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Research paper

Insights into peer-to-peer carsharing: Modelling and scenario analysis via a Bass diffusion agent-based model

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ABSTRACT

Our paper aims at estimating the uptake of peer-to-peer carsharing (P2PCS) in less-densely populated areas and how it could be influenced by innovation, social interaction and transport policies. We specified a Bass Diffusion agent-based model including two modules representing the supply and demand of P2PCS. Both modules are parametrized with data derived from a discrete choice survey of potential users (N = 449) representative of the population living in Friuli-Venezia Giulia, an Italian region bordering with Austria and Slovenia. We specified the rental rate as a dynamic variable that varies according to the excess of demand or supply. Innovation and imitation effects change the status of car owners and car drivers into potential P2PCS users. According to our simulations the P2PCS market would reach a steady state at a rental rate of 6.1 €/h with 7% of car owners and car renters engaging in the system. We also found that if the preferences for the servitization paradigm were more diffused, P2PCS would be used by 11% of the population at a rental rate of 5.5 €/h, and that adopting a package of highly effective policies supporting both the demand and the supply would increase the market share up to 42%.

1. Introduction

Local air pollution and congestion are major concerns in European urban areas. One fifth of the EU-28 population lives in cities with problems related to pollution or other environmental issues. The 2021 Global Traffic Scorecard estimates an average of 140 h lost in traffic congestion over the year in Paris, 134 in Brussels, and 106 in Rome. The European Green Deal adopted by the European Commission aims at a climate-neutral economy by 2050, calling for a 90% reduction in transport emissions and a shift to sustainable and smart mobility.

Carsharing (CS) has proven to reduce car ownership (Jain et al., 2021; Jochem et al., 2020; 2021; Shaheen, Martin, & Hoffman-Stapleton, 2021), distance travelled (Cohen & Shaheen, 2016, pp. 1–106; Dill et al., 2019; Martin, 2016; Shaheen et al., 2017, p. 162) and greenhouse gas emissions (Harris et al., 2021), and can significantly improve the sustainability of urban transport systems.

Mobility is fundamental for social inclusion and human well-being, especially for disadvantaged groups (EU_COM, 2021). Low-income segments of the population living in suburbs or rural areas face lower access to labor market and social and cultural activities due to low car ownership and poor public transport services and could highly benefit from CS services (Cohen & Shaheen, 2016, pp. 1–106; Cui & Aziz, 2019; Schwieterman & Smith, 2020). However, CS is a viable solution as long as it is provided in densely populated areas, otherwise is not financially sustainable.

Global consumer spending in shared-mobility services accounted for approximately $130 billion to $140 billion in 2019.[1] Peer-to-peer car sharing (P2PCS) is an innovative form of sharing mobility with negligible start-up and operating costs since car owners and renters are peers and share the privately owned vehicles through a platform. Compared to the traditional business-to consumer carsharing (B2CCS) service, it is less capital intensive, therefore is potentially more scalable to less dense cities and suburban areas (Hampshire & Sinha, 2011).

The P2PCS model is gaining high popularity, representing 25% of the worldwide carsharing market share in 2020 (Global Market Insights, 2021), and is expected to gain additional momentum by 2024 due to its higher cost-effectiveness compared to station-based and free-floating B2CCS models (Graphical Research, 2021). In Italy Auting was the

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[1] https://www.octotelematics.com/blog/shared-mobility-where-it-stands-where-its-headed/#:~:text=The%20shared%2Dmobility%20market%20accounted, percent%20of%20the%20total%20market.

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first P2PCS provider who started the business in 2017 and was followed by few newcomers such as Popmove, GetMyCar, I-Link. However, this form of CS has not reached a significant critical mass, yet, being offered especially in the largest cities of the northern part of the country.

Our goal is to predict the percentage of the population that would use the service and the rental rate that would be paid taking into account the innovation and the imitation effect and the potential impact of a package of transport policies supporting both the demand and the supply side of the market. To this aim, we performed a simulation analysis based on a Bass diffusion agent-based model including both a demand and a supply module. Both modules are based on an empirical survey involving a sample representative of the population living in Friuli-Venezia Giulia (FVG), an Italian region bordering with Austria and Slovenia. We interviewed 200 individuals to test if they would rent a car from a peer and 249 car owners to test if they would rent out their car to a peer. We studied the socio-economic characteristics and the psychological barriers influencing the potential demand and supply side of the market and used the estimates to feed the Bass diffusion agent-based model.

We validated the model comparing the outcome of a base case scenario with the market share and the rental rate equating the number of respondents who during the survey stated that they were willing to rent/rent out a car. We also performed a sensitivity analysis with reference to the uncertain parameters we specified in the model. To the best of our knowledge, this is the first paper applying an agent-based model to describe both sides of the P2PCS market. Moreover, most of the parameters we used to specify the simulation model are micro-founded and are based on a stated preference (SP) survey, increasing the consistency and reliability of our simulations.

In summary, this paper contributes to the literature as follows: a) it models the uptake of a P2PCS via a disaggregate Bass Diffusion agent-based model; b) it simultaneously studies the interaction between the demand and the supply side of the market and the social interaction taking place among agents belonging to each side of the market; c) it forecasts how the trend of using cars for mobility as a service, the servitization versus the ownership paradigm, will increase the diffusion of the P2PCS; d) it describes how transport policy packages could increase the P2PCS uptake.

The paper is structured as follows: Section 2 reviews the literature on P2PCS modelling, Section 3 describes the stated preference survey, Section 4 illustrates the simulation model, Section 5 presents the simulation and sensitivity analysis, Section 6 summarizes the policy scenario analysis, while Section 7 discusses the main results and describes the future research lines.

2. Literature review

2.1. Stated preferences surveys

Discrete choice models based on stated or revealed preference surveys are frequently used for transport modelling, especially when dealing with innovative services and means of transport, or new infrastructures (Ben-Akiva et al., 1985; de Dios Ortúzar & Willumsen, 2011).

While B2CCS has been extensively studied via stated preferences surveys, there are relatively few papers analyzing the potential demand and supply of P2PCS (Ferrero et al., 2018; Nansubuga & Kowalkowski, 2021). Most of them are focused either on the demand (Prieto et al., 2017; Shaheen et al., 2021; Uteng et al., 2019; Wilhelms et al., 2016) or the supply (Barbour et al., 2020; Dill et al., 2019; Olaru et al., 2021; Shaheen, Martin, & Hoffman-Stapleton, 2021; Wilhelms et al., 2017) side of the market. Only few studies analyze both sides of the market (Ballús-Armet, 2014; Munzel et al., 2019; Gaarsdal et al., 2017).[2] Recently, Prieto et al. (2022) carried out a survey involving 2159 licensed car drivers living in three dense urban areas (London, Madrid and Paris) with the aim of detecting what influences P2P shared mobility participation intentions. They found that environmentalism raises the probability of joining the service and that car owners who frequently use their car are rarely willing to engage in the market as peer-providers. Possession-self link, being younger and environmental sensitive, and living in city centers have a positive effect on users' propensity to participate in P2P shared mobility services.

However, according to Stathopoulos et al. (2017), many additional factors influence the choice of using an innovative transport service such as P2PCS, information on experience acquired by others being among the most important ones. Moreover, SP experiments are not able to capture the dynamic aspect of the diffusion process over time with respect to the social influence and/or spatial component dimensions (El Zarwi et al., 2017). Integrating discrete choice experiments within a Bass diffusion model could pursue the goal of more precisely predicting how a new market will develop over time.

2.2. Bass diffusion model

The Bass Diffusion model (Bass, 1969; Mahajan et al., 1990) was originally introduced with the aim of describing how the potential adopters of a new product are influenced in their adoption decision by external information channels such as advertising (Fourt & Woodlock, 1960) and by internal information channels driven by imitative behavior (Mansfield, 1961). The focus of the model is on the source of information triggering the adoption process. The model is widely used to predict the number of consumers who will buy an innovative product over time, therefore to estimate the long run sales curve or the product life cycle.

According to this model, the probability that potential adopters purchase a new product depends on (Duggan, 2017; Mahajan et al., 1990).

