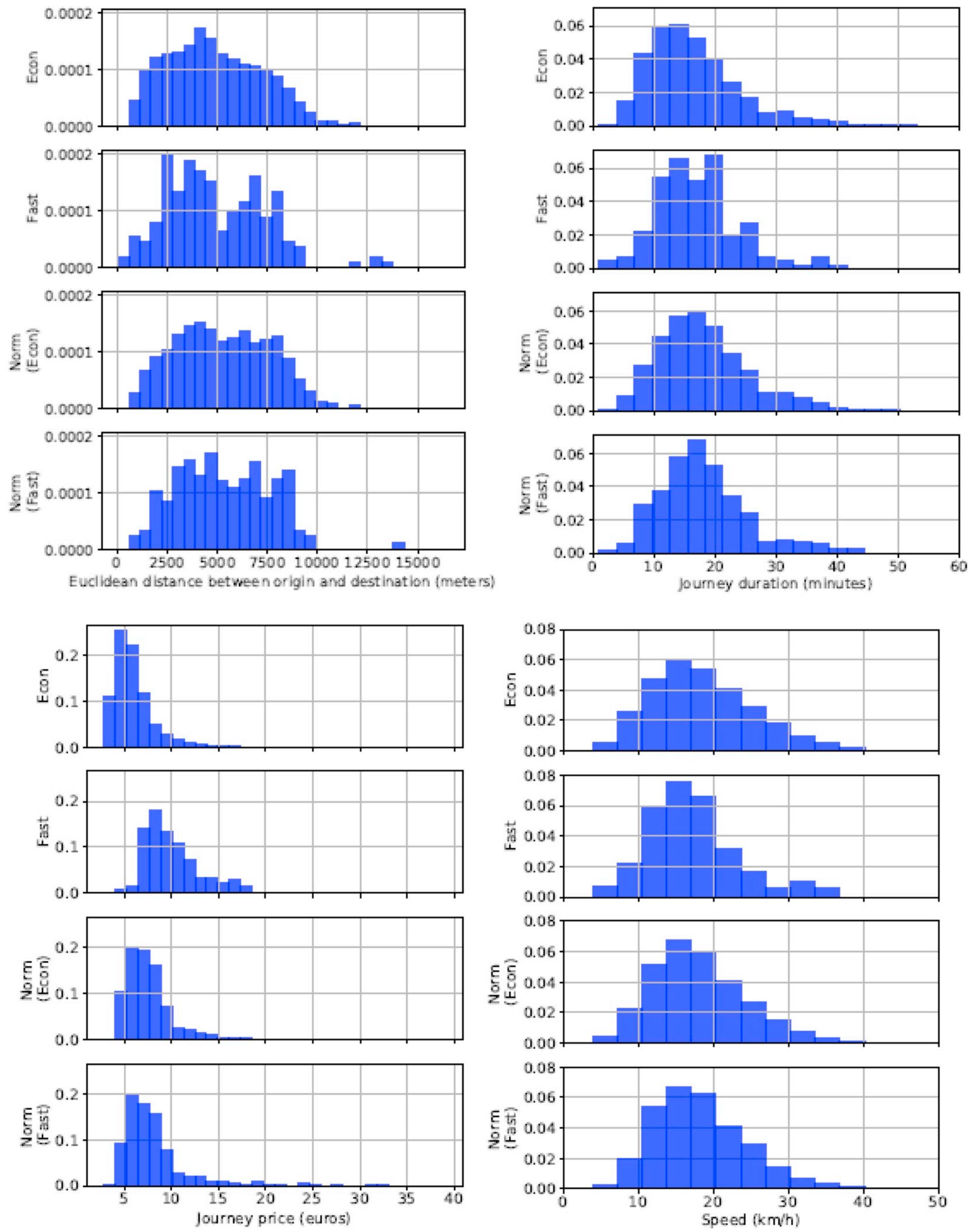

Fig. 13. Probability density distributions for Kutsuplus journeys by service class for a) journey distance, b) journey duration, c) journey price, and d) journey speed.

