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Sustainability vs. Price: Analysis of Electric Multi-Modal Vehicle Sharing Systems under Substitution Effects

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SUSTAINABILITY VS. PRICE: ANALYSIS OF ELECTRIC MULTI-MODAL VEHICLE SHARING SYSTEMS UNDER SUBSTITUTION EFFECTS

Research Paper

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Abstract

To pave the path for sustainable mobility, Information Systems are a promising tool to encourage users to adopt more sustainable mobility behavior. In this study, we investigate how potential demand management interventions affect the economic and environmental metrics of a multi-modal vehicle sharing operator. To this end, we narrow our focus on two important user characteristics, namely the users' flexibility and willingness to pay an additional premium for more environmentally sustainable vehicles. Our study employs a combined discrete-event and multi-agent simulation approach, which we calibrate with real-world rental data of leading free-floating vehicle sharing platforms. The results show that it is economically and ecologically disadvantageous for both the society and the fleet operator to simply increase users' mode choice flexibility. However, we clearly observe that this picture flips once users are willing to pay a surcharge to rent more environmentally sustainable vehicles.

Keywords: multi-modal mobility, sustainable mobility, agent-based simulation, sharing economy

1 Introduction

Mobility is the backbone of modern societies, ensuring social and economic welfare, but it is still far from being sustainable. In 2016, the transportation sector was one of the biggest polluters accounting for 27% of greenhouse gas emissions in Europe (European Environment Agency, 2018). In addition, cars stuck in traffic jams are not only inefficient and misused to some extent, but also produce up to 80% more greenhouse gas emissions compared to free traffic conditions (Treiber, Kesting, and Thiemann, 2008). Thus, stressed motorists and more severe health complications are the consequences of congested roads (Currie and Walker, 2011). In a recent report, the World Economic Forum has proposed introducing and implementing actual cost pricing mechanisms in urban cities to manage mobility demand by using pricing information that factor in the externalities incurred by a trip (Eckhard et al., 2021). London, for example, has already successfully introduced a precursor to this concept in the form of congestion pricing (Leape, 2006). In this context, shared mobility services might play a pivotal role in urban mobility systems as these business models pass on the marginal cost of a trip to users.

Free-Floating Vehicle Sharing (FFVS) platforms are a promising instantiation of the aforementioned shared mobility services and are poised to become an integral part of future urban mobility networks. They offer the platform-based rental of vehicles with the prospect of increasing vehicles utilization. Users can typically pick up and drop off vehicles anywhere within a confined operating area. The entire rental process, from searching to renting to payment, is handled via an app. Information Systems (IS) have a crucial role in the success of such platforms as, on the one hand, they enable the access of users to vehicles to fulfill their mobility tasks, and on the other hand, they support platform managers in strategical, tactical, and operational challenges (Brendel et al., 2017; Lu, Chen, and Shen, 2018; Willing et al., 2017). Presently, we observe that several FFVS operators have extended their vehicle fleet by adding more differentiated vehicle types in order to cater to their users' individual trip needs, signifying the role of IS in the success of such businesses. For example, Tier[1] started their offering with electric kick scooters and now also offers electric scooters.

From an economic and an environmental perspective, it is naturally attractive for the fleet operator to understand how she can selectively steer the demand for particular types of vehicles to achieve an overarching target (e.g., sustainability or profit-maximization). Current Green IS research shows that IS can be utilized in a targeted manner to introduce more environmentally sustainable business practices (Seidel, Recker, and Brocke, 2013). Similarly, FFVS platform operators can apply IS-based mechanisms to appropriately steer users' vehicle choices, for example, by presenting the environmental impact of each vehicle mode. However, current research offers little evidence on the degree of effectiveness of such demand management mechanisms for nascent multi-modal FFVS platforms. In this study, we adopt the perspective of such a multi-modal vehicle sharing fleet operator that offers incumbent shared electric vehicles for rental, namely electric kick scooters, scooters, and cars[2]. To ensure comparability, we exclude bikes from this study, given that they require physical activity, even if they have an assisting electric motor. Our overall objective is to explore whether it is economically and environmentally worthwhile to integrate IS-enabled behavioral interventions to manage users' mobility demand. Specifically, the impact of interventions on two user characteristics is interesting to investigate. First, Reck et al. (2021) reveal that users' mode choice behavior in vehicle sharing platforms is mainly dominated by the distance to be covered. However, the results also indicate that users may switch to other types of vehicles for certain distances. Hence, we examine how users' flexibility to substitute a vehicle impact economic and environmental measures. Second, transportation literature reveals that environmentally-friendly users are willing to pay a premium to use more sustainable means of transportation (Gaker et al., 2011). Due to the upcoming changes in the urban mobility sector and the associated efforts to make that sector more sustainable, it is both academically and practically important to identify, examine, and quantify potentially relevant factors for the transformation process of urban mobility. Thus, exploring how varying proportions of environmentally-friendly users in the population impact fleet performance is also engaging. Formally, we seek to answer the following research question: *How and to what extent do user characteristics (i.e., willingness to switch means of transportation and to pay a premium for greener alternatives) impact the economic and environmental metrics of a multi-modal FFVS operator?*

To answer this question, we draw on discrete-event and agent-based simulation techniques due to the prevailing complexity of urban mobility systems and their non-linear relationships (e.g., Ketter et al., 2016; W. Axhausen, Horni, and Nagel, 2016). We calibrate the simulation environment using a unique observational dataset of rental transactions for shared kick scooters, scooters, and cars that we have collected over a period of six months in Berlin, Germany. Precisely, to realistically predict users' mode choice behavior, we estimate a multinomial logistic regression model.

Our contributions are twofold. First, we conceptualize and set up a multi-modal mobility simulation in the realm of FFVS to provide a grounded basis to examine interventions in a highly complex and interwoven socio-technical system. Second, we examine and quantify to what degree potential demand-side management mechanisms through Green IS initiatives influence the profitability and environmental footprint of FFVS operators.

[1] https://www.tier.app/de/

[2] The difference between electric kick scooters and scooters is that in the former the driver has to remain to stand and in the latter she has to sit down. Also, electric scooters drive substantially faster than electric kick scooters and are therefore subject to mandatory helmet usage regulations in many cities.