- the potential market size or the total number of potential adopters when nobody has purchased the new product yet, m;
- the effectiveness of external factors triggering the transition from potential to actual adopters, p, also known as coefficient of innovation;
- the intensity of the imitative behavior, q, also known as coefficient of imitation;
- the frequency of social interaction, c, also known as contact rate;
- the number of individuals that have already purchased the new product at stage t-1 of the analysis, $N(t-1)$.

The number of new adopters at stage t of the analysis, S(t), is therefore described by Eq. (1):

$$S(t) = \left[p + qc\,\frac{N(t-1)}{m}\right][m - N(t-1)] \qquad \text{eq. 1}$$

where the first component represents the probability that a potential adopter will purchase the new product at stage t of the analysis, while the second component represent the number of individuals who have not purchased the new product yet.

According to the Bass Diffusion model, two different phenomena cause the diffusion of an innovation (Fig. 1). The first is the process by which a company promotes a new product among potential users and a part of them - the innovators – due to the information received decide to buy it. An important feature of this component of the model is that the

[2] Refer to Rotaris (2021a, 2021b) for a detailed description of this stream of literature.

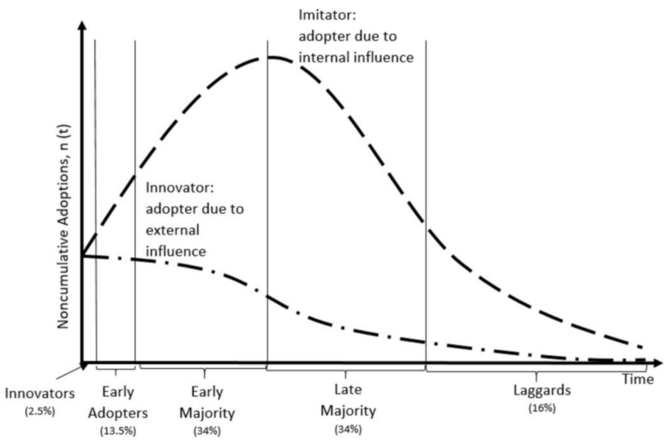

Fig. 1. *Noncumulative adoption of an innovation due to innovators and imitators (*adapted from Mahajan et al., 1990, p. 4, p.4).

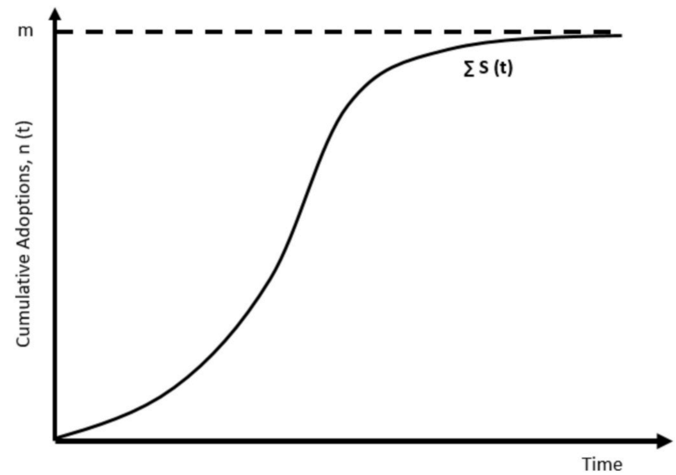

Fig. 2. *Cumulative adoption of an innovation (*adapted from Mahajan et al., 1990, p. 4, p.4).

number of current adopters does not influence the number of innovators, because the adoption choice of the innovators is assumed to be based exclusively on the information gathered from the company and not on the information collected from other consumers who have already adopted the product. In this component of the model the communication channel is also described as "external" to the social system, because is not based on the interaction between adopters and potential adopters. Since advertising is the main channel used by companies to communicate with (potential) customers, in the literature the coefficient of innovation, or the speed by which potential adopters become innovators, is typically described as the advertising effect (Bass, 1969; Mahajan et al., 1990; Roger, 1995). The model assumes also that the influence of the innovators in the diffusion process is greater at the initial stages of the market, but diminishes over time.

The second phenomenon is the imitative behavior of potential adopters. According to this second component of the model, the imitators decide to buy the new product because other individuals have done so as a side effect of social interaction. In the literature, this imitative mechanism is often referred to as the word-of-mouth effect to underline the fact that the communication channel driving the adoption process is internal to the social system and arises from the exchange of information between current adopters and potential adopters as opposed to the flow of information from the company to the potential adopters. The source of information can obviously be an innovator, so indirectly the information provided by the company can affect also this second component of the model, however this indirect effect is conditioned by the information exchanged among peers. In sectors such as tourism and collaborative consumption, imitative behavior is a highly influential information source that affects consumer decisions due to the difficulty of evaluating intangible products prior to consumption (Buczynski, 2013; Hawapi et al., 2017).

Each component of the model plays a role in determining the shape of the cumulative diffusion curve. The first component defines the steepness of the curve during the early stages of the market up to the point where the *Early majority* of the market is reached. The second component plays a significant role in shaping the diffusion curve as time elapses in the later stages of the market especially when dealing with the *Laggards* (Fig. 2). Therefore, although in the Bass Diffusion model innovation and imitation are specified as being independent phenomena, the cumulative diffusion curve is actually the joint result of both of them. Moreover, it is worth noting that the diffusion rate depends also on the time horizon taken into account, the level of social interaction, and the characteristics of the innovation (risks in using the new product, switching costs, compatibility issues with the products already in use, complexity of the new product).

The unknown parameters of the model, that is the innovation coefficient *p* and the imitation coefficient *q*, are generally assumed to be fixed and are estimated either via logit models or via other non linear regression models on the basis of time series data or intention to purchase surveys (Ganjeizadeh et al., 2017). The methodology used to collect and analyze the data are highly case specific as depicted in the remainder of this Section.

In the literature there are only two studies applying the Bass Diffusion model to the carsharing market, however, differently from what we have done, they both study a standard B2C service focusing exclusively on the demand side of the market. More specifically, Zhang et al. (2020) used an aggregate Bass Diffusion model to study whether imitators are important in the uptake of a B2C one-way carsharing system using small electric vehicles in Toyota, Japan. They performed the analysis at the CS station level assuming that each station has its own market of potential adopters and introducing in their model a spatial dimension. They clustered the stations into four categories (residential, business, public services and transit hub) in order to reduce the number of parameters to be estimated. They calibrated the model using the time series data collected for the first 32 months of operation of the service. They used the least squares method and the gradient descent method to estimate both the station-specific and the global parameters that best fit the data collected at each station. They iteratively took steps proportional to the negative of the objective function's gradient at the current point until a sufficiently accurate value of the estimated data was reached. To test for convergence they used different initial parameter settings. Following this procedure the authors estimated a social influence parameter of 0.001, meaning that 1000 users would attract one additional user, while in other similar case studies applying the Bass model the parameter ranges from 0.02 to 0.06 (Putsis, 1996). They also estimated a hesitation factor of 0.032, representing the number of hesitant adopters over 1000 who initially refuse to adopt the CS service but who will adopt it in the following month. Finally, they estimated station specific influence parameters ranging from 0.031 to 0.187.

Luna et al. (2020), instead, tested via a system dynamic model how policies increasing the annual growth rate of an electric-carsharing scheme and reducing the number of internal combustion vehicles 15 years of age or older change the fleet composition, the CS uptake and the CO_2 emissions in Fortaleza, Brazil. They used historical data to calibrate the model and estimated a coefficient of innovation for electric vehicles of 0.001 and a coefficient of imitation of 0.136. Their model include five modules: a module describing the internal combustion fleet, the electric vehicle module, the e-carsharing module, the population module, and the CO_2 emissions module. Both the internal combustion module and the electric vehicle module are based on the Bass Diffusion model.

Chin et al. (2018), instead, focused on the estimation of the imitation

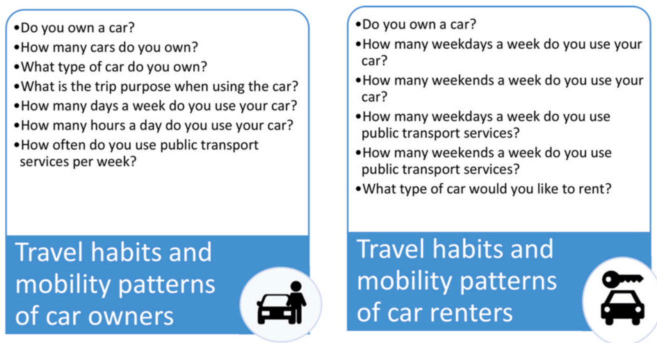

Fig. 3. Items administered to car owners and car renters to monitor their travel habits and mobility patterns.

