FACTORS INFLUENCING DEMAND IN FREE-FLOATING VEHICLE SHARING PLATFORMS: REAL-WORLD EVIDENCE FROM MULTIMODALITY

Research Paper

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Abstract

Free-floating vehicle sharing platforms offer flexible and sustainable means of transportation and have thus proliferated swiftly in many cities around the globe. The operations management of these platforms prevalently relies on sophisticated information systems along with detailed demand models. Despite the emergence of such platforms and the first apparent tendencies towards multimodality, virtually no comprehensive and comparative demand models exist for the prevailing modes. Using econometric modeling, we empirically examine the effect of a rich set of factors on demand for free-floating shared cars, scooters, electric kick scooters, and bikes using a unique real-world geo-tagged rental dataset. Our analyses indicate that demand for all transportation modes considered is widely determined by factors pertaining to trip comfort, trip purpose, and user characteristics. We also provide evidence that said platforms are a key component to enable sustainable intermodal mobility as we observe demand peaks for shared vehicles close to public transportation facilities.

Keywords: mobility-as-a-service, multimodal mobility, platforms, sharing economy

1 Introduction

Sustainability concerns are and will remain in the coming decades a herculean task for our modern society. The transportation sector being one of the biggest polluters makes a substantial detrimental contribution to environmental concerns (European Environment Agency, 2018). In response, new mobility concepts are urgently investigated to counteract this trend such as the electrification of vehicles (Canals Casals et al., 2016), the design of markets for mobility (Cramton, Geddes, and Ockenfels, 2018), and the development of innovative shared mobility business models (Shaheen and Chan, 2016). Specifically, free-floating vehicle sharing - the shared use of a car, electric kick scooter, or other modes of transport - is experiencing a renaissance due to the proliferation of information and communication technologies and is poised to become an integral part of the sustainable mobility system of the future (Nair and Miller-Hooks, 2011).

Bearing a close resemblance to the sharing economy (Sundararajan, 2017), free-floating vehicle sharing (FFVS) services facilitate the platform-based rental of vehicles with the prospect of increasing efficiency and utilization of vehicles. Typically, vehicles of FFVS platforms (e.g., Bird, ShareNow, Tier) float freely within a confined service area where users can pick them up and drop them off anywhere. In this respect, information systems have a decisive stake by providing information on the availability and access to vehicles via mobile devices. Beyond the customer's perspective, information systems play both a managerial and a sustainable role for FFVS operators specifically by giving strategic guidance for defining the fleet's service area (Willing et al., 2017), by identifying spatial pricing strategies (Brendel et al., 2017), and by facilitating high service quality to customers and profit maximization (i.e., vehicles are located where they are most needed) (Lu, Chen, and Shen, 2018). As such, supply and demand of shared vehicles is more efficiently managed by IS and contributes to the alleviation of inefficient use of scarce resources in sharing systems as postulated by Watson, Boudreau, and Chen (2010). Importantly, a wide range of information systems harnessed by FFVS operators for managerial challenges share one commonality: They are reliant on accurate spatio-temporal demand models (Lu, Chen, and Shen, 2018; Schmöller et al., 2015).

Despite the introduction of numerous FFVS platforms for various kind of modes such as cars (ShareNow, formerly Car2Go and DriveNow), scooters (emmy), kick scooters (Tier), and bikes (nextbike), there still exists little knowledge in the academic literature about influential factors that explain users' demand for FFVS. Information Systems (IS) research in the context of sustainable mobility services (e.g., vehicle sharing) exhibits a rather theoretical perspective while neglecting empirical validation and thus lacking real-world applicability (Brendel and Mandrella, 2016). Moreover, even if an empirical study is conducted, researchers often utilize data with a limited set of transportation modes (e.g., only car-sharing (Schmöller et al., 2015) or bike-sharing (Pal and Zhang, 2017)) or influential demand factors, and hence fail to gain comprehensive and coherent insights. Lack of comparability, particularly between transportation modes, is a severe issue since the mobility data used in various studies are mostly collected from different cities. The aim of our study is to widen current knowledge of relevant factors influencing the demand for different types of modes in the context of FFVS. Formally, we seek to investigate the following research question: *What are relevant factors determining the demand in free-floating vehicle sharing platforms for cars, scooters, kick scooters, and bikes and which factors amplify or attenuate said demand?*

To answer this question, we draw on spatial big data analytics and econometric modeling techniques, specifically generalized linear models. The analyses we conduct rely on a unique observational dataset of rental transactions for cars, scooters, kick scooters, and bikes that we have gathered over a prolonged period of six months in Berlin, Germany. Our dataset contains over 2.7 Million geo-tagged transactions from leading providers, namely ShareNow, emmy, Tier, nextbike, and Call a Bike.

We provide three central contributions. Firstly, we identify numerous relevant factors that determine demand in FFVS, specifically those that are considerably influential (i.e., amplify or attenuate) on demand, and propose a conceptual framework arguing that demand is mainly explained by trip comfort, trip purpose and user characteristics. Secondly, we set up an empirical model to provide a grounded basis to unravel statistically significant and influential demand factors and thus lend strong support to validate our proposed conceptualization. Thirdly, we explore said influential demand factors on a variety of available transportation modes in FFVS (i.e., cars, scooters, kick scooters, bikes) in the same city and during the same time period, making the results highly comprehensible.

We proceed as follows. We begin by reviewing prior literature on the role of Information Systems in shared mobility platforms and shed light on demand factors that have seen independent consideration across studies of FFVS platforms. We then provide a conceptualization of our findings and set up an empirical model to validate it. Next, we survey our empirical results and conclude by discussing the implications, limitations, and contributions of this research.