We proceed as follows. We begin by positioning our work in the realm of Green IS and Shared Mobility and provide a review of the pertaining literature. Next, we explain our discrete-event and agent-based simulation model from the perspective of a user (demand-side) and an operator (supply-side). We then present our simulation results and conclude by discussing the implications and limitations of this work.

2 Background and Related Work

Our work is generally positioned in Green IS (Brocke et al., 2013) and in the intersection with sustainable mobility (Brendel and Mandrella, 2016). Particularly, this study uses methods grounded in IS (e.g., Ketter et al., 2016) to understand and analyze the impact of vehicle sharing user preferences and how potential intervention strategies might lead to more sustainable mobility behavior. Therefore, we review the literature on Green IS and its applications on sustainable mobility systems where IS-enabled methods can support the better organizational performance of such systems. Also, we present the background of FFVS systems to explain in detail how we make the core assumptions of our model for simulating the traffic environment and user behavior, and clarify our contribution to bridging the current gap.

2.1 Green IS and Intersections with Sustainable Mobility Systems

Over the past few decades, the IS community has studied how to improve the efficiency and productivity of a wide variety of organizations (Hitt and Brynjolfsson, 1996). In light of rising climate change concerns, environmental sustainability has gained great attraction in different fields, including IS. The study of IS for environmental sustainability comprises two research directions: Green IS and Green IT (Brocke et al., 2013; Dedrick, 2010). As the largest stream, Green IS (also covering our study) refers to the studies investing in designing and implementing IS to improve environmental sustainability (Malhotra, Melville, and Watson, 2013). Nevertheless, Bjorn-Andersen et al. (2016) highlight a lack of actionable and impactful IS solutions to tackle the coming environmental challenges at global scale.

The transportation system, as one of the main contributors to climate change, is an interesting domain for Green IS researchers to employ IS as an enabler for green and sustainable mobility systems (Hildebrandt et al., 2015). Kang et al. (2020) have already shown how technological factors of IT-enabled service systems can affect the service performance in a changing ecosystem such as ride-hailing services. Electromobility and the associated charging challenges are one of the main areas in mobility research that attracts IS scholars to pave the path toward a mass adoption of electric vehicles (EVs) by providing business models to integrate with the energy sector (Brandt, Wagner, and Neumann, 2012), developing charging network to provide distributed non-home charging opportunities (Ahadi et al., 2021), and designing pricing mechanisms to avoid additional loads from EVs (Valogianni et al., 2020). In the same direction Hanelt, Busse, and Kolbe (2017) show that in addition to supporting green technologies such as EVs, IS can improve the organisational performance of eco-innovations to support the business transformation toward sustainability. An example in the mobility domain is the application of IS in shared mobility services, where IS has the potential to exploit the sustainable impacts of such services by supporting digitalization (e.g., booking or paying) and decision-making problems from the fleet operators' perspective (e.g., fleet and infrastructure development and fleet operating). This is also true for ride-hailing services in which the support side (drivers) also can benefit from IS. Using discrete choice experiments, Hong et al. (2020) show how influencing factors such as ensuring wage and information security encourage drivers to sacrifice their flexibility by committing minimum working hours, which is also varied among different driver populations.

Green IS has also been embraced by the design science (DS) community (Rai, 2017). DS researchers have brought forward numerous concrete and actionable IS artifacts targeted at solving pressing sustainability issues. For example, Willing et al. (2017) propose a decision support system (DSS) to address service region design and fleet sizing problems of shared cars, Brendel et al. (2017) compute carsharing pricing areas and analyze its effect on spatial vehicles availability, and He, Hu, and Zhang (2020) and Kahlen et al. (2017) provide models that avoid unbalanced networks by making appropriate repositioning and recharging decisions. Additionally, a crucial requirement of using IS as a DSS to improve the system performance is having an accurate understanding of users' preferences (Bichler, Gupta, and Ketter, 2010). As shown by Willing, Brandt, and Neumann (2017), rental transaction data are a particularly valuable asset in successfully modeling user behavior. Having access to big historical trip data of shared vehicles allows the researchers to describe the mobility demand and trip patterns more accurately, which is a core input for our model in this study to approximate the demand for shared vehicles in urban areas.

Apart from designing DSS, many researchers advocate that IS can reduce the adverse environmental effects of unsustainable behaviors (Elliot, 2011; Melville, 2010). The Energy Informatics discipline is a well-known example that investigates the development of IS to improve the energy consumption behavior of business and private users. In this direction, Oppong-Tawiah et al. (2014) combine design science and experimental approaches to study the use of mobile applications encouraging pro-environmental behaviors by reporting their energy usage patterns in a working place. Also, Loock, Staake, and Thiesse (2013) simulate the energy-efficient behavior of private consumers and show that a proper feedback system can significantly affect energy conservation in private households. A few recent papers also contribute to encouraging more environmental modes of mobility by developing intervention strategies. Flüchter and Wortmann (2014) investigate the impact of an IS-enabled social normative feedback intervention on the intrinsic motivation of participants of an e-bike commuting competition. Diederich et al. (2019) design an artifact to steer users to more sustainable mobility behavior and show that a persuasive and human-like design of the communicating agent with users could positively impact using more sustainable types of vehicles. However, to the best of our knowledge, there is no specific Green IS discipline and not many related works studying interventions on users' mobility behavior and the resulting impacts on environmental sustainability.

2.2 Free-Floating Vehicle Sharing Systems

Among the numerous shared mobility services, FFVS enjoys a lot of popularity as it offers nearly the flexibility of owning a private vehicle while circumventing high acquisition costs. Users typically use an app to find a vehicle nearby, pick it up and drop it off anywhere within a predefined service area. While all sustainable benefits such as reducing private car ownership, FFVS might also have a negative side. As an example, Becker, Ciari, and Axhausen (2017b) show that most of the free-floating carsharing trips are on routes that are connected using public transportation, which might be interpreted as negative impact on public transportation usage. Also, Luo et al. (2021) conclude similar results for e-scooter trips; in other words, they claim that e-scooters might compete with bus systems while replacing riding and walking trips that can negatively affect users health (Thoreau, 2015). Admittedly, their results are not generalizable, but their study rings a bell to pay more attention to FFVS fleet management to avoid such negative impacts. This idea could even gain more importance when a combination of different FFVS modes is offered. To date, most of the providers have been offering a homogeneous fleet with individual vehicle types such as cars, scooters, electric kick scooters, and bikes. Recently, novel companies (e.g., Go, Tier, and Lime) have entered the smart mobility market, providing numerous vehicle types in a joint platform.