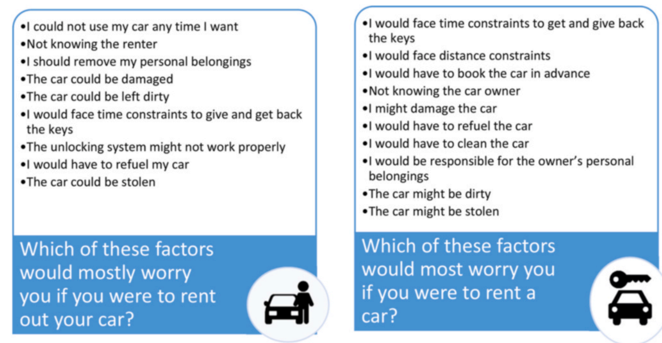

Fig. 4. Items administered to car owners and car renters to test their concerns about P2P car rental.

effect and studied how information to consumers about the sellers and usage of products and services through Internet-based technologies (electronic word-of-mouth, e-WOM) influence the willingness to use the carsharing services provided by GrabCar, a ride-hailing platform for taxi booking available in Malaysia. They performed a survey involving 95 respondents who had already experienced the GrabCar services and estimated via a multiple regression model the impact of electronic referral, e-WOM and brand image on the respondent's purchase intention. The authors found that although e-WOM has no direct effect on purchase intention, it has a significant and positive effect on brand image, which has a positive and significant relationship with purchase intention.

2.3. Agent-based modelling

Agent-based models differ from aggregate Bass Diffusion models because they are capable to forecast adopters or market shares of new services taking into account not only how individuals interact in the market but also how they differ in terms of preferences and socio-demographic characteristics. Moreover, they can be calibrated in order to be transferable across different geographical, social and cultural contexts. The main obstacle of applying agent-based-modelling is the estimation of the parameters to be used to predict the market evolution.

Although there are few studies integrating the stated preference approach and the disaggregate Bass Diffusion agent-based model with reference to the transport sector, in particular with reference to the market diffusion of electric vehicles and plug-in hybrid electric vehicles (Scorrano & Danielis, 2022), there are no studies focusing on carsharing. A remarkable exception is El Zarwi et al. (2017) who integrated a discrete latent class choice model with a disaggregate Bass Diffusion technology adoption model to forecast the adoption of a B2C carsharing system given different potential investment strategy scenarios and taking into account socio-demographic variables and the spatial configuration of the service. To calibrate the model they used revealed preference time series data collected over 2 years from a one-way carsharing system in a major city in the United States. They estimated a latent class logit model. In the utility function of the innovators they included the characteristics of the decision-maker and the attributes of the new technology. In the utility function of the imitators they added also the influence exerted by the current adopters represented by the increase in the number of adopters registered in the previous month. They estimated that the population of the city they studied comprised 0.22% innovators, 16.80% imitators, and 82.98% non-adopters, and that the coefficient of imitation was 0.14 per hundred of adopters at (t-1). They used the model to predict the effectiveness of new pods either outside a second major technology firm or in a new zip code in the downtown region and of on-street parking facilities. Differently from what we have done, however, they analyzed a B2C carsharing service and studied only the demand side of the market, indeed, to the best of our knowledge, there is no study focusing on P2PCS applying the disaggregate Bass Diffusion model.

3. Stated preference survey

We conducted a face-to-face survey in November–December 2019 by randomly selecting individuals at meeting places (e.g., squares, shopping centers, supermarkets) in different towns of Friuli-Venezia Giulia, an Italian region characterized by less densely populated areas. We interviewed only individuals having a driving license and being 21 years old or older. We collected 449 interviews using a questionnaire structured into four sections. We interviewed 249 car owners potentially willing to rent out their car and 200 potential car renters. The socio-demographic characteristics of each sample and of the population living at the time of the interviews in Friuli-Venezia Giulia are reported in Table 8 in the Appendix. The first set of questions aimed at understanding the respondents' travel habits and mobility patterns (Fig. 3).

The second set of questions focused on the respondents' willingness to use a P2PCS and on the rental rate they would accept to rent out or to rent a car. We proposed a payment card with the following values: €5/h; €10/h; €15/h; €20/h; €30/h; €40/h; €50/h and "other". To the car owners we asked to state the minimum value among those proposed to rent out a car, to the car renters we asked to state the maximum hourly rental rate to rent a car. We showed the payment card only once to each respondent. The third set of questions asked what the respondent would be worried about if using a P2PCS service as a car owner or as a car renter (Fig. 4). Finally, the fourth set of questions aimed at collecting standard socio-economic data (e.g., age, gender, level of education, income, occupation, place of residence, environmental consciousness[3]).

The sample we interviewed was representative of the population living in Friuli-Venezia Giulia by age and gender. The car owners' sample (249 individuals) was slightly larger than the car renters' one (200 individuals). The majority of both samples was 25–44 years old (41% car owners; 35% car renters) or 45–64 years old (39% car owners; 39% car renters). Each sample was equally balanced between males (52%) and females (48%). Most of the individuals we interviewed as car owners had a high school diploma (49%) or a master degree (36%), while the majority of the individuals we interviewed as potential car renters had a high school diploma (35%) or a bachelor degree (30%). With reference to both samples, the majority of the respondents were employees (55% car owners; 48% car renters) and had a family income in the €30,000-€70,000 range (45% car owners; 68% car renters). The majority of the individuals in both samples owned more than one car and used the car on a daily basis for leisure, commuting or shopping.

[3] To measure the environmental sensitivity of the interviewees, we asked them to rate the following sentence on a 5-point Likert scale: "I am increasingly concerned about the environmental sustainability of the place where I live".

Most of the individuals belonging to the car owners' sample would be bothered of not using the car while rented out ("imp. of car availability" in Table 3), and would be concerned of not knowing the renter ("distrust on renters" in Table 3) and having the car damaged ("damages concerns" in Table 3). Most of the individuals belonging to the renters' sample would be bothered of booking the car in advance ("need booking in advance" in Table 4) and would be worried of time and distance constraints ("km concerns" in Table 4).

The willingness to accept to rent out the car stated by car owners ranged between €5/h and €30/h, while the willingness to pay to rent a car stated by car renters ranged between €3/h and €10/h.

In order to detect what factors significantly influence the values stated by the respondents, we estimated two binary logistic models, one for each sample type. The dependent variable Y is a dummy equal to one or zero according to the answer given by the interviewed with reference to the willingness to rent out or to rent a car at the rental rates proposed. The independent variables referring to agent type q are the r socio-economic characteristics SE_{rq}, the k mobility habits MH_{kq}, the m psychological barriers and misconceptions about how the service works PBM_{mq} and the hourly rental rate RR_i. The binary logistic model predicts the probability P that the decision maker q either accept or refuses to rent out or to rent a car given the hourly rental rate RR_i and the other independent variables characterizing the respondent (Eq. (2)).

$$P_q(accept_i) = \frac{1}{1+\exp-\left(ASC_i+\sum_r \varphi_{ri} SE_{rq}+\sum_k \beta_{ki} MH_{kq+}\sum_m \gamma_{mi} PBM_{mq}+\delta_i RR_i\right)} \quad \text{eq. 2}$$

We estimated the parameters of the binary logistic models by maximum likelihood estimation using the Apollo package in R. We tested different specifications of the binary logistic models. In Table 1 we reported the best fitting ones.