experience to justify paying a premium when compared to FPT. Contrastingly, development of promotions and other incentive strategies should understand different user profiles, with varying probability of accepting the ridesharing by understanding the relations between urban transport modes. Moreover, future pilots should consider the role of public-private partnerships for defining mobility management plans in charting out piloting stages. Finally, study findings also raise implications for data collection practices in the future pilots, having in mind disaggregated performance measures, but also establishing protocols for data exchange between public and private sector, due to the potential for mutual benefits. In the future, DRT piloting activates should aim to collect per anonymised user their journey order, offer, and service acceptance/rejection data, such as journey order timestamp, drop-off timestamp and journey price.

5.2. Contribution to scholarly knowledge

DRT service evaluation methods have good previous examples providing basis for further development (Alonso-González, Liu, et al., 2018; Ferreira et al., 2007). However, few studies had employed empirical data to examine the unique travel patterns of DRT journeys, and have mostly focused on a specific set of performance measures that could be developed using constrained data sources. This research contributes to the further methodological development for evaluation of empirical DRT experiences. In general, this research contributes to bridging the gap in evaluation frameworks using detailed journey data

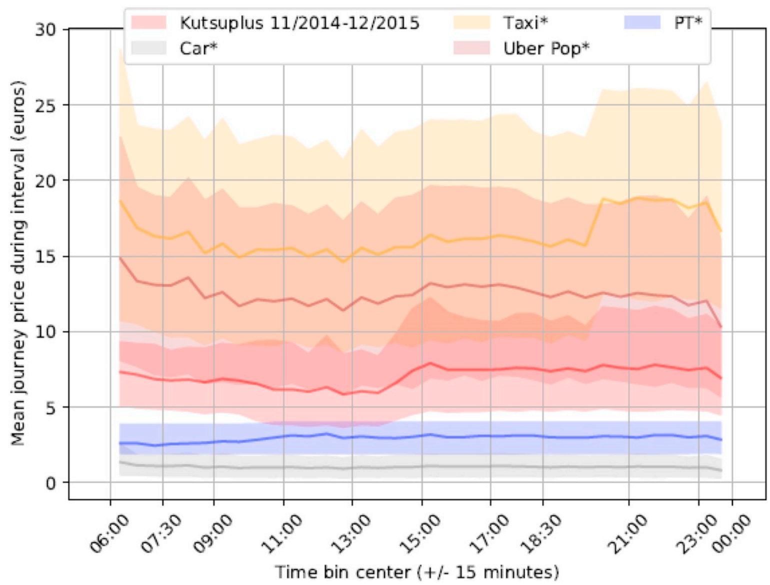

Fig. 14. Cost variation for alternative transport modes during the day.

including pricing and user properties, and service comparison with alternative urban transport modes. In particular, this research contributes with a detailed Kutsuplus journey analysis in relation to the service timeline and spatiotemporal patterns, highlighting several important similarities or differences in comparison with the previous literature. Nonetheless, the methodological framework presented here is not to be interpreted as an unchangeable, but rather as a point for further reflective development of performance measures. Thus, there are several potential pathways for further development of planning and evaluation methods and corresponding processes.

Although passenger travel data is important for understanding the service, future methodological frameworks should account for automated data collection of qualitative user feedback using experience sampling methods. Real-time user feedback and questionnaires can benefit from recent proliferation of social media and smart phone apps. With such data collection, questions could be asked about habituation of DRT services over repeated use experiences in longitudinal studies. In addition, further analysis of journey data could focus on the identifying the effects from service marketing or weather patterns. However, further advancements in our understanding of societal learning with the simultaneous development of emerging mobility services requires deeper understanding of user experiences and cultural norms in relation to the evolving technological visions (Alonso-González et al., 2018; Lyons, Hammond, & Mackay, 2019; Mladenovic, 2019Mladenovic, Lehtinen, Soh, & Martens, 2019; Mulley & Nelson, 2016; Pangbourne et al., 2019). Thus, development of quantitative evaluation methods should go hand in hand with the implementation of qualitative evaluation methods, such as interviews and focus groups (Sihvola et al., 2012). Moreover, studies of local and international media discourses around emerging on-demand mobility services is one of the potential pathways for developing the understanding of deeper cultural meanings that could enable or block transition.