2 Background and Related Work

2.1 The Role of Information Systems in Free-Floating Vehicle Sharing

In recent decades, information systems have established themselves as a key engine for increasing the productivity and efficiency of organizations (Hitt and Brynjolfsson, 1996). In light of the looming concern about climate change and the associated, and to some extent irreversible consequences, IS scholars are advocating the use of IS to address societal environmental challenges by responding to the drivers of climate change, for example through the efficient use and management of scarce resources - i.e., the sustainable management of supply and demand - with the help of "Green IS" and similar solutions (Watson, Boudreau, and Chen, 2010). Indeed, one of the main contributors to climate change is the mobility sector, largely due to emissions of environmentally harmful greenhouse gases and inefficient use of vehicles (European Environment Agency, 2018). More recently, however, novel IS-enabled business innovations for urban mobility have emerged in an attempt to alleviate the adverse environmental impact of urban mobility, for example, by sharing vehicles (e.g., ShareNow) or rides (e.g., Uber). Consequently, sustainable mobility research along with "Green IS" initiatives has been identified as a promising research stream for IS scholars to address societal and environmental challenges (Harnischmacher, Herrenkind, and Weilbier, 2020).

The realization and, importantly sustainable, operation of novel mobility platforms such as FFVS involves considerable managerial hurdles, which is the reason why IS are leveraged to cope with strategic, tactical and operational challenges (Brandt and Dlugosch, 2020; Hein et al., 2018). Several researchers (He et al., 2017; Rickenberg, Gebhardt, and Breitner, 2013; Willing et al., 2017) proposed promising decision support systems (DSS) to facilitate the strategic planning for fleet siting and sizing for consolidation (i.e., in already operating cities) and expansion purposes (i.e., business development in new cities). IS are also successfully used in the context of pricing, particularly in the determination of dynamic prices to control demand for vehicles (Brendel et al., 2017). In another line of research, Kahlen, Ketter, and Dalen (2018) reported that fleet operators of shared electric vehicles might form so-called Virtual Power Plants using DSS to address imbalances in the electric grid, a challenge that is becoming increasingly important due to the increasing share of renewable energies. A striking operational challenge for operators is the spatio-temporal imbalance of demand and supply of vehicles, which in turn naturally affects the sustainability of such sharing systems due to inefficient use of scarce resources (Watson, Boudreau, and Chen, 2010). Indeed, network imbalances may occur frequently in free-floating fleets due to the fact that popular vehicle pick-up and drop-off locations often do not coincide (He, Hu, and Zhang, 2020). To cope, several studies suggested to use centrally executed re-positioning systems that leverage historical rental data to form expectations about the supply and demand in the future and hence solve an optimization problem to identify the ideal relocation of vehicles (He, Hu, and Zhang, 2020; Prinz, Lichtenberg, and Willnat, 2020; Willing et al., 2017). Both the described use of IS, be it DSS or re-positioning systems, for overcoming these hurdles, as well as, from a managerial point of view, the decision formation process for a cost effective roll out and operation of FFVS largely rely on the accurate understanding of user behavior (Bichler, Gupta, and Ketter, 2010). Mobility data can help to carry out natural experiments of user preferences and deduct accurate demand models, which was previously only possible, and in that often unsatisfactory, using surveys (Willing, Brandt, and Neumann, 2016). Yet, current research studies on relevant factors for demand estimations in FFVS are inconsistent (i.e., do not cover the variety of available vehicles, specifically novel modes of transportation), over-simplistic (i.e., utilize a limited set of factors) and incomparable (i.e., data are collected from different cities for different modes).

2.2 Determinants of Demand in Free-Floating Vehicle Sharing

Over the last years, many researchers have developed a considerable interest in FFVS due to its striking proliferation across many metropolitan cities (Shaheen and Cohen, 2013). In the following, we provide an exhaustive review of the current body of literature and synoptically emphasize relevant demand factors used in shared mobility, particularly FFVS, research.

There is a remarkable amount of literature on the effect of determinants related to trip comfort on users' mobility demand. Several researchers (Ampudia-Renuncio, Guirao, and Molina-Sanchez, 2018; Guidon et al., 2019) identified that the availability of vehicles in the proximity of users impacts their willingness to commence a rental. In fact, the authors found that users regard shared vehicles only as viable option if they are located within a walking distance of 300 to 500 meters. During the trip, the quality of travel (Van Exel and Rietveld, 2009), the quality of infrastructure (Kain and Fauth, 1978), and the vehicle type play a crucial role in terms of trip comfort (Paundra et al., 2017). Furthermore, to investigate the impact of exogenous factors, Gebhart and Noland (2014) analyzed the effect of meteorological conditions on the demand for shared mobility services and showed that there is a positive correlation between temperature and demand and a negative correlation between precipitation and demand.

Second, prior literature suggests that trip purpose largely explains demand dynamics in FFVS platforms. While vehicles in FFVS are used selectively for a range of activities, shared cars are predominantly rented for commuting, recreational, business, and shopping purposes (Becker, Ciari, and Axhausen, 2017; Ciari, Bock, and Balmer, 2014; Wielinski, Trépanier, and Morency, 2015). Particularly in the absence of a privately owned vehicle, users of FFVS engage in car-sharing services for shopping purposes (Le Vine and Polak, 2019). Similar results emerge for bike-sharing users (Chen et al., 2018; Li et al., 2018). Using big urban data, Willing et al. (2017) employed Point-Of-Interest (POI) data acting as a proxy for trip purposes to understand the effects of different POI on FFVS users. In a similar fashion, Du, Deng, and Liao (2019) showed that free-floating bike-sharing users utilize these services for intermodal mobility. Beyond that, Reiss and Bogenberger (2017) have revealed that temporal aspects (e.g., time of day) are essential to understand demand dynamics.

Finally, the next set of determinants we review pertains to user characteristics as existing studies agree on their paramount importance to explain users' demand in FFVS. In light of this, several researchers found that socio-demographic characteristics of users have an impact on the usage of car-sharing services (Kopp, Gerike, and Axhausen, 2015; Le Vine and Polak, 2019; Müller, Correia, and Bogenberger, 2017) and bike-sharing services (Li et al., 2018). In effect, it has been shown that age (Le Vine and Polak, 2019), income, education, employment status (Kopp, Gerike, and Axhausen, 2015; Li et al., 2018; Müller, Correia, and Bogenberger, 2017), household type (Müller, Correia, and Bogenberger, 2017), and vehicle ownership (Paundra et al., 2017) considerably explain users' demand in FFVS.