Both the willingness to rent out and the willingness to rent a car are influenced by age ("younger than 45" in Table 1) and occupational status ("employed"; "unemployed"; "student" vs. retired in Table 1); indeed, it is higher for young individuals and for employees. The willingness to rent out a car is higher for females ("female vs male" in Table 1) and for individuals with a low family income ("low income <€30k" in Table 1),[4] while the willingness to rent a car is higher for individuals living in rural areas ("living in urban areas" in Table 1). Car use frequency ("car used each weekday" in Table 1) reduces both the willingness to rent out and the willingness to rent a car. As expected, there is a positive relationship between the willingness to rent out a car and the rental rate ("rental rate €/h" in Table 1) and a negative relationship between the willingness to rent a car and the rental rate. Several psychological factors and misconceptions on how the P2PCS works significantly influence the willingness to use the service. On the supply side of the market, important factors deal with the concern that the car could be damaged ("damages concerns" in Table 1), the possibility that the car is needed while rented ("imp. of car availability" in Table 1) and a sense of distrust on strangers ("distrust on renters" in Table 1). On the demand side of the market, significant factors are related to potential distance ("km concerns" in Table 1) and cleaning constraints ("mandatory car cleaning" in Table 1). Also the possibility that the car is damaged ("damages concern" in Table 1) or stolen ("concern about car stolen" in Table 1), the need of booking ("need booking in advance" in Table 1) and refueling the car ("refueling need" in Table 1), and a sense of distrust on strangers ("distrust on owner" in Table 1) play a significant role. Additional details on the methodology used to carry out the research and on the results obtained are available in Rotaris (2021a).

4. Simulation model

We developed a simulation model aimed at representing the interaction between the potential demand and the potential supply of P2PCS, therefore it comprises both a demand and a supply module. Each module is designed as an agent-based model with interactive agents choosing to rent out a car (supply side) or to rent their car (demand side) according to the rental rate set in the market. The value of the rental rate decreases as long as the number of car owners willing to rent out their car exceeds the number of agents willing to rent a car and increases as long as the number of agents willing to rent a car exceeds the number of car owners willing to rent out their car. When the number of car owners equates the number of car renters, the rental rate reaches a steady state around the equilibrium value (Fig. 5). We specified the rental rate as a dynamic variable whose value changes by a factor of €0.02 times the difference between the number of agents willing to rent out a car and the number of agents willing to rent a car.[5] The value of the rental rate variable is updated each day since the model time units are days. Additional details on the supply module and on the demand module follow.

4.1. Description of the supply module of the simulation model

The supply module describes the process according to which an agent owing a car might end up renting out his/her car. The process includes two phases. In the first phase, the agent (element 1, Fig. 6) takes into account the opportunity of renting out his/her car based on the information campaigns on the characteristics of the service, that is the innovation effect (element 2, Fig. 6), or on the word-of-mouth phenomenon, that is the imitation effect (element 3, Fig. 6). Therefore, due to the innovation or the imitation effect, the agent status might change from car owner (element 1, Fig. 6) to car owner potentially willing to rent out the car (element 4, Fig. 6). We used Eq. (1) described in Section 2.2 to estimate this first status transition.

To operationalize this component of the simulation model, we assumed that the coefficient of innovation is equal to 0.06 (as in Putsis, 1996), and that the coefficient of imitation is equal to 0.06 (that is the average value of the estimate found by Luna et al., 2020, and Zhang et al., 2020). We also assumed that the contact rate is equal to 0.01%, in line with the estimates obtained by Dunbar (1992) according to which 150 is the maximum number of people with whom one can maintain a stable social relationship.

In the second phase, the agent potentially willing to rent out his/her car chooses whether to do it (element 8, Fig. 6). The agent takes his/her decision on the basis of the rental rate set in the market (element 6,

[4] The percentage of individuals with a family income up to €30,000 is half the value recorded for the population living in the Friuli-Venezia Giulia region. This difference might have affected the results we obtained regarding the role of income level in the willingness of renting and renting out a car.

[5] For the price change factor, we tested different values ranging from 0.005 euros to 0.035. We chose 0.02 euros since it was the most effective value in monitoring how the price converged toward the equilibrium while triggering an appreciable variation of both the demand and the supply.

Table 1
Binary logistic models of the willingness to rent out (car owners' sample) or to rent (car renters' sample) a car.

Willingness to rent out a car			Willingness to rent a car		
Car owners	Estimate	p-val	Car renters	Estimate	p-val
constant	−6.75	0.00	constant	−2.91	0.03
younger than 45	1.74	0.00	younger than 45	1.04	0.01
employed (vs retired)	1.54	0.00	employed (vs retired)	1.41	0.00
unemployed (vs retired)	1.96	0.00			
student (vs retired)	1.62	0.00			
female (vs male)	0.88	0.00			
low income (<€30k)	1.73	0.00			
			living in urban areas	−0.94	0.02
environmental conscious	0.64	0.00			
car used each weekday	−0.78	0.00	car used each weekday	−1.76	0.00
car used <6 h/d	0.53	0.02			
owing a city car	1.19	0.00	willing to rent a city car	4.30	0.00
rental rate €/h	0.18	0.00	rental rate €/h	−0.93	0.00
damages concerns	0.89	0.00	damages concern	−1.50	0.00
time constraints concerns	1.03	0.00			
			km constraints	4.16	0.00
			mandatory car cleaning	0.90	0.02
			concern about car stolen	3.91	0.00
			need booking in advance	2.05	0.08
imp. of car availability	−1.19	0.00			
			refueling need	−3.32	0.00
distrust on renters	−1.95	0.00	distrust on owner	1.87	0.01
N. individuals	249		N. individuals	200	
N. observations	1245		N. observations	800	
LL (0)	−862.97			−554.52	
LL (final)	−320.66			−112.98	

Fig. 6) and his/her preferences, mobility habits, socio-demographic characteristics, psychological barriers, and latent misconceptions on how the service works (element 5, Fig. 6). We used Eq. (2) and the estimates of the parameters of the binary logistic model described in Table 1 (Section 3) to estimate this second status transition of the car owners.

4.2. Description of the agents belonging to the supply module

To define the characteristics of the agents of the supply side of the market we used the socio-demographic characteristics of the population living in Friuli-Venezia Giulia (Table 2). We assumed that each socio-demographic characteristic (e.g., gender or age) is a discrete random variable whose probability density function is defined as reported in Table 2. We obtained the sociodemographic profile of each agent by extracting from the discrete probability function of each socio-demographic characteristic one of the possible outcomes. Therefore, while in the simulation model, each agent has a different socio-demographic profile, overall the agents belonging to the supply side of the market resemble the socio-demographic characteristics of the population living in Friuli-Venezia Giulia.

With reference to the mobility habits and to the latent psychological barriers, we used the data collected from our sample according to which 22% of the respondents own a city car, 70% use it on a daily basis and 54% use it more than 6 h per day. As for the latent psychological barriers, 26% of the respondents were concerned that the car could be damaged, 16% that they might deal with time constraints, 63% that they might need the car while it was rented out, while 43% were concerned of renting out the car to a stranger (Table 3).

Also to define the mobility habits and the latent psychological barriers of each agent of the supply side of the market we used the data collected from the sample of car owners. More specifically, we assumed that each characteristic observed for the sample of car owners (e.g. type of car owned or latent distrust on renters) is a discrete random variable whose probability density function is described as reported in Table 3. To define the profile of each agent we extracted from the discrete probability function of each random variable one of its possible outcomes. Therefore, although the mobility habits and the latent psychological barriers of the agents of the supply side of the market are individual-specific, overall they resemble the characteristics of the sample of car owners we have interviewed.

It should be noticed that, although we assumed that the factors affecting the agents' choice are identical across the sample, consistently with the estimates reported in Table 1, since the socio-demographic characteristics, the mobility habits, and the latent psychological barriers are individual-specific, as the simulation runs each agent ends up taking a different decision. The heterogeneity of the simulated choices, therefore, is due to the different characteristics of the agents rather than the heterogeneity of the preferences of the agents with respect to the factors affecting their choice.

4.3. Description of the demand module of the simulation model

The demand module has the same structure as the supply module. It describes the process according to which an agent aged 21 or older and holding a driving license might end up renting a car. The process includes two phases. In the first phase of the process, the agent (element 1, Fig. 7) takes into account the opportunity of renting a car on the basis of the innovation effect activated by information campaigns and advertising (element 2, Fig. 7) and the imitation effect triggered by the interaction with agents who have already rented a car (element 3, Fig. 7). In this first phase of the process, due to the innovation or the imitation effect, the agent status might change from being an individual having the characteristics needed to rent a car (element 1, Fig. 7) to an individual potentially willing to rent a car (element 4, Fig. 7). Similarly to the procedure we used for the supply module, we estimated this first status transition applying Eq. (1) described in Section 2.2. To operationalize this component of the simulation model, we used the same value of the innovation coefficient, imitation coefficient, and contact rate that we used for the supply module.