Further advancements of DRT service algorithms could aim for improving demand prediction, especially taking into account different daily demand patterns and user types. Similarly, advancements of methods for integrated planning and scheduling of FPT routes could be combined with definitions of spatio-temporal zones and vehicle dispatching for meeting the given demand pattern and user experiences. Here, further advancements using complex temporal networks methods (Holme & Saramäki, 2012), especially multi-layered networks, can provide fruitful pathways for developing and understanding service levels from the user perspective. Along the lines of agent-based frameworks (Narayan et al., 2017), such modelling methods can represent reality to a sufficient degree while also not being data collection and computationally intensive as microsimulation methods. However, given the lack of established planning support frameworks, there is a need for further formulation of decision-making processes into functional requirements for useful support systems (e.g., Mladenovic, Mangaroska, & Abbas, 2017; Pelzer, 2017). The development of such decision support systems should be conducted in close collaboration with transport and urban planning practitioners, understanding the localized interdependencies between data, models, and knowledge management practices.

Acknowledgement

This research has been funded by the Academy of Finland, through DecoNet project (No. 295499) and PROFI 4 initiative, as well as through Finest Twins center. In addition, the authors would like to thank Teemu Sihvola for providing Kutsuplus journey data, and Helsinki Region Transport Authority for providing valuable information and feedback. In particular, the authors would acknowledge the help of Ossi Berg, Markku Huotari, and Kari Rissanen. Moreover, the authors have benefited from discussions with Jani-Pekka Jokinen and Moshe Givoni. Finally, the authors acknowledge the feedback of anonymous reviewers that have helped improve the argumentation of this research.

References

Alonso-González, M. J., Durand, A., Harms, L., van Oort, N., Cats, O., Hoogendoorn-Lanser, S., & Hoogendoorn, S. (2018). Will car users change their mobility patterns with Mobility as a Service (MaaS) and microtransit?–A latent class cluster analysis. *hEART* (2018).

Alonso-González, M. J., Liu, T., Cats, O., Van Oort, N., & Hoogendoorn, S. (2018). The potential of demand-responsive transport as a complement to public transport: An assessment framework and an empirical evaluation. *Transportation Research Record, 2672*(8), 879–889.

Ambrosino, G., Nelson, J. D., Boero, M., & Pettinelli, I. (2016). Enabling intermodal urban transport through complementary services: From flexible mobility services to the shared use mobility agency: Workshop 4. Developing inter-modal transport systems. *Research in Transportation Economics, 59*, 179–184.

Brake, J., Mulley, C., Nelson, J. D., & Wright, S. (2007). Key lessons learned from recent experience with flexible transport services. *Transport Policy, 14*(6), 458–466.

Brake, J., & Nelson, J. D. (2007). A case study of flexible solutions to transport demand in a deregulated environment. *Journal of Transport Geography, 15*(4), 262–273.

Brake, J., Nelson, J. D., & Wright, S. (2004). Demand responsive transport: Towards the emergence of a new market segment. *Journal of Transport Geography, 12*(4), 323–337.

Cetin, T., & Deakin, E. (2019). Regulation of taxis and the rise of ridesharing. *Transport Policy, 76*, 149–158.