Due to their flexible nature, a key aspect of (multi-modal) FFVS platforms is understanding users' behavior. Researchers show that the rental patterns of shared vehicles vary among different modes, where contextual factors, including purpose, time, and location, play a significant role. For example, using spatial demand description Li et al. (2018) and Reck et al. (2021) show that shared vehicles are primarily utilised close to the city center and particular Point-of-Interests. Also, using time-series and temporal analysis, researchers demonstrate that except holidays, most of the rentals occur during peak hours while there is daily and monthly seasonality (Ciari, Bock, and Balmer, 2014; Du and Cheng, 2018). For more details, we refer readers to the work of Liao and Correia (2020).

In another group of papers, traditional transportation research shows that the mode choice decision of users is generally formed along multiple dimensions. The traffic volume (Van Exel and Rietveld, 2009), environmental conditions (Gebhart and Noland, 2014), convenience (Aziz et al., 2018), and trip characteristics (Du and Cheng, 2018; Heilig et al., 2018) are the most notable and influential determinants. To shape the users' choice model, we use the findings of Guidon et al. (2019) and Reck et al. (2021). The authors show that users regard shared vehicles only as a viable option if they are located within walking distance of 300 to 500 meters. Also, they specify that the mode choice process of FFVS users is primarily dominated by the distance to be covered and the time of the day, which is considered in detail in our present research. Next, individual user characteristics are another set of explanatory factors. Many researchers show that socio-demographic features (e.g., age, income) have an effect on users' mode choice decisions (Le Vine and Polak, 2019; Müller, Correia, and Bogenberger, 2017). Lastly, Li and Kamargianni (2020) investigate latent characteristics and show that users with more willingness of being a green traveler prefer more sustainable vehicles with higher probabilities, supporting our assumption of considering diverse user populations.

3 Methodology

We now lay out our combined discrete-event and agent-based simulation strategy to answer the proposed research question. The study of urban mobility – a socio-technical system – is largely considered a wicked problem owing to the presence of numerous complex and nonlinear relationships (Ketter et al., 2016; Schroer et al., 2022). Therefore, simulation-based research methods are suitable for modeling and analyzing urban mobility systems such as vehicle sharing platforms (Becker, Ciari, and Axhausen, 2017a; W. Axhausen, Horni, and Nagel, 2016). Inspired by the architecture of MatSim, an agent-based urban transportation simulation framework developed by W. Axhausen, Horni, and Nagel (2016), three constituents need to be modeled, namely the user's perspective (demand side), the operator's perspective (supply side), and the underlying mobility infrastructure. Specifically, we focus our analysis on one single FFVS platform offering shared electric kick scooters, scooters and cars in one region, namely Berlin, Germany. In the following, we describe the modeling details of the first two perspectives, where the latter is implicitly specified.

3.1 Demand: User Perspective

We begin by explaining the user's demand perspective. Users are the consumers of available rental vehicles to fulfill their mobility demands. The goal of a user in the mobility system we have modeled is to get from A to B under given boundary conditions. The quantity of users arriving in the system differs in both temporal and spatial dimensions. Thus, we partition the time of day into four-hour buckets (Γ) and discretize the geographic area in scope using a geodesic grid with a hexagon radius of approx. 1.3km represented by the set $\mathscr{H}$. Consequently, we model users' mobility demand as a spatio-temporal (non-stationary) Poisson process with arrival rate λ_{th}, where $t \in \Gamma$ and $h \in \mathscr{H}$ (Shortle et al., 2018). We term the arrival region and time of each user i as $o_i \in \mathscr{H}$ and $t_i \in \Gamma$, respectively. To determine the destination d_i of each trip, we draw on a multinomial distribution with $d_i \sim Mult_{|\mathscr{H}|}(1, \{p_1, \ldots, p_{|\mathscr{H}|}\} | t \in \Gamma, o \in \mathscr{H})$, considering the possible destinations as outcome categories (p_h). The pertaining outcome probabilities are dependent on the trip origin (o) and the time of the day (t). Taken together, the trip demand of user i is specified by the triplet (o_i, d_i, t_i). These preceding relationships motivate the discrete-event nature of the proposed simulation environment. However, more differentiated user behavior, such as nonlinear mode choice decisions, cannot yet be captured following this discrete-event approach and requires agent-based simulation paradigms (Railsback, Lytinen, and Jackson, 2006; Zhang et al., 2020).

Hence, we turn our attention to the mode choice decision of users in the multi-modal vehicle sharing simulation. Theoretically, users have access to three different shared vehicle modes, namely kick scooters,

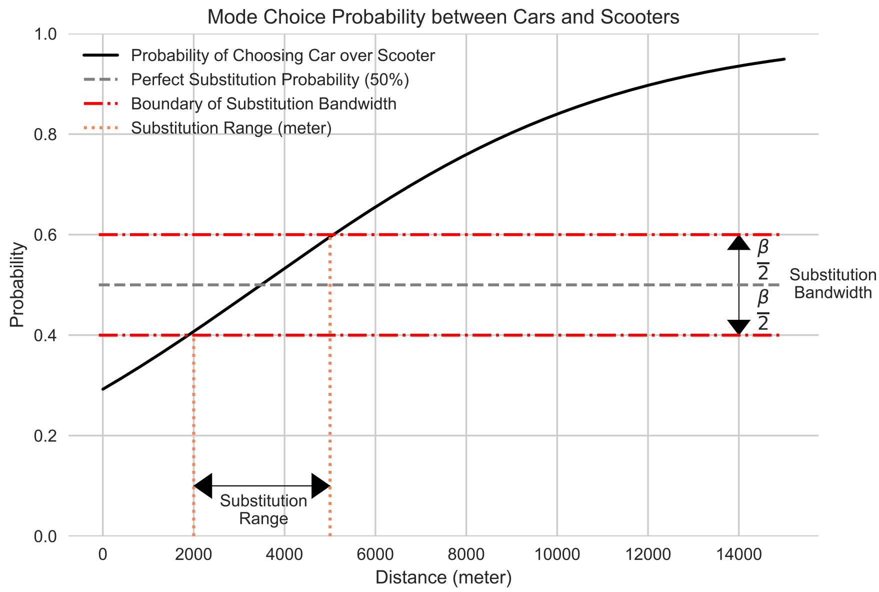

Figure 1. Mode choice behavior between cars and scooters using a multinomial logistic regression model considering a substitution bandwidth given by β.