In the second phase of the process, the agent potentially willing to rent a car (element 4, Fig. 7) chooses whether to do it (element 8, Fig. 7). The agent takes his/her decision on the basis of the rental rate set in the market (element 6, Fig. 7) and his/her preferences, mobility habits, socio-demographic characteristics, psychological barriers, and latent misconceptions on how the service works (element 5, Fig. 7). We used Eq. (2) and the estimates of the parameters of the binary logistic model described in Table 1 (Section 3) to estimate this second status transition of the car renters.

4.4. Description of the agents belonging to the demand module

To define the characteristics of the agents of the demand side of the market we used the socio-demographic characteristics of the population living in Friuli-Venezia Giulia (Table 2). We assumed that each socio-demographic characteristic of the sample of the car renters is a discrete random variable whose probability density function is described as reported in Table 2 Section 4.2. To characterize each agent of the demand, we extracted from the discrete probability function of each socio-demographic characteristic one of the possible outcomes. Therefore, although the socio-demographic characteristics of the agents are individual-specific, overall they resemble the socio-demographic

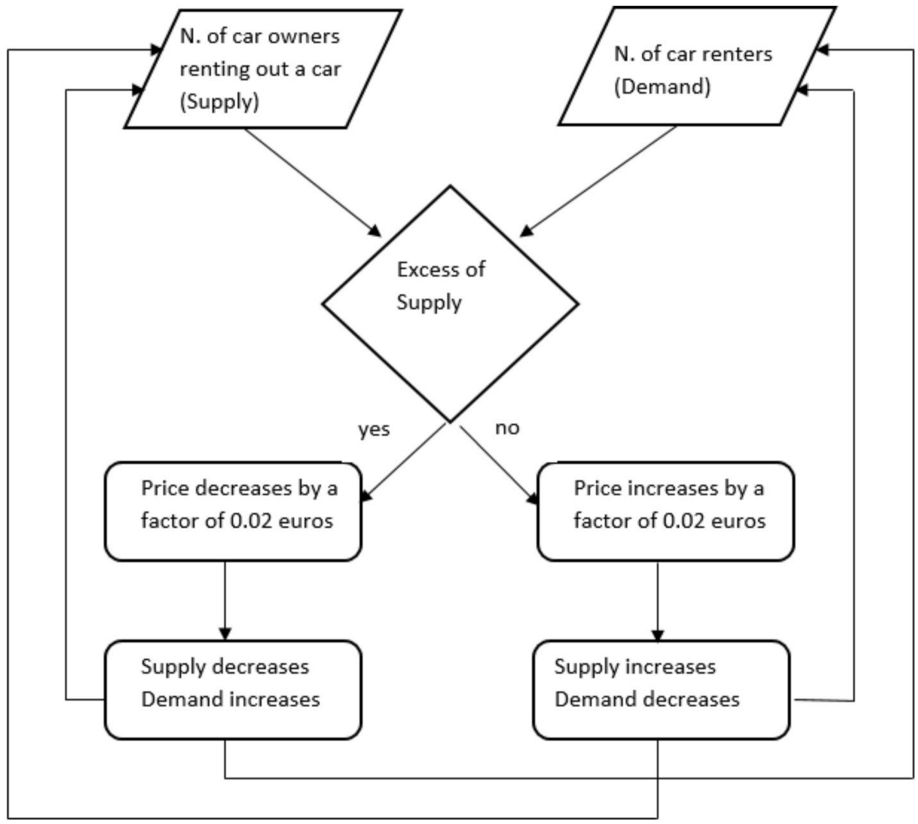

Fig. 5. Flowchart of the simulation model.

characteristics of the population living in Friuli-Venezia Giulia.

With reference to the mobility habits, we referred to those stated by the sample according to which 49% of the respondents traveled by car on a daily basis and 15% would rent a city car. As for the latent psychological barriers, based on the survey results, we knew that 60% of the respondents were concerned about any distance constraints, 60% about the need to book the car in advance, 30% that the car should be cleaned and 55% that it should be refueled at the end of the rental. Additionally, we knew that 56% were concerned about renting a car from a stranger and 52% were concerned that the car could be damaged or could be stolen (7%) (Table 4).

Using the data on the mobility habits and latent psychological barriers collected from the sample of car renters, we assumed that each characteristic observed for the sample is a discrete random variable whose probability density function is described as reported in Table 4. To define the profile of each agent we extracted from the discrete probability function of each variable describing the mobility habits or the latent psychological barriers one of its possible outcomes. Therefore, also with reference the mobility habits and the latent psychological barriers of the agents, they differ at the individual level but at the aggregate level resemble the characteristics of the sample of car renters we interviewed.

4.5. Model validation

In our case study, validating the simulation model is particularly challenging, since in Friuli-Venezia Giulia P2PCS is rarely used and there is no empirical evidence on the number and value of transactions that have been carried out since the service was launched by Genial Move and Auting. Moreover, due to the COVID-19 pandemic, both platforms have temporarily dismissed the service. The average hourly rental rate of a city car as recorded in Milan in December 2019, just before the COVID-19 pandemic started, was 6.6 €/h. [6]

Therefore, since there are no data on the demand and supply of P2PCS, we can not empirically validate our simulation model. However, both the demand and the supply modules are grounded on discrete choice modelling theory (Hensher & Johnson, 2018), which has been largely proven to be valuable to understand and model individuals' behavior with reference to innovative transport systems (Hörl et al., 2019; Le Pira et al., 2017). Moreover, the results of the discrete choice experiment we performed to model the individuals' willingness to rent out and to rent a car are consistent with the evidence reported in the literature (Rotaris, 2021b).

It is not possible, instead, to compare the outcome of our simulation model with other simulation studies. Indeed, to the best of our knowledge, there is no other research adopting a Bass Diffusion agent-based model simultaneously taking into account the innovation effect and the imitation effect within each side of the P2PCS market and the interaction between the demand and the supply side of the P2PCS market.

However, we can compare the equilibrium rental rate predicted by our simulation model (Fig. 8), assuming that no innovation effect and imitation effect is needed to activate the market, with the rental rate equating the percentage of individuals who, according to the survey we carried out, stated to be willing to rent out/rent a car. The simulation model predicted that with a rental rate of 6.1 €/h, 7% of car owners and car renters would engage in the market, while, according to our survey, 8% of the respondents would be willing to rent out or rent a car if the

[6] https://www.ilsole24ore.com/art/car-sharing-privati-dubbi-e-opportunita-che-cosa-e-e-come-funziona–AFaRhKD?refresh_ce=1.