Chen, X., Zheng, H., Wang, Z., & Chen, X. (2018). Exploring impacts of on-demand ridesplitting on mobility via real-world ridesourcing data and questionnaires. *Transportation,* 1–21.
Chen, Z., Liu, X. C., & Wei, R. (2019). Agent-based approach to analyzing the effects of dynamic ridesharing in a multimodal network. *Computers, Environment and Urban Systems, 74*, 126–135.
Circella, G., & Alemi, F. (2018). Transport policy in the era of ridehailing and other disruptive transportation technologies. *Advances in transport policy and planning. Vol. 1. Advances in transport policy and planning* (pp. 119–144). Academic Press.
Cohen, T. (2018). Being ready for the next Uber: Can local government reinvent itself? *European Transport Research Review, 10*(2), 57.
Davison, L., Enoch, M., Ryley, T., Quddus, M., & Wang, C. (2012). Identifying potential market niches for demand responsive transport. *Research in Transportation Business & Management, 3*, 50–61.
Davison, L., Enoch, M., Ryley, T., Quddus, M., & Wang, C. (2014). A survey of demand responsive transport in Great Britain. *Transport Policy, 31*, 47–54.
Deakin, E., Frick, K. T., & Shively, K. M. (2010). Markets for dynamic ridesharing? Case of Berkeley, California. *Transportation Research Record, 2187*(1), 131–137.
Dong, Y., Wang, S., Li, L., & Zhang, Z. (2018). An empirical study on travel patterns of internet based ride-sharing. *Transportation research part C: Emerging Technologies, 86*, 1–22.
Ferreira, L., Charles, P., & Tether, C. (2007). Evaluating flexible transport solutions. *Transportation Planning and Technology, 30*(2–3), 249–269.
Finn, B. (2012). Towards large-scale flexible transport services: A practical perspective from the domain of paratransit. *Research in Transportation Business & Management, 3*, 39–49.
Furuhata, M., Dessouky, M., Ordóñez, F., Brunet, M. E., Wang, X., & Koenig, S. (2013). Ridesharing: The state-of-the-art and future directions. *Transportation Research Part B: Methodological, 57*, 28–46.
Gehrke, S. R., Felix, A., & Reardon, T. G. (2019). Substitution of ride-hailing services for more sustainable travel options in the greater Boston region. *Transportation Research Record, 2673*.
Häme, L. (2013). *Demand-responsive transport: Models and algorithms.* Aalto University.
Henao, A., & Marshall, W. E. (2018). The impact of ride-hailing on vehicle miles traveled. *Transportation,* 1–22.
Henao, A., & Marshall, W. E. (2019). The impact of ride hailing on parking (and vice versa). *Journal of Transport and Land Use, 12*(1).
Hoffmann, K., Ipeirotis, P., & Sundararajan, A. (2016). *Ridesharing and the use of public transportation*.
Holme, P., & Saramäki, J. (2012). Temporal networks. *Physics Reports, 519*(3), 97–125.
Hyytiä, E., Aalto, S., Penttinen, A., & Sulonen, R. (2010). A stochastic model for a vehicle in a dial-a-ride system. *Operations Research Letters, 38*(5), 432–435 (Elsevier).
Hyytiä, E., Penttinen, A., & Sulonen, R. (2012). Non-myopic vehicle and route selection in dynamic DARP with travel time and workload objectives. *Computers & Operations Research, 39*(12), 3021–3030.
Jin, S. T., Kong, H., Wu, R., & Sui, D. Z. (2018). Ridesourcing, the sharing economy, and the future of cities. *Cities, 76*, 96–104.
Jokinen, J., Sihvola, T., Hyytiä, E., & Sulonen, R. (2011). *Why urban demand responsive transport? Paper presented in in IEEE forum on integrated and sustainable transportation systems (FISTS), Vienna, Austria*.
Jokinen, J. P. (2016). *Economic perspectives on automated demand responsive transportation and shared taxi services - analytical models and simulations for policy analysis.* Aalto University.
Jokinen, J. P., Sihvola, T., & Mladenovic, M. N. (2019). Policy lessons from the flexible transport service pilot Kutsuplus in the Helsinki capital region. *Transport Policy, 76*, 123–133.