scooters, and cars. However, Reck et al. (2021) show that in FFVS systems, users primarily choose the vehicle mode based on the distance to be covered from their origin to the destination. Other determinants play a subordinate role. Our explanatory investigations also reveal that kick scooters are on average used for short distance trips ($\sim$ 1km), scooters for medium distance trips ($\sim$ 2-3km), and cars for medium-long distance trips ($\sim$ 4-5km) as depicted in Figure 2. In order to factor in this realization, we represent the users' mode choice behavior by estimating a multinomial logistic regression model, where the explanatory variable is the euclidean distance of user trip i (i.e., the distance between o_i and d_i) and the discrete output refers to the available vehicle modes. Here, we make the assumption that the mode choice decision process is not influenced by vehicle supply. In other words, a user determines the preferred vehicle type based on trip distance, and if the desired vehicle type is not available nearby, she foregoes (i.e., leaves the system) the trip leading to a missed trip and missed revenue for the operator. However, taking a closer look at Figure 2, the users' vehicle choice process is not a clear-cut decision. We clearly observe overlapping rental trip patterns where different vehicles have been used for similar distances. For example, cars and scooters deem suitable for rental trips between 3km and 4km. These observations motivate us to introduce and factor in substitution effects in users' mode choice process. We assume that a user's choice process is neutral with respect to two or more vehicle types for her trip, provided that the resulting vehicle choice probabilities do not deviate substantially. Recall that the vehicle choice probabilities depend on the explanatory variables, which in our case corresponds to the trip distance. Following and extending the ideas of Mahajan and Ryzin (2001), we integrate a substitution boundary $\beta \in [0,1]$ and operationalize substitution effects in our mode choice process as follows. After having determined the mode choice probabilities $\{p_{im}\}_{m=1}^{M}$ for the available vehicles modes $m \in M$, we set vehicle type m as a feasible vehicle option for user i if the respective choice probability p_{im} is greater than the dominant choice probability $\max\{p_{im}\}_{m=1}^{M}$ adjusted by the predefined substitution boundary β as defined in the following Equation 1.

$$\hat{p}_{im} := \begin{cases} 1, & p_{im} \geq \max\{p_{im},\}_{m=1}^{M} - \beta, \\ 0, & \text{otherwise}. \end{cases} \tag{1}$$

Figure 1 provides a concise illustration of the resulting substitution process with a substitution boundary of $\beta = 20\%$, however, for the sake of clarity only for scooters and cars. In situations where the vehicle choice probabilities fall within the dashed red line representing the substitution region (we termed it substitution bandwidth), users are neutral whether to rent a scooter or a car for their rental trip. The resulting dashed orange line also reveals that a substitution case might happen for trips with a distance to be covered of 2km and 4.5km.

Lastly, we allow two types of users in the simulation to capture the heterogeneity of different populations in cases where substitution effects emerge. Basically, we assume that if the user can decide between several vehicles types due to substitution effects, the user prefers the cheapest alternative for her trip. We coin this user group as price-sensitive users. On the other hand, current literature suggests that a growing proportion of users are willing to pay a premium to opt for vehicles that are more sustainable (Gaker et al., 2011). Consequently, we also include users in our simulation environment, who invariably choose a more sustainable vehicle when multiple vehicle types are suitable for their trip. Sustainability of vehicles in the present context is defined by the energy consumption of the considered vehicles per distance unit (kWh/km). We consider vehicles that use less energy for the same distance to be more sustainable. We term this user group as environmentally-friendly users. Users are then assigned to either the first or second population group based on a Bernoulli distribution $\mathscr{B}(\theta)$, where $\theta \in [0,1]$ corresponds to the probability of belonging to the environmentally-friendly user group.

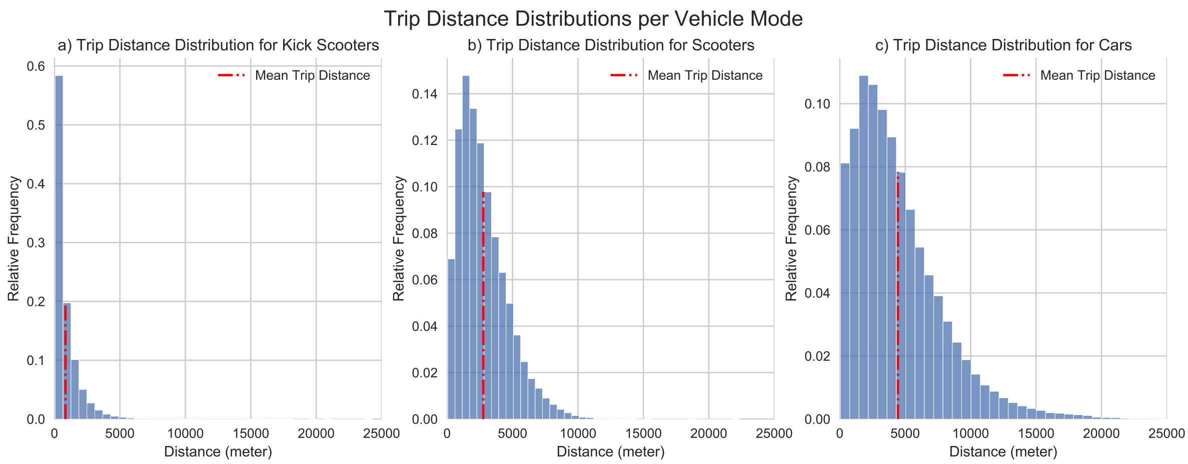

Figure 2. Trip distance distribution for a) kick scooters, b) scooters, and c) cars.