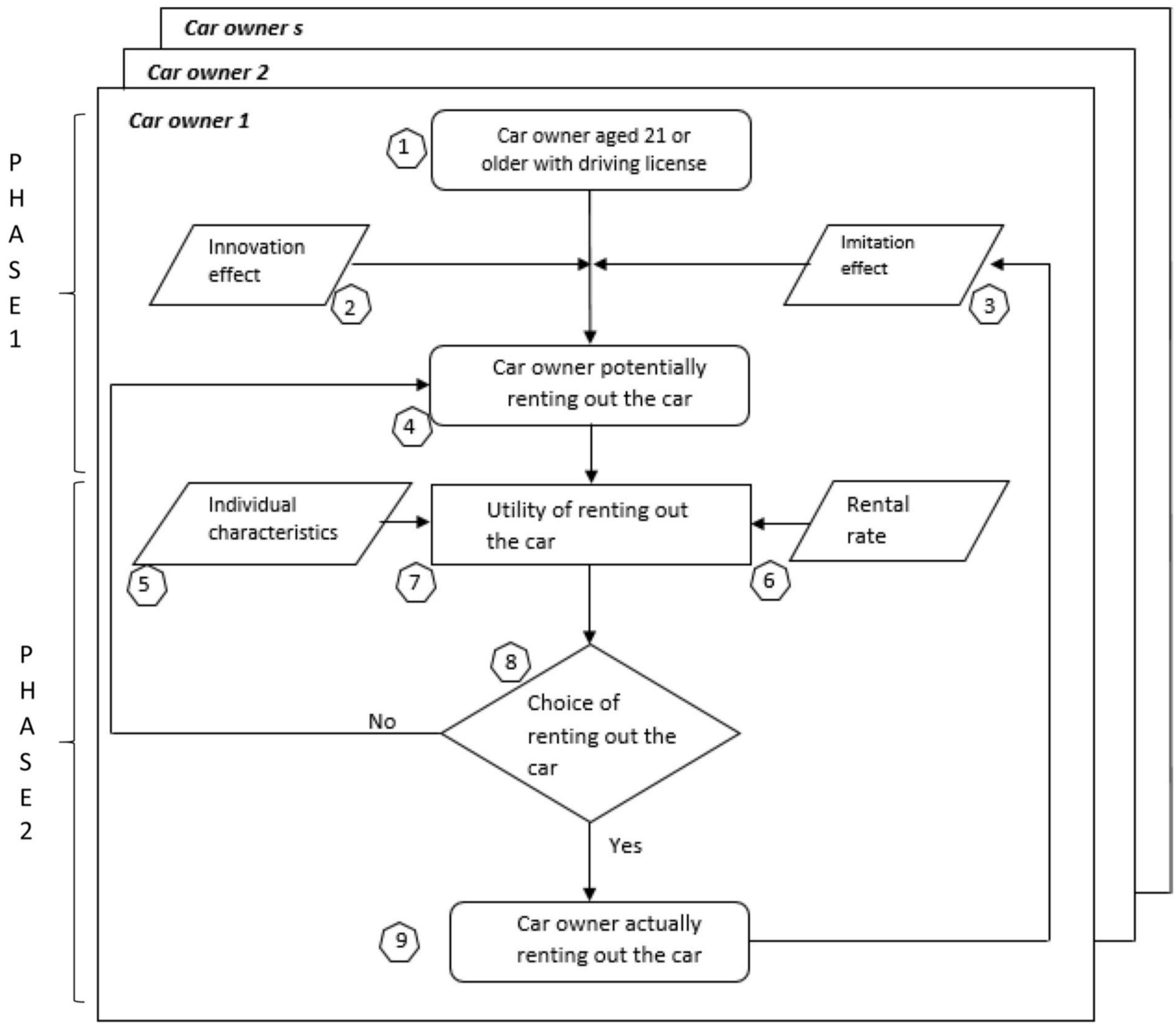

Fig. 6. Flowchart of the supply module of the simulation model.

Table 2
Socio-demographic characteristics of the population living in Friuli-Venezia Giulia.

Characteristic	Population distribution in Friuli-Venezia Giulia
Gender	49% male; 51% female
Age	41% aged 21–44; 59% aged 45-80
Occupational status	38% employee; 7% unemployed; 5% student; 45% other
Family income	71% lower than €30,000; 29% equal or higher than €30,000
Residential location	19% dense urban areas; 81% other

Table 3
Mobility habits and latent psychological barriers of the sample of car owners.

Characteristic	Frequency distribution within car owners
Type of car	22% city car; 78% other
Car use days a week	70% daily basis; 30% other
Car use hour a day	54% more than 6 h; 46% other
Damages concerns	26% yes; 74% no
Time constraints concerns	16% yes; 84% no
Imp. car availability	63% yes; 37% no
Distrust on renters	43% yes; 57% no

rental rate were 7 €/h. The results of the simulation model and the stated preference survey are hence consistent proving the reliability of our simulation model.

5. Simulation results and sensitivity analysis

5.1. Reference scenario

Our previous research on P2PCS in Friuli-Venezia Giulia (Rotaris, 2021a) proved that there is a significant potential demand and supply of peered carsharing services and that the main reason preventing the uptake of the service is that very few people know how it works and are aware of its availability. We used our simulation model to assess if an innovation effect activated by marketing campaigns and an imitation effect generated by word-of-mouth could influence the market uptake. Assuming a coefficient of innovation of 0.06, a coefficient of imitation of 0.06, and a contact rate of 0.01% we found that the innovation effect and the imitation effect will not change the value of the equilibrium rental rate (6.1€/h) nor the percentage of agents willing to engage in the market (8%) (Fig. 9).

However, the interaction between the demand and the supply will take more time to reach a steady state, a scenario where the difference between the number of agents willing to rent out a car and the number of agents willing to rent a car is smaller than 4%. Indeed, when we assume that no innovation or imitation effect occurs, the number of agents of the demand and of the supply depends exclusively on the characteristics of

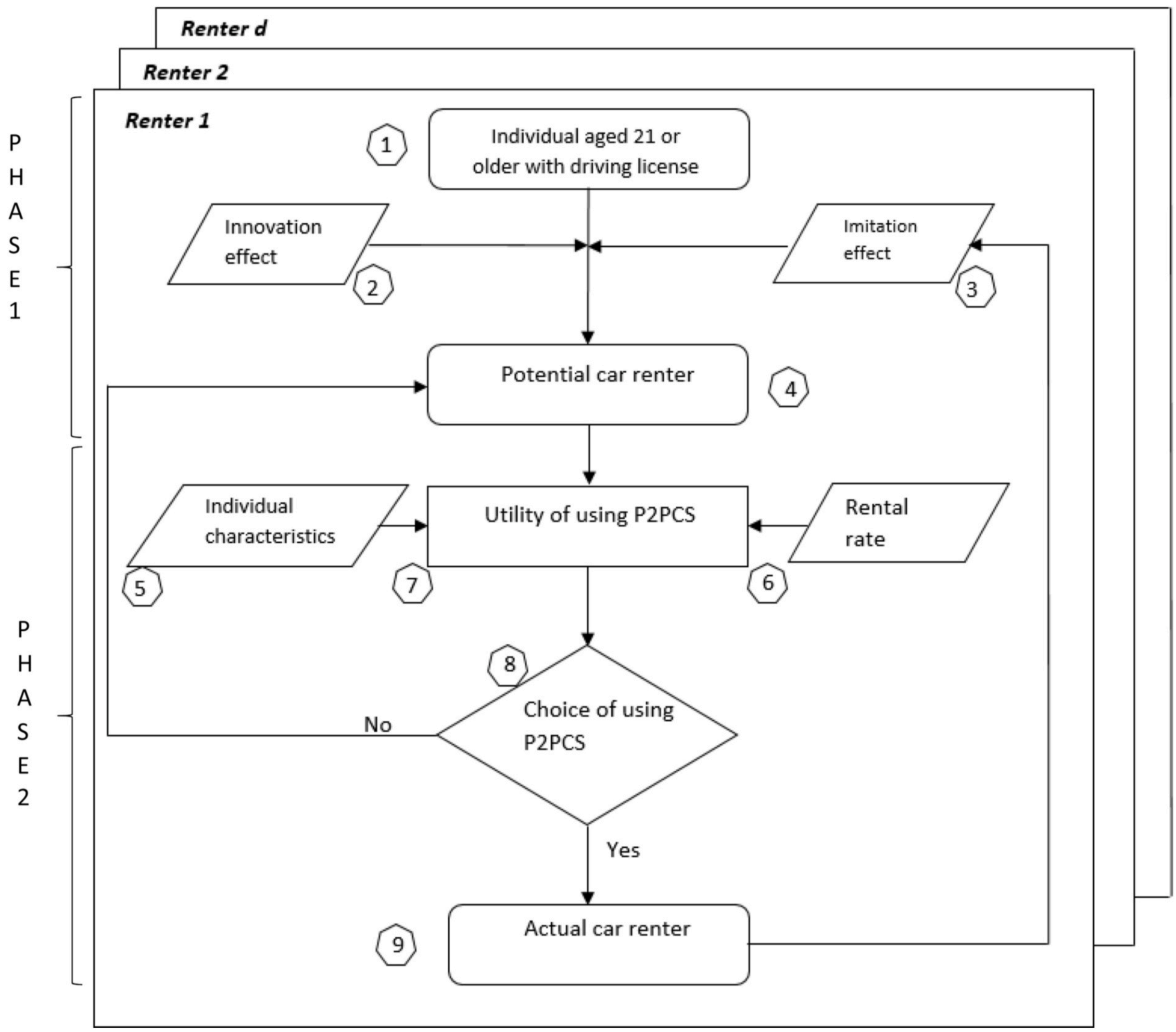

Fig. 7. Flowchart of the demand module of the simulation model.