2.3 Conceptualization and Hypothesis Development

In light of our research question, the review of the literature revealed several prevalent influences on customers' demand in FFVS platforms. On closer examination, we observe that three dimensions of demand factors surface which we term as a) trip comfort, b) trip purpose and c) user characteristics as depicted in the following Figure 1. Accordingly, we presume that these three dimensions describe demand dynamics to a large extent. In order to investigate the effects of the respective dimensions, we formulate the following hypotheses:

[H1] Hypothesis 1: Trip comfort significantly determines vehicle demand in FFVS platforms.

[H2] Hypothesis 2: Trip purpose significantly determines vehicle demand in FFVS platforms.

[H3] Hypothesis 3: User characteristics significantly determine vehicle demand in FFVS platforms.

Realizing that the demand dimensions in our conceptualization are empirically elusive, we harness several canonical instantiations of each respective dimension (see white rectangles in each dimension in Figure 1). To represent trip comfort, we utilize meteorological conditions, physical activity en route, and the availability of vehicles. Trip purpose is modeled using fine-grained spatial POI data along with temporal features. Finally, we instantiate user characteristics with socio-demographic data.

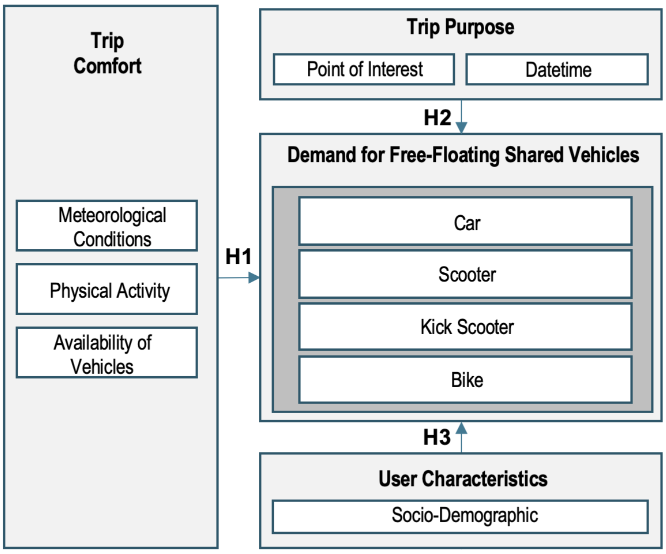

Figure 1. Conceptual Demand Model for Free-Floating Vehicle Sharing

3 Data and Method

3.1 Real-Time Rental Data

Our empirical estimation approach relies on a unique FFVS dataset, which we retrieved in an automated fashion via the application programming interface (API) of ShareNow, Tier, emmy, nextbike, and Call a Bike. We collected trip rental data in five-minute intervals over a period of slightly less than six months, from 01^{th} October 2019 to 20^{th} March 2020 for Berlin, Germany. Our dataset consists of 2,043,909 car trips; 182,325 scooter trips; 401,839 kick scooter trips and 114,040 bike trips. We observed for each trip the origin and destination, start and end date of the trip, and the type of the vehicle. In addition, we also collected information about the availability of vehicles to capture important supply information. Exact routes traveled and possibly selected price tariffs - such as two-hourly or daily tariffs - are not available due to privacy reasons. Apart from rental trip data, we also collected information about socio-demographic data from the Berlin micro census 2018 as well as the most recent German nationwide census from 2011. We harness publicly available weather data in hourly resolution from weather.com and POI data from OpenStreetMap. Furthermore, we utilized the latter to calculate precise routes to obtain information on traveled distance and elevation.

To ensure data quality, multiple data cleansing steps were carried out. First, we removed trip records that started or ended outside the respective service areas in scope. Next, we stripped out rental records that span more than 24 hours or exhibit an idle duration of more than 48 hours. Finally, we excluded data from our dataset if we encountered severe technical issues with the API of the respective FFVS provider. For example, we excluded all rental records for a day and a provider from our dataset if more than 10% of the API requests on that day failed.

3.2 Dependent and Independent Variables

3.2.1 Capturing Demand in Spatio-Temporal Resolution

In close resemblance with the approach of Willing et al. (2017), we employ a dependent variable that acts as a proxy for vehicle demand and measures the total number of trips within a confined area at a given time period. More concretely, we estimate the number of rentals in a discrete region and time period as a function of other contextual demand factors. We then assign the resulting demand score to each trip that was undertaken during that specific time and location. To do so, we discretize the geographic areas of the city in question (i.e., Berlin) using a hexagonal geodesic grid with a hexagon radius of approx. 174m represented by the set $\mathscr{H}$. FFVS literature suggest acceptable walking distances of up to 500m (Ampudia-Renuncio, Guirao, and Molina-Sanchez, 2018; Herrmann, Schulte, and Voß, 2014), which supports this choice. In order to capture the temporal dimension, the times in scope are stratified into six four hour bins. These temporal bins constitute the set Γ. Each spatio-temporal cell is indexed by $(h,\gamma) \in \mathscr{H} \times \Gamma$. We define the spatio-temporal demand for each cell as the expected number of rental starts conditioned on region $h \in \mathscr{H}$ and time $\gamma \in \Gamma$ as $Demand_{(h,\gamma)} := E[T|h,\gamma]$. We choose this particular dependent variable on account of the fact that it preserves as much information as possible. Alternatively, as similarly proposed by Brandt and Dlugosch (2020), we might use the time between rentals, often coined as idle duration, as a proxy for vehicle utilization. However, we argue that idle duration is not capable of capturing demand variations in temporal resolution as it does not account for the number of trips made.

3.2.2 Instantiation of Trip Comfort

In order to empirically validate the impact of trip comfort on demand, we include five related factors. Firstly, we assess the impact of meteorological features such as $Temperature$ and $Precipitation$ on vehicle demand for each respective mode as meteorological conditions have been shown to considerably influence vehicle demand in FFVS networks (Cohen et al., 2016; Hao et al., 2019). Secondly, we survey the impact of expected physical activity. Using the expected traveled elevation change as a proxy for physical activity, we expect to observe a deterrent effect (i.e., demand decreases) once the traveled trip entails considerable ascent (in meters). We term it as $ElevationChange$. Next, we include the availability of vehicles in terms of nearby vehicle supply and overall fleet size. We argue that these information approximate the accessibility to shared vehicles, which has been shown to be an influential determinant by Becker, Ciari, and Axhausen (2017). Thus, incorporating these factors - termed as *LocalSupply* and *GlobalSupply* - enables us to assess the impact of available vehicles on demand.