3.2 Supply: Operator Perspective

We now turn our attention to the operator of the multi-modal FFVS fleet. The overarching goal of a fleet operator is, naturally, to maximize profit through the rental of vehicles, which depends largely on the availability of vehicles at locations and times where and when exactly vehicles are in demand by customers. In order to ensure the availability of demanded vehicles, the operator must offer a certain number of (different) vehicles for short-term rental. We presume that a total of N vehicles are provided, where $N = \sum_{m=1}^{M} N_m$, and $N_m, \forall m \in M$, corresponds to the number of vehicles of type m. The optimal determination of the fleet size is a dedicated research question on its own and has already been solved in the literature for mono-modal fleets (Benjaafar et al., 2021; George and Xia, 2011), and thus is not part of the present research. We assume a reasonable fleet configuration based on existing empirical studies (e.g., Demircan, Muires, and Ketter, 2021).

To ensure vehicle availability, the operator must allocate vehicles across the operating area according to the user's mobility demand. In this context, the operator must take account of the demand heterogeneity as different types of vehicles are demanded at different places and times. In our simulation, we impose a heuristic vehicle allocation approach. We assume that the operator allocates the different types of vehicles to regions $h \in \mathscr{H}$ based on spatially differentiated demand patterns. The core rationale is to place more vehicles in regions where trip rentals for vehicle type m are high. Accordingly, we specify for each vehicle type m a dedicated multinomial distribution with $r_m \sim Mult^m_{|\mathscr{H}|}(N_m, \{p^m_1, \ldots, p^m_{|\mathscr{H}|}\})$. Using historical rental activity data, we estimate the distribution with the help of maximum-likelihood methods. After, we employ for each vehicle type m under consideration the pertaining distribution to sample N_m vehicle allocations in a spatial dimension. Eventually, all vehicles in scope (i.e., N vehicles) are initially allocated to a region h in order to meet expected customer demand.

Throughout the day, shared vehicles circulate within the operating area, leading naturally to demand and supply imbalances as vehicles are moved from high-demand areas to low-demand areas. As a result, users' demands in the following business days may not be effectively met. To counteract, operators typically rely on relocation strategies with dedicated service workers. These service workers relocate vehicles daily (or multiple times a day) from low-demand areas to high-demand areas to recover the initially defined vehicle allocation (or a similar fleet state). In the present simulation, we assume that the vehicle sharing operator employs a daily relocation strategy to recover the initial vehicle allocation state. Furthermore, rented vehicles consume electricity to fulfill the mobility requests of users. Again, we assume that the fleet operator utilizes service workers to ensure that fleet vehicles are fully charged on a daily basis. Taken together, we summarize the operational costs incurred as $DailyOpex_m$ taking into account the differentiated cost structures for different vehicle types. In addition to operating costs, capital costs incurred for the acquisition of vehicles are also a crucial cost factor. We break down the cost of capital to a daily level by considering the common depreciation periods. We term this vehicle-specific capital cost as $DailyCapex_m$.

The revenue of a vehicle sharing fleet operator corresponds to the sum of all respective trip revenues during the considered period (Kahlen et al., 2017; Nair and Miller-Hooks, 2011). Typically, the revenue of a trip is calculated by the trip duration times a minute rental price. Rental prices are differentiated among different vehicle modes. For example, while the rental price per minute for a shared car at ShareNow is 0.26€/min, the rental price for a shared scooter at Emmy corresponds to 0.23€/min. Hence, we can define the daily revenue with vehicle type m of a fleet operator as $DailyRevenue_m = \sum_{k=1}^{K^m} \Delta_k * \alpha_m$, where K^m is the total number of daily trips with vehicle mode m, Δ_k is the rental duration in minutes of trip k, and α_m refers to the rental price per minute for mode m. Eventually, we can define the overall profit function of the fleet operator as follows.

$$DailyProfit := \sum_{m=1}^{M} \sum_{k=1}^{K^m} \Delta_k * \alpha_m - \big(\sum_{m=1}^{M} N_m * (DailyCapex_m + DailyOpex_m) \big) \tag{2}$$

3.3 System Level Dependant and Independent Variables

In this section, we briefly present the dependent and independent variables of our simulation environment relevant to addressing the research question. The two independent variables of the simulations are the *SubstitutionBoundary* (i.e., β) and the structure of the *PopulationType* (i.e., θ). The dependent outcome variables of interest can be grouped into economic and environmental indicators. From an economic perspective, we examine the *DailyProfit* and *ServiceQuality* of the fleet operator under varying substitution boundaries and population types. The former is defined in Equation 2, the latter is defined as the fraction of fulfilled rental trips divided by total trip requests (i.e., $\frac{\sum ServedTrips}{\sum TripRequests}$). Further, we investigate the impact of different specifications of the independent variables on the overall *EnergyConsumption* to operate the fleet and meet users' mobility demand. To do so, we calculate the energy consumption for each trip based on the travelled distance (e.g., meter) times the energy consumption per spatial unit (e.g., kWh/meter), whereas the trip-level energy consumption depends on the selected vehicle. We expect that the total energy consumption decreases as the users' mode choice flexibility increases, and users are willing to pay a green premium to rent more sustainable vehicles modes in cases where multiple vehicle types are suitable for a trip.

4 Numerical Experiments

In this section, we first describe the considered historical data used and the specification of the simulation environment. We then present and discuss the experimental scenarios and the resulting findings.