Komanduri, A., Wafa, Z., Proussaloglou, K., & Jacobs, S. (2018). Assessing the impact of app-based ride share systems in an urban context: Findings from Austin. *Transportation Research Record: Journal of the Transportation Research Board, 2672*, 34–46.
Kujala, R., Weckström, C., Darst, R. K., Mladenović, M. N., & Saramäki, J. (2018). A collection of public transport network data sets for 25 cities. *Scientific data, 5*, 180089.
Kujala, R., Weckström, C., Mladenović, M. N., & Saramäki, J. (2018). Travel times and transfers in public transport: Comprehensive accessibility analysis based on Pareto-optimal journeys. *Computers, Environment and Urban Systems, 67*, 41–54.
Li, W., Pu, Z., Li, Y., & Ban, X. J. (2019). Characterization of ridesplitting based on observed data: A case study of Chengdu, China. *Transportation Research Part C: Emerging Technologies, 100*, 330–353.
Liimatainen, H., & Mladenović, M. N. (2018). Understanding the complexity of mobility as a service. *Research in Transportation Business & Management, 27*, 1–2.
Lyons, G., Hammond, P., & Mackay, K. (2019). The importance of user perspective in the evolution of MaaS. *Transportation Research Part A: Policy and Practice, 121*, 22–36.
Mageean, J., & Nelson, J. D. (2003). The evaluation of demand responsive transport services in Europe. *Journal of Transport Geography, 11*(4), 255–270.
Mladenovic, M., Lehtinen, S., Soh, E., & Martens, K. (2019). Emerging urban mobility technologies through the lens of everyday urban aesthetics: Case of self-driving vehicles. *Essays in Philosophy, 20*(2).
Mladenović, M. N. (2019). How should we drive self-driving vehicles? Anticipation and collective imagination in planning mobility futures. *The governance of smart transportation systems* (pp. 103–122). Cham: Springer.
Mladenovic, M. N., Mangaroska, K., & Abbas, M. M. (2017). Decision support system for planning traffic operations assets. *Journal of Infrastructure Systems, 23*(3), 05017001.
Mohamed, M. J., Rye, T., & Fonzone, A. (2019). Operational and policy implications of ridesourcing services: A case of uber in London, UK. *Case Studies on Transport Policy* in press.
Mulley, C., Nelson, J., Teal, R., Wright, S., & Daniels, R. (2012). Barriers to implementing flexible transport services: An international comparison of the experiences in Australia, Europe and USA. *Research in Transportation Business & Management, 3*, 3–11.
Mulley, C., & Nelson, J. D. (2009). Flexible transport services: A new market opportunity for public transport. *Research in Transportation Economics, 25*, 39–45.
Mulley, C., & Nelson, J. D. (2016). Shaping the new future of paratransit: An agenda for research and practice. *Transportation Research Record, 2542*(1), 17–24.
Mulley, C., Nelson, J. D., & Wright, S. (2018). Community transport meets mobility as a service: On the road to a new a flexible future. *Research in Transportation Economics, 69*, 583–591.
Narayan, J., Cats, O., van Oort, N., & Hoogendoorn, S. (2017). Performance assessment of fixed and flexible public transport in a multi agent simulation framework. *Transportation Research Procedia, 27*, 109–116.
Nelson, J. D., & Phonphitakchai, T. (2012). An evaluation of the user characteristics of an open access DRT service. *Research in Transportation Economics, 34*(1), 54–65.
Nelson, J. D., Wright, S., Masson, B., Ambrosino, G., & Naniopulous, A. (2010). Recent developments in flexible transport services. *Research in Transportation Economics, 29*, 243–248.
Pangbourne, K., Mladenovic, M., Stead, D., & Milakis, D. (2019). Questioning mobility as a service: Unanticipated implications for society and governance. *Transportation Research Part A* in press.
Pangbourne, K., Stead, D., Mladenović, M., & Milakis, D. (2018). The case of mobility as a service: A critical reflection on challenges for urban transport and mobility governance. *Governance of the smart mobility transition* (pp. 33–48). Emerald Publishing Limited.