3.2.3 Instantiation of Trip Purpose

Traditionally, trip purpose has a long history in transportation research (Cools et al., 2010; Li et al., 2013). Following the methodology of Willing et al. (2017), we model trip purpose using temporal (i.e., day of week, time of day) and spatial factors (e.g., POI densities). Evidently, temporal considerations play an essential part in determining the demand for mobility in its entirety (e.g., morning commute to work, evening commute, bar hours), and consequently for FFVS. Spatially, we draw on exhaustive POI data with 16 categories (e.g., education, shops, transport) to capture the numerous amenities of a city. We then calculate for each category a spatial density using kernel density estimation (KDE) (Parzen, 1962). To do so, we first calculate a hexagonal geodesic grid that discretizes the geographic areas of the city (Sahr, White, and Kimerling, 2004). As previously explained, we choose a fine-grained hexagon cell diameter of approximately 0.4km across. Next, we add the POI data and aggregate the occurrences of each POI by category for each hexagon cell. Finally, we assign each cell centroid an Epanechnikov kernel $K(u) = \frac{3}{4}(1-u^2)\mathbb{1}_{|u|\leq 1}$ due to its advantageous statistical properties in terms of efficiency and confinedness (Marron and Nolan, 1988) and opt for a bandwidth of 1000m to account for the linear decreasing influence of POIs. We then calculate the respective kernel density estimates for all 16 POI categories. To exemplify, Figure 2 illustrates our procedure for the category 'transport'.

Armed with these densities, we calculate the probability for each trip in our dataset. In other words, each record now has 16 probabilities assigned reflecting the trip purpose - the higher the probability, the higher the likelihood that trip was undertaken due to the underlying amenity. To allow comparison between POI categories, we normalize the respective probabilities to the range $[0,1]$.

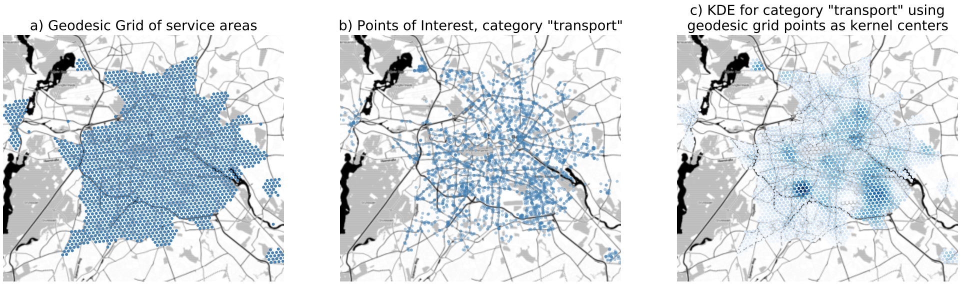

Figure 2. Three-Step Procedure for calculating the Kernel Density Estimate for the POI 'transport'

3.2.4 Instantiation of User Characteristics

Knowledge about the effect of user characteristics on FFVS services largely focuses on car-sharing (Becker, Ciari, and Axhausen, 2017; Brandt and Dlugosch, 2020; Schmöller et al., 2015) and bike-sharing (Chen et al., 2018; Du and Cheng, 2018) provider, but remains silent about other novel modes such as scooters and kick scooters. Realizing that access to user profiles along with rental data poses a significant privacy concern, we harness an alternative approach by using fine-grained socio-demographic data without violating users' confidentiality. In our effort to coherently understand who uses FFVS, we thus need to understand the socio-demographic distribution across the city and what potential relationships emerge between socio-demographic characteristics and FFVS demand for all vehicle types. We therefore introduce three types of socio-demographic factors, namely $Age\ Group$, $Number\ of\ Companies$, $Population\ Type$.

3.3 Demand Estimation using Generalized Linear Models

We now turn our attention to the empirical model to assess the influential demand factors and to validate our proposed conceptional demand framework from Section 2.3. Methodically, we draw on widely-used econometric procedures, namely Generalized Linear Models (GLM) with normally distributed residuals (Nelder and Wedderburn, 1972). In order to investigate how the respective factors influence vehicle demand, we assign each trip i a demand score as suggested in Section 3.2.1. If a factor is a relevant influence on vehicle demand, we expect to identify a statistically significant effect (either negative or positive) on our outcome variable $Demand_{(h,\gamma)} = E[T|h,\gamma]$.

For our empirical research model, we parameterize the GLM as follows

$$log(E[T|h,\gamma]+1) = \beta_0 + \beta_1 P + \beta_2 U + \beta_3 C + \varepsilon. \quad (1)$$

The demand-related factors for trip purpose, user characteristics, and comfort are captured by the vectors P, U, C, respectively. The error term is given by ε. Since the regression is specified in terms of a log-linear relationship, the regression coefficients β can be approximately interpreted as the percentage change in $Demand_{(h,\gamma)}$ for a one unit change in the respective control variable. Also, as the log of 0 is not defined, we add a value of 1 on the left-hand side of Equation 1.

4 Results

4.1 Descriptive Analysis

We begin by exploring the summary statistics for each transportation mode, then turn our attention to survey rental demand patterns in spatio-temporal resolution using explorative data analytics. Exhaustive summary statistics of our dataset for cars, scooters, kick scooters, and bikes are presented in Table 1. Several interesting patterns emerge. We clearly notice that the fleet size varies considerably between providers. We also observe that the idle duration for cars is strikingly low compared to other means of transport indicating that the overall demand for car-sharing is higher. Interestingly, the summary statistics reveal that kick scooters are predominantly used for very short distances (~1km) compared to bikes (~2km), scooters (~2.8km) and cars (~4.4km). Also, we observe that kick-scooters are rented for a very short period of time compared to other vehicle types. This is an indication that kick scooters are used more as a substitute for walking. Unlike the other transportation modes, it is also apparent that cars are on average more often rented further away (~5km) from the city center. Expectantly, highly motorized vehicles are the preferred mode of transport for routes where increased physical activity is anticipated (i.e., elevation change). With respect to temporal aspects, we observe that the rental density for all types of vehicles peaks during the evening hours and that the rental densities are evenly distributed over the days of the week. Next, it can be seen that users of uncovered vehicles (i.e., scooters, kick scooters, and bikes) are also more susceptible to meteorological conditions. Surprisingly, the last rows reveal that, on average, users of FFVS can theoretically - provided they are registered customers of the respective provider - choose between any mode of transport that best meets their needs due to the high availability of alternatives.