4.1 Data & Specification of the Simulation Environment

In the following, we provide an overview of the data used and the specification of our simulation environment. In order to model users' mobility behavior, we have collected a unique dataset of rental transactions of Tier (shared electric kick scooters), emmy (shared electric scooters), and ShareNow (shared cars) via their respective APIs. The collection process was performed using web scrapers. These companies were (and some are still) one of the leading providers in terms of market share for the respective vehicle classes in Berlin, Germany. We extracted information of available vehicles 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. We observe for each vehicle the exact spatial location (latitude, longitude), vehicle type along with temporal information. Using these availability data of vehicles, we approximated vehicle trip information. While being used by a user, a vehicle is no longer available and visible in the app. We harness this circumstance to spot rental trips, which allow us to derive the origin, the destination, the duration of rental trips. Our dataset consists of 1,983,246 car trips; 173,212 scooter trips; 375,181 kick scooter trips. Using these rental transactions, we then determined the Poisson and multinomial stochastic processes to model spatio-temporal user arrivals and origin-destination routes, respectively. Further, we estimated a multinomial logistic regression model representing the mode choice decision process of users. Note that we have aligned the alternative specific constants to compensate for the unequal sample sizes of each mode. We further assume that the maximum willingness to walk to rent a kick scooter is 200m (Reck et al., 2021), for a scooter 350m, and 500m for a car (Herrmann, Schulte, and Voß, 2014). Contrary to Wortmann et al. (2021), we argue that an acceptable walking distance of 500m for scooters is presumably too high, which is why we decided to take the mean between the acceptable walking distance of kick scooters and cars (i.e., 350m). We now turn to the specification of the vehicle fleet. We assume that the fleet operator employs three types of shared electric vehicles, namely kick scooters, scooters, and cars. The entire fleet consists of 4,500 vehicles, with equal representation of each vehicle type (i.e., $N_m = 1,500$). The rental prices are set to 0.19€/min for kick scooters, 0.23€/min for scooters, and 0.26€/min for cars and are in line with current market rental prices of leading vehicle sharing providers. Current literature (Wortmann et al., 2021) and industry reports (Heineke et al., 2019; Steinmann et al., 2019) estimate daily operational (capital) costs of 10.72€ (0.8€) for kick scooters, 5.2€ (2.44€) for scooters, and 21.01€ (8.85€) for vehicle sharing operators. The surprising fact that scooters have lower daily operational costs than kick scooters is due to the fact that kick scooters need to be collected, charged, and relocated more frequently than scooters. We calibrate the average velocity of each vehicle (incl. reservation time adjustments) based on the findings of Demircan, Muires, and Ketter (2021), more precisely, we set the average velocity of kick scooters to 47m/min, of scooters to 133m/min, and of cars to 158m/min. This also implies that on average cars are more affordable than scooters, and scooters are more affordable than kick scooters when average velocities are factored in. The battery capacities (and the energy consumption) of kick scooters, scooters, cars are set to 0.46kWh (0.012kWh/km), 4.8kWh (0.048kWh/km), and 17.6kWh (0.197kWh/km). An overview of the vehicle-level specification is provided in Table 1. Lastly, we set the time horizon of our simulation environment to one day (i.e., $T = 1440$min).

Parameter	Kick Scooter	Scooter	Car	Source
Number of Vehicles (N_m)	1,500	1,500	1,500	Derived from Demircan, Muires, and Ketter (2021).
Rental Price (€/min)	0.19	0.23	0.26	Official website of leading providers. [3]
Exp. Daily Revenue (€/vehicle)	13.26	11.73	43.68	Derived from Demircan, Muires, and Ketter (2021).
Daily Operational Cost (€/vehicle)	10.72	5.2	21.01	Derived from Heineke et al. (2019), Steinmann et al. (2019), and Wortmann et al. (2021).
Daily Capital Cost (€/vehicle)	0.8	2.44	8.85	Derived from Heineke et al. (2019), Steinmann et al. (2019), and Wortmann et al. (2021).
Avg. Velocity (m/min)	47	133	158	Derived from Demircan, Muires, and Ketter (2021).
Battery Capacity (kWh)	0.46	4.8	17.6	Specification from official supplier website.[4]
Energy Consumption (kWh/km)	0.012	0.048	0.197	Specification from official supplier website.[2]
Acceptable Walking Distance	200m	350m	500m	Herrmann, Schulte, and Voß (2014) and Reck et al. (2021).

Table 1. Parameter specification for shared kick scooters, scooters, and cars in the simulation.

4.2 Results

We begin by presenting the different experimental instances considered, then continue to explore the summary statistics, and lastly turn our attention to the influence of the $SubstitutionBoundary$ and $PopulationType$ on economic and environmental system-level outcome measures of the fleet operator, namely $DailyProfit$, $ServiceQuality$, and $EnergyConsumption$ using regression analysis.

We consider in total eight different experimental instances, where we vary the $SubstitutionBoundary$ β from 0% to 20% with a gradual increment of 5%. Also, we either set the $PopulationType$ to completely price-sensitive (i.e., $\theta = 0$) or to completely environmentally-friendly (i.e., $\theta = 1$). Next, we simulate all eight different simulation instances and keep all other parameters fixed within these simulation runs and evaluate the resulting economic and environmental metrics. We then apply a Monte Carlo approach (Mooney, 1997) and repeat the simulation of the eight experimental instances 100 times to recover a sample distribution of the outcome variables.

We next explore the summary statistics of the simulation results for economic and environmental metrics reported on Table 2 and 3. Our results reveal a striking relationship. An increase of users' mode choice flexibility (i.e., β) generally leads to less revenue and $TotalProfit$ as they typically then opt for the more affordable vehicle option. We only observe an increase in $TotalProfit$ once users also exhibit the willingness to pay a premium for more sustainable vehicles. This is also reflected in the disaggregated revenue calculation, as we find that the revenue from shared car rentals is more distributed among the other types of vehicles as more users become flexible and environmentally friendly. Additionally, irrespective of the $PopulationType$, we observe that the $ServiceQuality$ considerably increases (from 80% to 88%) when users are willing to use alternative transportation modes for their trip.