Pelzer, P. (2017). Usefulness of planning support systems: A conceptual framework and an empirical illustration. *Transportation Research Part A: Policy and Practice, 104*, 84–95.
Puche, M. L. (2019). Regulation of TNCs in Latin America: The case of uber regulation in Mexico City and Bogota. *The governance of smart transportation systems* (pp. 37–53). Cham: Springer.
Rayle, L., Dai, D., Chan, N., Cervero, R., & Shaheen, S. (2016). Just a better taxi? A survey-based comparison of taxis, transit, and ridesourcing services in San Francisco. *Transport Policy, 45*, 168–178.
Rissanen, K. (2014). Kutsuplus.Fi - A novel, automated real-time demand responsive public transport service. *Proceedings of the 10th ITS European congress*.
Rissanen, K. (2016). *Kutsuplus - final report.* Helsinki, Finland: Helsinki Regional Transport Authority Publications.
Ronald, N., Thompson, R., & Winter, S. (2017). Simulating ad-hoc demand-responsive transportation: A comparison of three approaches. *Transportation Planning and Technology, 40*(3), 340–358.
Ryley, T. J., Stanley, P. A., Enoch, M. P., Zanni, A. M., & Quddus, M. A. (2014). Investigating the contribution of demand responsive transport to a sustainable local public transport system. *Research in Transportation Economics, 48*, 364–372.
Schwieterman, J. P. (2019). Uber economics: evaluating the monetary and travel time trade-offs of transportation network companies and transit service in Chicago, Illinois. *Transportation Research Record, 2673*(4), 294–304.
Shaheen, S., & Chan, N. (2016). Mobility and the sharing economy: Potential to facilitate the first-and last-mile public transit connections. *Built Environment, 42*(4), 573–588.
Shaheen, S., & Cohen, A. (2018). Shared ride services in North America: Definitions, impacts, and the future of pooling. *Transport Reviews,* 1–16.
Sharmeen, F., & Meurs, H. (2019). The governance of demand-responsive transit systems—A multi-level perspective. *The governance of smart transportation systems* (pp. 207–227). Cham: Springer.
Sihvola, T., Häme, L., & Sulonen, R. (2010). *Passenger-pooling and trip-combining potential of high-density demand-responsive transport, in 89th annual meeting of transportation research board*.
Sihvola, T., Jokinen, J. P., & Sulonen, R. (2012). User needs for urban car travel: Can demand-responsive transport break dependence on the car? *Transportation Research Record, 2277*(1), 75–81.
Su, R., Fang, Z., Luo, N., & Zhu, J. (2018). Understanding the dynamics of the pick-up and drop-off locations of taxicabs in the context of a subsidy war among e-hailing apps. *Sustainability, 10*(4), 1256.
Velaga, N. R., Nelson, J. D., Wright, S. D., & Farrington, J. H. (2012). The potential role of flexible transport services in enhancing rural public transport provision. *Journal of Public Transportation, 15*, 7.
Weckström, C., Kujala, R., Mladenović, M. N., & Saramäki, J. (2019). Assessment of large-scale transitions in public transport networks using open timetable data: Case of Helsinki metro extension. *Journal of Transport Geography, 79*, 1–13.
Weckström, C., Mladenović, M. N., Ullah, W., Nelson, J. D., Givoni, M., & Bussman, S. (2018). User perspectives on emerging mobility services: Ex post analysis of Kutsuplus pilot. *Research in Transportation Business & Management, 27*, 84–97.
Wenzel, T., Rames, C., Kontou, E., & Henao, A. (2019). Travel and energy implications of ridesourcing service in Austin, Texas. *Transportation Research Part D: Transport and Environment, 70*, 18–34.
Young, M., & Farber, S. (2019). The who, why, and when of Uber and other ride-hailing trips: An examination of a large sample household travel survey. *Transportation Research Part A: Policy and Practice, 119*, 383–392.
Yu, H., & Peng, Z. R. (2019). Exploring the spatial variation of ridesourcing demand and its relationship to built environment and socioeconomic factors with the geographically weighted Poisson regression. *Journal of Transport Geography, 75*, 147–163.