	Cars	Scooters	Kick Scooters	Bikes
Observations	2,043,908	182,325	401,839	114,030
Fleet size (#Vehicle)	2,182	461	1,333	1,351
Expected idle time (in minutes)	187	406	443	810
Expected trip duration (in minutes)	47	32	17	26
Expected distance (in km)	4.44	2.78	0.98	2.11
Expected distance to center at start (in km)	4.90	3.68	3.46	3.25
Expected elevation change (in m)	0.04	-0.02	-0.06	-0.17
Time Bucket				
00:00-03:59	5%	5%	8%	11%
04:00-07:59	8%	4%	8%	3%
08:00-11:59	19%	20%	17%	22%
12:00-15:59	22%	24%	24%	22%
16:00-19:59	28%	31%	25%	27%
20:00-23:59	18%	17%	18%	15%
Day of Week				
Monday	13%	13%	13%	14%
Tuesday	13%	14%	14%	15%
Wednesday	14%	14%	14%	15%
Thursday	14%	15%	15%	16%
Friday	16%	16%	15%	16%
Saturday	16%	15%	16%	13%
Sunday	14%	12%	13%	12%
Temperature Bucket				
below 0°C	3%	2%	3%	2%
0-5°C	34%	28%	28%	27%
5-10°C	44%	43%	41%	38%
10-15°C	14%	18%	18%	19%
15-20°C	5%	9%	8%	11%
above 20°C	1%	1%	1%	2%
Precipitation	16%	11%	12%	10%
Expected outside supply of vehicles				
Trip started with a bike	1.00	0.41	2.14	4.03
Trip started with a car	1.49	0.36	1.16	1.79
Trip started with a kick scooter	1.02	0.49	5.08	3.80
Trip started with a scooter	1.04	0.53	1.71	2.66

Table 1. Summary Statistics of Free-Floating Shared Car (ShareNow), Scooter (emio), Kick Scooter (Tier) and Bike (nextbike&Call a Bike) Rental Trips from Berlin

To analyze spatial demand dynamics, we harness again spatial KDE to calculate two-dimensional rental densities as depicted in Figure 3. We observe that various rental pattern - particularly hotspots - between transportation modes surface. The rental densities for cars are more evenly distributed across the city. Spatially, the demand for scooters and bikes exhibit the same pattern, yet with a slightly higher demand for bikes towards the city center. Compared to the other modes, the demand for kick scooters is concentrated on a compact geographical area close to the city center of Berlin. Evidently, the rental density of each mode are partly confined by the underlying service areas. However, the service areas of scooters, kick scooters and bikes don't display chief differences while the service area of cars (ShareNow) is substantially more spacious.

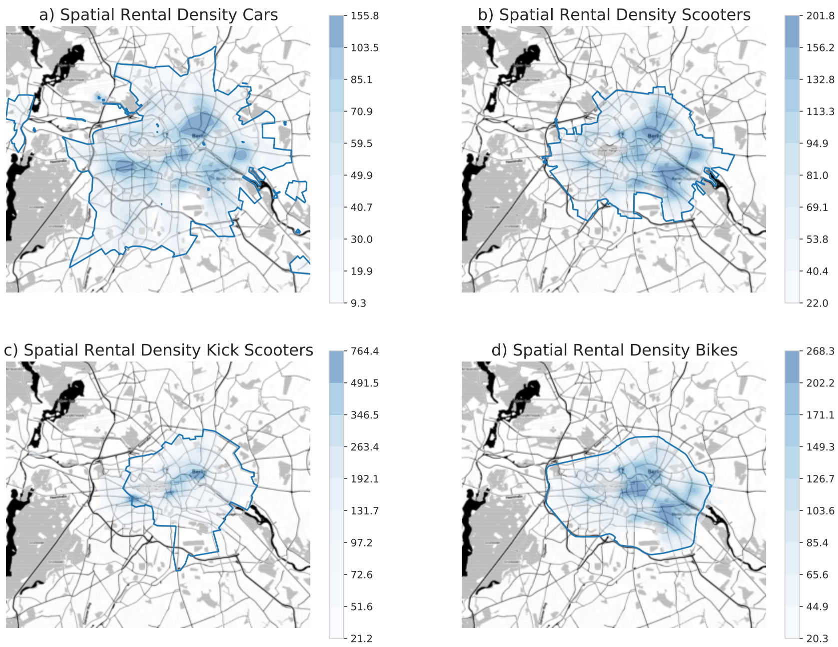

Figure 3. Spatial Demand Densities for a) Cars, b) Scooters, c) Kick Scooters, and d) Bikes in Berlin using Kernel Density Estimation. Services Areas are denoted by Continuous Lines.

4.2 The Effect of Trip Comfort on Demand

We now lay out the results of our regression analysis to uncover influential demand factors and shed light on the validity of the proposed conceptual demand model for FFVS from Section 2.3. To do so, we examine the influence of the factors from the respective dimensions (i.e., trip comfort, trip purpose, and user characteristics) sequentially by splitting the result tables accordingly. Note that we estimated one regression model for each transportation mode in question, albeit - due to the sake of clarity - we present the results in multiple tables. We begin with the effect of trip comfort on demand in FFVS, then proceed with trip purpose and finally examine the relationship between user characteristics and demand.