Table 4
Mobility habits and latent psychological barriers of the sample of car renters.

Characteristic	Frequency distribution within car owners
Type of car	15% city car; 85% other
Car use days a week	49% daily basis; 51% other
Km constraints concern	60% yes; 40% no
Booking concerns	60% yes; 40% no
Cleaning concerns	30% yes; 70% no
Refueling concerns	55% yes; 45% no
Distrust on renters	56% yes; 44% no
Damages concerns	52% yes; 48% no
Car stolen concerns	52% yes; 48% no

the agents and on the value of the rental rate. Since the characteristics of the agents do not change according to the value of the rental rate, the rental rate is the only factor driving the number of agents willing to rent out or rent a car. Therefore, for low values of the rental rate, there are only a few agents willing to rent out a car and many agents willing to rent a car, but as the rental rate increases the difference between the number of agents belonging to the two groups decreases (Fig. 10, Chart b).

When we analyze also the innovation and imitation effects, instead, the strength of the impact of an increase of the rental rate differs according to the stage and the side of the market that we take into account. Indeed, the innovation and imitation effects reinforce the positive impact of a rental rate increase on the supply side, while they mitigate the negative impact of a rental rate increase on the demand side. The magnitude of the reinforcing and mitigating effect is smaller in the initial stages of the market when dealing with the "innovators" and the "early adopters", reaches a maximum with the "early majority", and starts decreasing in the final stages of the market with the "late majority" and the "laggards" (Fig. 1). Moreover, for low values of the rental rate, in our case study up to 2–2.5 €/h, the innovation and imitation effects more than compensate the negative impact caused by an increasing rate on the number of agents willing to rent a car. While for rental rates that are higher than 3 €/h the innovation and imitation effects start diminishing and are not large enough to compensate for the negative impact caused by higher rental rates (Fig. 10, Chart a) so the number of agents willing to rent a car start diminishing. The different impact that the innovation and imitation effects produce on the supply and demand side of the market cause the longer time needed to reach the steady state.

5.2. Scenario analysis

The automotive sector, like many other industries, is facing the transition from consuming goods to consuming services (Fritze et al., 2018; Genzlinger et al., 2020). On the supply side of the market, car-sharing providers allow customers to rent a car even for short periods

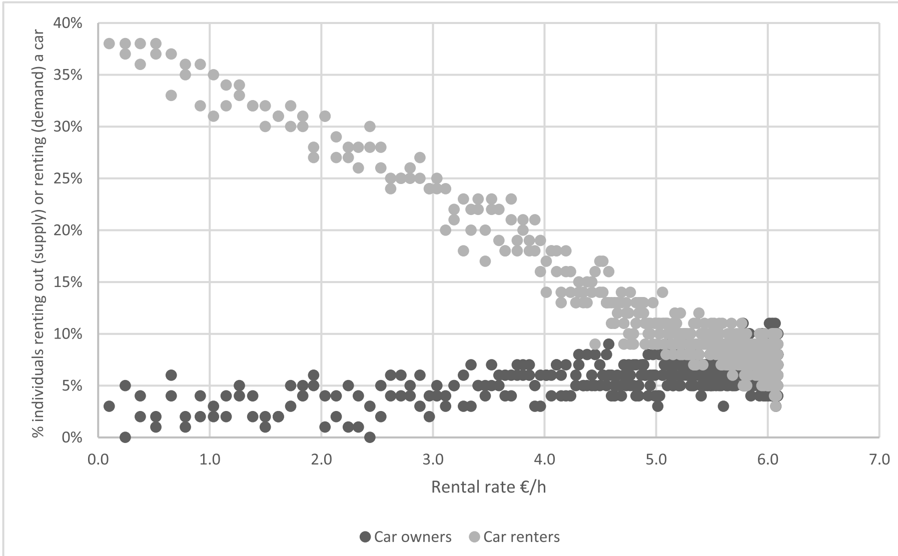

Fig. 8. Percentage of car owners (supply side of the market) and car renters (demand side of the market) according to the rental rate (€/h).

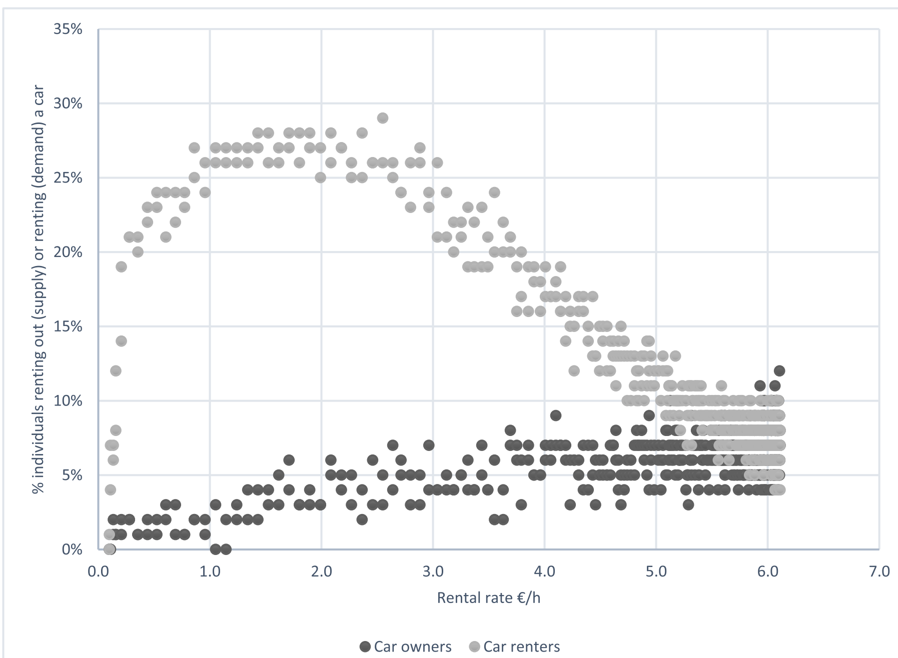

Fig. 9. Percentage of individuals renting out (supply side of the market) or renting (demand side of the market) a car according to the rental rate given the innovation and the imitation effect.

covering all costs, turning the standard automotive business model of selling a car, to a business model based on servitization (Kanatlı & Karaer, 2021). As for the demand side of the market, for an increasing number of young individuals the car is not a status symbol anymore, it is mostly used for leisure and only if strictly necessary (Bayart et al., 2020; Burkhardt & Millard-Ball, 2006; Burlando et al., 2019; Garikapati et al., 2016; Klein & Smart, 2017; Nitschke, 2020; Qing et al., 2018). In order to test how the P2PCS market would change if most of the population preferred to use rather than own a car, as young people do, we analyzed a scenario in which 80% of the population has the same preference structure as the younger segment of the sample we interviewed. According to our simulation model, the steady state would be reached at a rental rate of 5.5€/h and the percentage of agents using the service would be 11%.

We also checked whether a population characterized by a large percentage of individuals highly sensitive to environmental sustainability issues would increase the P2PCS uptake (Bulteau et al., 2019; Gheorghiu & Delhomme, 2018; Shaheen et al., 2016). However, since according to our survey, environmental sensitivity would marginally affect only car owners, both the rental rate and the percentage of agents using the service when the market reaches its steady state will not be affected (Table 5).