Our results indicate not only from an economic perspective but also from an environmental lens remarkable benefits as reported in Table 3. As users' flexibility in mode choice grows, $EnergyConsumption$ increases from 6,416 kWh to 7,594 kWh to serve all rental trips. However, our results indicate that this finding is moderated again by the $PopulationType$; more specifically, we reveal that more environmentally-friendly users lead to a considerable reduction in $EnergyConsumption$ (i.e., from 6,414 kWh to 5,656 kWh with a substitution boundary of $\beta = 0.2$). We similarly notice this tendency in the number of kilometers driven and the time spent on the road with environmentally more harmful vehicles. For example, if users are willing to switch to more sustainable vehicle types (and momentarily pay a surcharge) and are more flexible in terms of their vehicle preferences, a system-wide reduction of 36% in kilometers traveled with cars are attainable. In addition, we determined how many of the trips made could be replaced by

[3] https://www.tier.app/ (Kick Scooter), https://emmy-sharing.de (Scooter), https://www.share-now.com/ (Car).
[4] https://eu.okai.co/products/es200 (Kick Scooter), https://www.govecs-scooter.com (Scooter), https://www.smart.com/ (Car).

	Price-Sensitive Population				Sustainable Population			
	$\beta = 0.00$	$\beta = 0.05$	$\beta = 0.10$	$\beta = 0.20$	$\beta = 0.00$	$\beta = 0.05$	$\beta = 0.10$	$\beta = 0.20$
Exp. Total Revenue (€)	90,891	90,839	90,760	90,305	90,891	93,670	96,277	100,867
By Kick Scooter (€)	9,827	8,413	7,108	4,530	9,827	11,574	13,540	18,135
By Scooter (€)	17,437	14,311	10,840	5,930	17,437	21,516	25,166	31,713
By Car (€)	63,627	68,116	72,811	79,845	63,627	60,579	57,571	51,018
Exp. Total Profit (€)	17,346	17,294	17,215	16,760	17,346	20,125	22,732	27,322
Exp. Service Quality	0.8	0.82	0.84	0.88	0.8	0.82	0.84	0.88
Exp. Daily Fulfilled Trips	12,214	12,502	12,795	13,319	12,214	12,517	12,816	13,298
Daily Missed Trips	2,990	2,701	2,409	1,883	2,990	2,675	2,365	1,863

Table 2. Summary statistics of the economic key measures for different population types (θ) and varying substitution boundaries (β).

	Price-Sensitive Population				Sustainable Population			
	$\beta = 0.00$	$\beta = 0.05$	$\beta = 0.10$	$\beta = 0.20$	$\beta = 0.00$	$\beta = 0.05$	$\beta = 0.10$	$\beta = 0.20$
Total Energy Consumption (kWh)	6,416	6,744	7,081	7,594	6,416	6,249	6,075	5,656
By Kick Scooter	14	12	10	6	14	17	20	27
By Scooter	488	400	303	166	488	602	704	887
By Car	5,914	6,332	6,768	7,422	5,914	5,631	5,351	4,742
Total Trip Distance (km)	50,991	51,615	52,193	53,106	50,991	51,878	52,592	53,410
By Kick Scooter	1,922	1,622	1,350	822	1,922	2,296	2,723	3,733
By Scooter	10,159	8,337	6,316	3,455	10,159	12,535	14,662	18,476
By Car	38,910	41,656	44,527	48,828	38,910	37,046	35,207	31,200
Total Trip Duration (h)	6,024	5,979	5,932	5,840	6,024	6,257	6,480	6,892
By Kick Scooter	681	575	479	292	681	814	966	1,324
By Scooter	1,264	1,037	786	430	1,264	1,559	1,824	2,298
By Car	4,079	4,366	4,667	5,118	4,079	3,883	3,690	3,270
Kick Scooter Trips (N_{ks})	2,058	1,854	1,649	1,206	2,058	2,291	2,533	3,042
Kick Scooter $\succ$ Scooter	0	28	50	40	0	476	955	1,909
Kick Scooter $\succ$ Car	0	0	0	14	0	0	0	1,278
Scooter Trips (N_s)	4,134	3,741	3,126	1,649	4,134	4,695	5,126	5,748
Scooter $\succ$ Kick Scooter	0	646	1,302	1,054	0	191	385	793
Scooter $\succ$ Car	0	163	361	793	0	1,593	3,297	5,502
Car Trips (N_c)	6,022	6,907	8,020	10,464	6,022	5,531	5,158	4,507
Car $\succ$ Kick Scooter	0	0	0	1,809	0	0	0	170
Car $\succ$ Scooter	0	1,697	3,495	7,058	0	264	547	1,025

Table 3. Summary statistics of environmental key measures for different population types (θ) and varying substitution boundaries (β).

alternative vehicle types for different substitution boundary values β. If a rental trip was made with vehicle type m, but could also be made with type m', we have denoted this in Table 3 as $m \succ m'$.

Lastly, we lay out the results of the regression analysis to uncover the influence of $SubstitutionBoundary$ and $PopulationType$ on economic and environmental system-level metrics. Since the regression is specified in terms of a log-linear relationship, the regression coefficients $SubstitutionBoundary$ and $PopulationType$ can be approximately interpreted as the percentage change in the economic and environmental outcome metrics for one unit change in the respective coefficients. Accordingly, three linear regression models using a Gaussian error distribution are estimated. Our estimated models are significant with excellent R^2 values between 91% ($TotalProfit$, Column (1)) and 97.8% ($ServiceQuality$, Column (2)). First, from an economic lens, we find that a unit increase in users' mode choice flexibility (i.e., $SubstitutionBoundary$) leads to 0.2% less $TotalProfit$ for the fleet operator. Having users that are environmentally friendly and are willing to pay a surcharge for more sustainable means of transport lead in general to 2% more $TotalProfit$. In fact, we find a significant interaction effect between $PopulationType$

and *SubstitutionBoundary*. In case that the users are environmentally-friendly (i.e., $\theta = 1$), a unit increase of users' mode choice flexibility (β) leads to additional 2.4% *TotalProfit*. We also identify that an unit increase of β increases the *ServiceQuality* by 0.4%. Adopting the environmental lens, we show that generally an increase in users' mode choice flexibility β leads to an increase of *EnergyConsumption*. However, again, we reveal that this pattern is moderated by *PopulationType*. If the *PopulationType* is assumed to be more environmentally friendly (i.e., $\theta = 1$) and more flexible in terms of mode choice, we observe a system-wide reduction of 1.5% per unit increase of β. In summary, users mode choice flexibility is only preferable for the operator and as a society if the users are also willing to switch from cheaper (and presumably more comfortable) alternatives to more costly but sustainable means of transportation.