In Table 2 we examine the effect of trip comfort factors on demand. $Temperature$ has a positive effect on vehicle demand (i.e., trips) for all means of transport ranging from 0.4% for cars (Column (1)) to 1.4% for scooters (Column (2)). On the other side, $Precipitation$ leads to a reduction of demand, particularly for uncovered vehicles resulting in approximately -2% less trips (Columns (2)-(4)). Considering $LocalSupply$, an increased availability of vehicles of the same provider positively moderates the demand in that area for all modes, with up to 8.3% increase per each additional available car (Column (1)). Equally, $GlobalSupply$, which represents the fleet size per 100 vehicles, also positively influences demand up to 3% for bikes (Column (4)). To put simply, 100 more bikes on the road lead, on average, to 3% more bike trips. $GlobalSupply$ for scooters, in contrast, exhibit surprisingly a negative influence when the fleet size is expanded (-10%, Column (2)). Lastly, we observe users' aversion to physical activity and hence presumably prefer less physically demanding means of transport for certain routes. For example, for each anticipated $ElevationChange$ of one meter, the demand for bikes (Column (4)) decreases by 0.3%.

4.3 The Effect of Trip Purpose on Demand

We next consider Table 3 to understand the impact of POI clusters (i.e., a realization of trip purpose) on users' demand in FFVS. Most interestingly, we see significant evidence that shared vehicles are strikingly utilized in the vicinity of $Transportation$ facilities, particularly kick scooters with up to 66% demand

	$ln(Demand+1)$			
	Car	Scooter	Kick Scooter	Bike
	(1)	(2)	(3)	(4)
Meteorological Conditions				
Temperature	0.004^{***}	0.014^{***}	0.009^{***}	0.007^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation	-0.004^{***}	-0.022^{***}	-0.026^{***}	-0.022^{***}
	(0.001)	(0.004)	(0.003)	(0.005)
Vehicle Availability				
LocalSupply	0.083^{***}	0.076^{***}	0.042^{***}	0.064^{***}
	(0.000)	(0.001)	(0.000)	(0.001)
GlobalSupply	0.029^{***}	-0.123^{***}	0.011^{***}	0.030^{***}
	(0.000)	(0.002)	(0.000)	(0.001)
Physical Activity				
ElevationChange	-0.000	-0.002^{***}	-0.004^{***}	-0.003^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-0.115^{***}	1.109^{***}	1.311^{***}	0.092^{***}
	(0.006)	(0.021)	(0.019)	(0.026)
R^2	52%	40%	45%	44%

Notes: Standard errors in parentheses, $^{*}p < 0.1$; $^{**}p < 0.5$; $^{***}p < 0.01$

Table 2. The Effect of Trip Comfort Factors on Vehicle Demand for (1) Cars, (2) Scooters, (3) Kick Scooters, and (4) Bikes in Berlin

surges at transportation hotspots (Column (3)) and bikes (53%, Column (3)) indicating that the transition towards intermodal mobility is set in motion. Furthermore, we find that vehicle demand in the vicinity of *Sustenance* amenities exhibits the largest overall positive influence for all four modes of rental vehicles (Column (1)-(4)). For kick scooters, we additionally observe a negative influence on demand (-2.6%) in the vicinity of *PublicPlaces*, which can be explained by recently enacted no-parking policies (i.e., zone restrictions) for kick scooter providers to prevent clutter in highly frequented pedestrian precincts. To keep it succinct: All four modes evince increased demand in close proximity to *Accomodation*, *Financial*, *Natural*, *Sustenance*, *Tourism* and *Transport*. In contrast, *Animals*, *Culture*, surprisingly *Education*, *Facilities*, *Leisure*, and *Service* have a predominantly negative effect on demand for all modes. We refer the reader to the official documentation of OpenStreetMap for a detailed and exhaustive description of POI categories (OpenStreetMap, 2020).

Next, we review temporal effects on demand in FFVS by focusing on Table 4. Temporal factors are captured by means of two dichotomous indicator variables (i.e., day of week, time of day) indicating on which weekday and at what time a trip was made. Hence, we use $0am-4am$ and *Monday* as our baseline specification for time of day and day of week variables, respectively. During business days, we observe a peak influence on *Friday* of 8% for cars and scooters (Column (1)-(2)), and approximately 5% for kick scooters and bikes. Yet, *Saturday* exhibits the highest overall influence on demand ranging from 9.9% (Column (1)) to 14.7% (Column (4)). In terms of the time of day, we find that the evening commuting hours (i.e., $4pm-8pm$) have the most pronounced impact on rental demand in FFVS, irrespective of the mode of transportation.

4.4 The Effect of User Characteristics on Demand

Table 5 reports the resulting effects of user characteristics on vehicle demand in FFVS. First, we investigate the effect of *Number of Companies* and *Population Type* (per 1000 units) harnessing micro census data on district-level in Berlin from 2018. In fact, we argue that *Number of Companies* can be interpreted as an indicator for the number of employees in a specific location throughout business working hours. We notice a positive influence of *Number of Companies* on rental demand for cars (0.6%, Column (1)), for scooters (1.4%, Column (2)) and for bikes (1.4%, Column (4)). Notably, we also unveil that the type of population impacts the usage of modes in FFVS. For example, we see that the more students live in