	Dependent variables (log-transformed):		
	Economic		Environmental
	Total Profit	Service Quality	Energy Consumption
	(1)	(2)	(3)
Substitution Boundary (β)	-0.002^{***}	0.004^{***}	0.008^{***}
	(0.0004)	(0.00003)	(0.0001)
Population Type (θ)	0.019^{***}	0.001^{**}	-0.002
	(0.006)	(0.001)	(0.002)
Sub. Boundary * Pop. Type ($\beta * \theta$)	0.024^{***}	0.00004	-0.015^{***}
	(0.001)	(0.00005)	(0.0001)
Constant	9.763^{***}	-0.218^{***}	8.772^{***}
	(0.004)	(0.0004)	(0.001)
Adjusted R^2	0.914	0.978	0.970
Note: Sample Size N = 800			$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 4. Regression results of substitution boundary (β) and population type (θ) on economic and environmental performance metrics.

5 Discussion and Conclusion

This study investigates whether it is economically and environmentally worthwhile to engage in IS-enabled interventions to foster green practices among users in a shared mobility context. We propose a discrete-event and agent-based mobility simulation to model a multi-modal FFVS platform (supply) and associated users (demand). We consider two important user characteristics to investigate whether interventions are valuable. First, we examine users' mode choice flexibility and pertaining substitution effects. Second, we explore the users' willingness to pay a green premium to rent more environmentally sustainable vehicles. We, then, assess the impact of both user characteristics on multiple economic (i.e., profit, service quality) and environmental (i.e., energy consumption) metrics relevant to the fleet operator. We calibrate our simulation environment using real-world rental transactions for shared kick scooters, scooters, and cars from leading FFVS operators from Berlin, Germany. Overall, our work contributes to the body of literature at the intersection of Green IS and urban mobility research. We do so by providing a conceptual framework to simulate the behavior of shared mobility users, shared mobility operators, and potential intervention mechanisms. In particular, our contribution lies in quantifying the impact of promising user interventions on the profitability and environmental footprint of FFVS operators.

Our results reveal an important dilemma regarding the two user characteristics considered. We show that increasing users' mode choice flexibility and thus their willingness to substitute a vehicle is environmentally detrimental as more users prefer vehicle choices that are generally cheaper (there are also other influencing factors such as traffic congestion and parking availability varied among different populations, which are out of this work's scope). In the current market environment with the current rental prices per minute, a shared car is on average cheaper than a shared scooter for medium long distances, which are the most probable trips with vehicle substitution, simply because a car can move faster, even considering traffic time. Thus, if the users are still price-sensitive but more flexible in mode choice, this leads to more rentals of cheaper vehicles that are more environmentally unsustainable. In total, significantly more energy is consumed and more trips are conducted by shared cars. Economically, the total profit hardly changes while service quality improves significantly. This means that with the current price schemes, and with a high penetration of price-sensitive users, the fleet operators can only leverage the users' substitution effect to address more trips (higher acceptance rate), which on the other hand, reduces total profits and increase environmental costs. Therefore, to positively affect the economic and environmental metrics, it is significantly valuable to consider users' substitution effect and characteristics as an influencing criterion for a better price tariff design. However, we clearly observe that this picture flips once users are willing to pay a surcharge to rent more environmentally sustainable vehicles. In total, substantially less energy is consumed to meet users' mobility demand as more and more users switch from shared cars to other – less detrimental – vehicle types. These findings corroborate similar studies on the impact of introducing MaaS platforms to foster unbiased mode choice decisions (Becker et al., 2020; Sochor, Karlsson, and Strömberg, 2016). For the fleet operator, it is also attractive from an economic point of view to engage in an incentive mechanism to encourage users to opt for more sustainable but also more expensive vehicles, as the overall profit increases remarkably.

Our study has several implications for managers and researchers alike to understand the impact of user characteristics on the economic and environmental performance of FFVS platforms. In light of growing sustainability concerns, fleet operators should explore and employ different incentive regimes to steer users' mobility demand from unsustainable modes to more sustainable modes, even if the former are momentarily more affordable. A convenient way to do this would be to display the energy consumption of each mode for the requested trip. Another option would be to use nudging techniques by listing the most sustainable modes first (Lehner, Mont, and Heiskanen, 2016; Seidel, Recker, and Brocke, 2013). In addition, operators could adjust current rental prices by internalizing the externalities incurred, ultimately making the more sustainable vehicles more affordable (Cramton, Geddes, and Ockenfels, 2018). Scientifically, our present findings have important implications for designing IS artifacts to manage users' demand in urban mobility research (e.g., Hevner et al., 2004). From a theoretical point of view, our simulation-based evidence contributes to a deeper understanding of configurations of socio-technical systems (Bostrom and Heinen, 1977; Leavitt, 1965). To be more precise, urban mobility systems constitute a socio-technical system whose configuration depends on different constituents such as the available vehicles and the user characteristics (Canitez, 2019). Our study widens the current understanding of the impact of the aforementioned constituents on economic and environmental measures for businesses and society. It motivates the IS community to develop and test actionable intervention mechanisms.

Our research does not come without limitations. The current mode choice model incorporates only the travel distance, as recent research shows that this factor is most decisive. In the future, we will integrate other factors, like the time of day, trip purpose, number of passengers, and the environmental impact of each mode to better reflect the users choice behavior. Going further, we assume that the user has frictionless access to different mobility platforms and has near-perfect information about their trip options, namely which vehicles are available nearby, which vehicle is more sustainable, and which is cheaper. However, this assumption is indeed largely justified in the near future given the proliferation of Mobility-as-a-Service apps, such as Google Maps, FreeNow, or Urbi. Furthermore, in the current study we assume that we can effectively influence the user's willingness to pay a green surcharge and user's mode flexibility with the help of IS-enabled incentive systems. Future work, however, must clarify how such incentive systems should be designed and assessed their efficacy. Last, we invite other scholars to replicate the research work utilizing data from other regions to corroborate the generalizability of our findings.

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