	$ln(Demand+1)$			
	Car	Scooter	Kick Scooter	Bike
	(1)	(2)	(3)	(4)
Accomodation	0.447*** (0.004)	0.412*** (0.014)	0.224*** (0.010)	0.331*** (0.018)
Animals	−0.093*** (0.002)	−0.184*** (0.009)	−0.165*** (0.009)	−0.260*** (0.014)
Culture	−0.094*** (0.004)	−0.044*** (0.012)	−0.085*** (0.009)	−0.026 (0.016)
Education	−0.054*** (0.003)	0.031*** (0.012)	−0.267*** (0.011)	−0.027* (0.016)
Facilities	−0.087*** (0.003)	−0.094*** (0.010)	0.065*** (0.008)	0.036*** (0.014)
Financial	0.271*** (0.004)	0.376*** (0.012)	0.287*** (0.010)	0.276*** (0.016)
HealthCare	−0.000 (0.004)	0.003 (0.016)	0.228*** (0.019)	0.002 (0.027)
Historic	0.085*** (0.002)	0.078*** (0.009)	−0.030*** (0.008)	0.021* (0.012)
Leisure	−0.179*** (0.006)	−0.870*** (0.028)	−0.644*** (0.022)	−0.677*** (0.037)
⋮	⋮	⋮	⋮	⋮
Natural	0.021*** (0.004)	0.284*** (0.014)	0.129*** (0.008)	0.236*** (0.015)
PublicPlaces	0.013*** (0.002)	0.112*** (0.009)	−0.026*** (0.007)	0.022** (0.011)
Service	−0.640*** (0.005)	−0.695*** (0.019)	−0.480*** (0.015)	−0.582*** (0.027)
Shops	0.127*** (0.005)	0.198*** (0.017)	−0.016 (0.013)	0.293*** (0.022)
Sustenance	0.789*** (0.005)	0.631*** (0.017)	0.611*** (0.015)	0.446*** (0.024)
Tourism	0.297*** (0.003)	0.263*** (0.011)	0.060*** (0.007)	0.139*** (0.014)
Transport	0.307*** (0.004)	0.471*** (0.014)	0.657*** (0.012)	0.525*** (0.019)
Constant	−0.115*** (0.006)	1.109*** (0.021)	1.311*** (0.019)	0.092*** (0.026)
R^2	52%	40%	45%	44%

Notes: Standard errors in parentheses, $^{*}p < 0.1$; $^{**}p < 0.5$; $^{***}p < 0.01$

Table 3. The Effect of Point-Of-Interest Factors (Trip Purpose) on Vehicle Demand for (1) Cars, (2) Scooters, (3) Kick Scooters, and (4) Bikes in Berlin

an area, the more kick scooters are utilized for mobility purposes (2%, Column (3)). A comparable but attenuated result emerges for the alternative modes (Column (1), (2), (4)). The number of *Employed* residents have a negative yet negligible effect on demand for all vehicle types, and could be explained by the access to and the ownership of private vehicles. In addition, the results indicate that lower-income residents (*Unemployed*) tend to be more reluctant to use kick scooters (−6.5%, Column (3)) and bikes (−1.3%, Column (4)).

Second, we examine the effect of *Population Age* on vehicle demand using high-resolution spatial census data ($100m^2$ cells), where the unit of analysis is per capita. The first thing we realize is that the number of young adults ($18y-29y$) has no noticeable influence, albeit being significant and negative, on vehicle

	$ln(Demand+1)$			
	Car	Scooter	Kick Scooter	Bike
	(1)	(2)	(3)	(4)
Day Of Week				
Tuesday	0.026*** (0.001)	0.034*** (0.004)	0.012*** (0.003)	−0.015*** (0.006)
Wednesday	0.031*** (0.001)	0.036*** (0.004)	−0.006* (0.003)	−0.003 (0.006)
Thursday	0.041*** (0.001)	0.051*** (0.004)	0.016*** (0.003)	0.003 (0.006)
Friday	0.081*** (0.001)	0.080*** (0.004)	0.049*** (0.003)	0.051*** (0.006)
Saturday	0.099*** (0.001)	0.135*** (0.004)	0.103*** (0.003)	0.147*** (0.006)
Sunday	0.014*** (0.001)	0.066*** (0.005)	0.023*** (0.003)	0.109*** (0.006)
⋮	⋮	⋮	⋮	⋮
Time of Day				
$4am-8am$	0.037*** (0.002)	0.020*** (0.008)	0.077*** (0.004)	0.041*** (0.009)
$8am-12pm$	0.360*** (0.002)	0.387*** (0.006)	0.353*** (0.004)	0.525*** (0.006)
$12pm-4pm$	0.453*** (0.002)	0.476*** (0.006)	0.529*** (0.004)	0.611*** (0.006)
$4pm-8pm$	0.599*** (0.001)	0.650*** (0.006)	0.653*** (0.004)	0.788*** (0.006)
$8pm-12am$	0.381*** (0.002)	0.452*** (0.006)	0.412*** (0.004)	0.532*** (0.006)
Constant	−0.115*** (0.006)	1.109*** (0.021)	1.311*** (0.019)	0.092*** (0.026)
R^2	52%	40%	45%	44%

Notes: Standard errors in parentheses, $^{*}p < 0.1$; $^{**}p < 0.5$; $^{***}p < 0.01$

Table 4. The Effect of Temporal Factors (Trip Purpose) on Vehicle Demand for (1) Cars, (2) Scooters, (3) Kick Scooters, and (4) Bikes in Berlin

	$ln(Demand+1)$			
	Car	Scooter	Kick Scooter	Bike
	(1)	(2)	(3)	(4)
Number of Companies	0.006^{***} (0.000)	0.014^{***} (0.000)	0.000 (0.000)	0.015^{***} (0.001)
Population Type				
Students	0.005^{***} (0.000)	0.010^{***} (0.001)	0.020^{***} (0.001)	0.007^{***} (0.001)
Employed	-0.001^{***} (0.000)	-0.001^{***} (0.000)	-0.003^{***} (0.000)	-0.001^{***} (0.000)
Unemployed	-0.006^{***} (0.000)	-0.008^{***} (0.001)	-0.065^{***} (0.002)	-0.013^{***} (0.002)
Immigrant	-0.000^{***} (0.000)	-0.002^{***} (0.000)	0.001^{***} (0.000)	-0.001^{***} (0.000)
⋮	⋮	⋮	⋮	⋮
Population Age				
$18y-29y$	-0.001^{***} (0.000)	-0.000^{***} (0.000)	-0.000^{***} (0.000)	-0.000^{***} (0.000)
$30y-49y$	0.001^{***} (0.000)	0.001^{***} (0.000)	0.000^{***} (0.000)	0.001^{***} (0.000)
$50y-64y$	-0.001^{***} (0.000)	-0.002^{***} (0.000)	-0.001^{***} (0.000)	-0.001^{***} (0.000)
Constant	-0.115^{***} (0.006)	1.109^{***} (0.021)	1.311^{***} (0.019)	0.092^{***} (0.026)
R^2	52%	40%	45%	44%

Notes: Standard errors in parentheses, $^{*}p<0.1$; $^{**}p<0.5$; $^{***}p<0.01$

Table 5. The Effect of User Characteristic Factors on Vehicle Demand for (1) Cars, (2) Scooters, (3) Kick Scooters, and (4) Bikes in Berlin

demand, which can be explained by the fact that age specification in this sub-population is not sufficiently explanatory. Next, we find that among adults aged $30y-49y$ there is a noticeable increase in demand by 0.1% for cars, scooters, and bikes (Column (1), (2), (4)) per capita. The results also demonstrate that the more older residents ($50y-64y$) reside within an urban region, the more the demand for vehicles diminishes, in fact by -0.1% for cars, kick scooters, and bikes (Column (1), (3), (4)), and by -0.2% for scooters (Column (2)). Finally, we recapitulate the empirical evidence just reviewed and conclude that we cannot reject the three hypotheses proposed in Section 2.3. Indeed, the dimensions trip comfort (**H1**), trip purpose (**H2**), and user characteristics (**H3**) embodied by their respective canonical instantiations significantly explain and determine vehicle demand in FFVS. This is strengthened by the fact that our empirical models exhibit a considerable explanatory power with R^2 values between 40% and 52%.

5 Conclusion

In this study, we reveal and quantify relevant demand factors for the predominant transport means in FFVS platforms. In order to do so, we first review the current body of knowledge on relevant demand factors, second form three hypotheses stemming from our proposed conceptualization, and third set up an experimental model to investigate the effect of numerous factors on vehicle demand. To empirically quantify, we leverage econometric modeling (i.e., GLM) along with a unique dataset with more than 2.7 million trip records for cars (ShareNow), scooters (emio), electric kick scooters (Tier), and bikes (nextbike & Call a Bike). To answer our core research question, we examine three hypotheses by shedding light on the effect of a) trip comfort, b) trip purpose, and c) user characteristics on demand.

We provide strong evidence that demand in FFVS platforms can largely be explained by the latent dimensions of trip comfort, trip purpose, and user characteristics and their respective operational instantiations. In line with hypothesis **H1**, our experiments corroborate with previous results in the context of ride-hailing networks (Babar and Burtch, 2020) showing that unfavorable meteorological conditions detrimentally effect demand, considerably for uncovered vehicle modes. Further, we identified that shared vehicle operators can adjust the number of available vehicles for demand management. This confirms recent findings in the literature by Benjaafar and Hu (2020). Next, we observe with respect to hypothesis **H2** that trip purpose realized in form of POI data and temporal aspects explains to a large extent demand dynamics, confirming largely the findings of (Willing et al., 2017). Importantly, we observe that kick scooters and bikes are commonly rented in the vicinity of public transportation facilities lending strong support that these modes are utilized for intermodal mobility (e.g., Willing, Brandt, and Neumann, 2017). Incidentally, the broadly circulated anecdotal evidence primarily claimed by newspapers that kick scooters are mainly used by tourist (i.e., in the vicinity of touristic amenities) for hedonistic purposes (Buckley, 2019) could not be confirmed by our analysis. Lastly, we demonstrate that user characteristics are of significant importance as well and hence we cannot reject hypothesis **H3**. Indeed, we found that the more students reside within an area the more demand for FFVS is generated, particularly for kick scooters. This indicates that well educated young adults are more open to novel mobility services and may even forego vehicle ownership concurring with the findings of Belgiawan et al. (2014) and Paundra et al. (2017).

Our study has several implications for managers and researchers alike to understand the relevant demand factors for predominant means of transport in FFVS. This research demonstrates that kick scooters and bikes are most probably used for intermodal trip planning. From a managerial perspective, operators of FFVS platforms and municipalities should seek to form cooperation agreements (e.g., enable reciprocal access to the API, development of a joint mobile app) to offer seamless mobility services to improve trip planning and payment processing. In order to make intermodal mobility fully operational, designated service areas in the vicinity of mass transit stations (i.e., bus or rail) in suburban areas should be promoted. We have also noticed that specific types of vehicles are more demanded in the proximity of certain POI's (e.g., cars nearby sustenance amenities), indicating that users prefer to choose the vehicle according to their individual needs. That said, FFVS operators should seek to extend their currently homogeneous vehicle fleet into a more needs-oriented vehicle fleet by integrating different types of vehicles (i.e., multimodal fleets). Scientifically, our present findings have important implications for designing and solving IS artifacts (Hevner et al., 2004) for FFVS networks and more generally in urban mobility research. Specifically, our comprehensive results for different types of vehicles can be harnessed to build IS artifacts to manage oversupply and undersupply regimes (Ketter et al., 2012) in shared mobility or to design complex and interwoven simulations to cope with wicked problems such as urban mobility (Ketter et al., 2016; W. Axhausen, Horni, and Nagel, 2016). Lastly, from a theoretical lens, our conceptual model along with the empirical evidence contributes to a deeper understanding of configurations of socio-technical systems (Bostrom and Heinen, 1977; Leavitt, 1965). Indeed, urban mobility systems constitute a socio-technical system whose configuration depends on different constituents such as the available vehicles, the mobility infrastructure and, the user behavior (Canitez, 2019). With our findings, we particularly enhance the understanding of the latter.

We are aware that our research may have three limitations. Firstly, we collected rental trip data for only six months from October 2019 until March 2020 preventing us from obtaining insights on demand factors during the summer months. Secondly, we lack access to user data for privacy reasons, which is why we have used an approximation based on socio-demographic data. Yet, we realize that this data source is most likely not sufficiently specific and detailed enough. Finally, the service areas of the respective mobility providers don't fully coincide, which could hamper the comparability of POI effects between modes.

Our study has raised up many questions in need of further research. Further investigations may consider evaluating additional factors that may also impact demand such as land use data or more specific user data, and may quantify the importance of each factor. In order to augment our analysis, more experimental studies are too needed to validate the consistency of our results across different cities. Finally, we propose that future research should be undertaken in the domain of mode choice behavior in FFVS to acquire profound knowledge about users' preferences for different vehicle modes.

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