5.3. Sensitivity analysis

In our simulation, the parameters defining both the innovation effect and the imitation effect are highly uncertain; therefore, we performed a sensitivity analysis to detect the magnitude of their influence on the

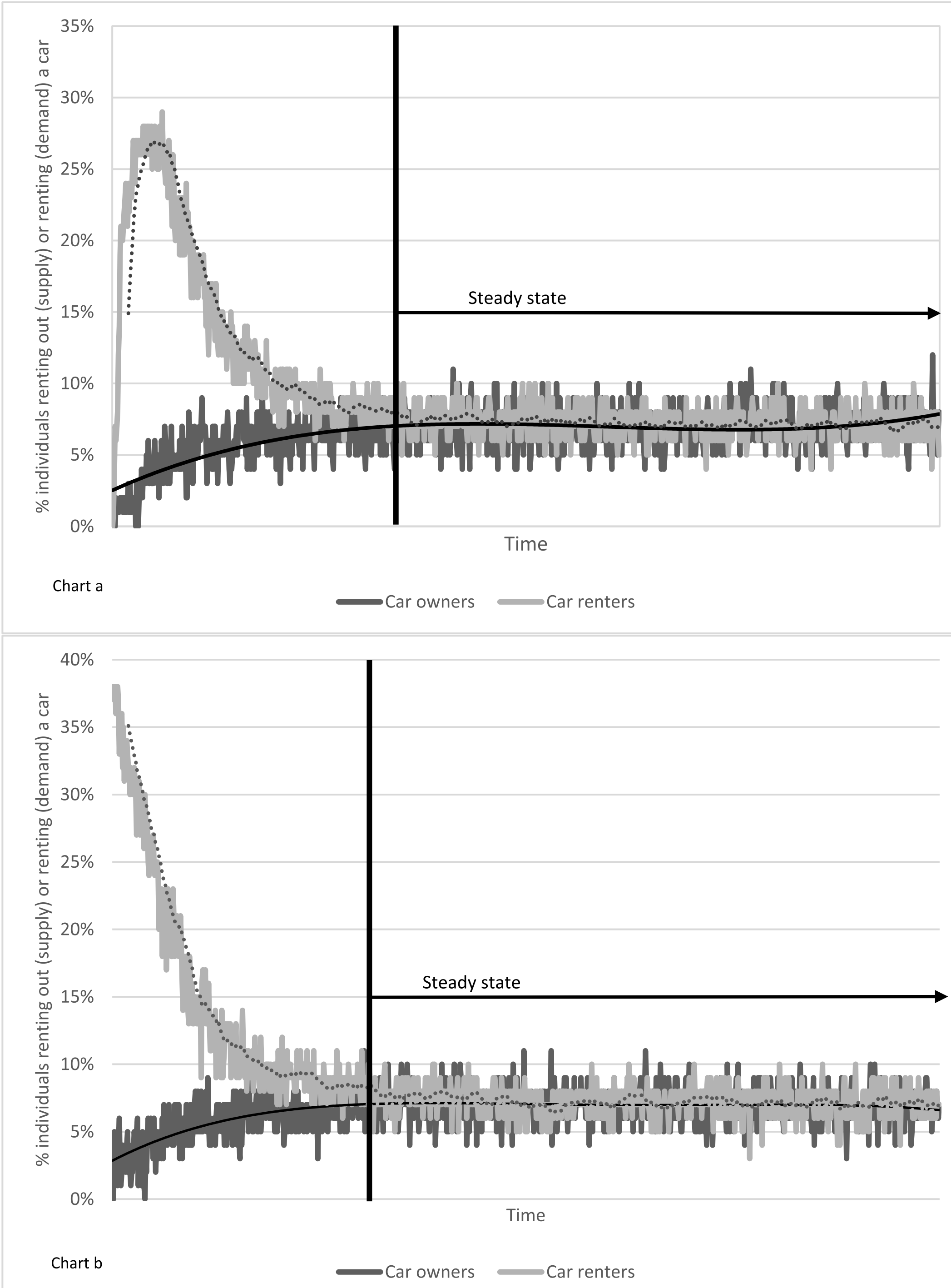

Fig. 10. Equilibrium rental rate and percentage of individuals willing to rent out (supply side of the market) or rent (demand side of the market) a car over time with (Chart a) and without (Chart b) innovation and word-of mouth effect.

value of the rental rate and on the percentage of agents using the service when the market reaches its steady state. We varied both the coefficient of innovation and the coefficient of imitation within the range of 0.01 (estimated by Zhang et al., 2020) – 0.136 (estimated by Luna et al., 2020). As for the contact rate, we varied it within the range 0.01%–0.02%, corresponding to the value estimated by Dunbar and twice the Dunbar's estimation, assuming that the new ICTs and the social networks could increase the number of people with whom one can maintain a stable social relationship. The impact on the value of the rental rate at steady state is negligible (Table 6), while the impact on the percentage of car renters (Table 6 and Fig. 11) and of car owners willing to rent a car is significant (Table 6 and Fig. 12). In Figs. 11 and 12 we depicted the number of simulations (vertical axis) in which at steady state we obtained the % of car renters and car owners reported in the horizontal axis (see Table 7).

6. Policy scenario analysis

In our case study, the potential P2PCS users are characterized by a significant latent negative a-priori toward the choice to engage in the

Table 5
Summary metrics of the scenario analysis at the steady state on the characteristics of the population.

Scenario analyzed	% of car owners renting out a car	% of car renters	Rental rate
Increase of the number of agents willing to rent rather than to buy a car	11%	11%	5.5 €/h
Increase of the number of agents concerned about environmental sustainability	8%	8%	6.1 €/h

Table 6
Sensitivity analysis of the rental rate at steady state as a function of innovation and imitation effect.

Variable analyzed	Outcome of the analysis
Rental rate at steady state	5.9 €/h - 6.1 €/h; expected value 6 €/h
Percentage of owners renting out a car at steady state	3–5% - 10–11%; expected value 7%
Percentage of renters at steady state	3–4% - 9–10%; expected value 7%

Table 7
Summary metrics of the scenario analysis at the steady state on the policies supporting the P2PCS.

Scenario analyzed	% of car owners renting out a car	% of car renters	Rental rate
High effective policies	42%	42%	6.6 €/h
Moderate effective policies	26%	26%	7.6 €/h
Mildly effective policies	10%	10%	7.8 €/h

market. Indeed, we estimated a significant negative constant of the binary logistics model of using the service both for car owners and car renters (Table 1). In the literature, however, several policies proved to be effective in reducing this negative preconception, including reserved parking spots, parking discounts, discounts on car ownership taxes, and reserved lanes (Münzel et al., 2019; Prieto et al., 2022; Shaheen & Cohen, 2020). Since there are no studies measuring the effectiveness of these policies in reducing the equilibrium rental rate or in increasing the percentage of users, we used our simulation model to predict the outcome of three possible scenarios. In the first scenario, we assumed that the package of policies is highly effective, such that they perfectly compensate the value of the negative alternative specific constant of both the car owners and the car renters. The outcome would be an increase of the P2PCS users up to 42% compared to the reference scenario with a small increase in the rental rate of 0.5€/h.

In the second scenario, we assumed that the policies are effective but that they are able to reduce the alternative specific constants by 2/3 of their estimated value. In this case, the P2PCS users will increase to 26% compared to the reference scenario, however, the rental rate will increase by 1.5€/h.

Finally, in the third scenario, we assumed that the policies have only a mild effect, reducing the alternative specific constants only by 1/3 of their estimated value. According to our results, the number of users would still be higher than in the reference scenario, that is 10% instead of 7%, however, also the rental rate would be increased by 1.7 €/h.

7. Conclusions

Our work is based on the results of a survey we carried out in 2019 in Friuli-Venezia Giulia (Italy) to analyze the potential demand and supply of a P2PCS service in less-densely populated areas. We have developed a disaggregated Bass Diffusion agent-based model capable of simulating how the adoption rate of a P2PCS would change according to the characteristics of the population and the effectiveness of the policies subsidizing and supporting the service. We estimated that the market would reach a steady state with 7% of car owners and car renters engaging in the market and a rental rate of 6.1 €/h.

We validated the results of our simulation model against the data we collected in 2019, showing the robustness of the results we obtained. We performed a simulation analysis to check the impact of the innovation effect and the imitation effect, since they have not been studied with reference to the P2PCS market yet, and are still highly uncertain. We demonstrated that, although the rental rate when the market reaches the steady state would not be significantly affected by the magnitude of the two effects, the percentage of the individuals who would engage in the market would remarkably change, ranging from a minimum of 3–4% to a maximum of 10–11%.

We also studied via a scenario analysis what would be the impact in terms of rental rate and percentage of users if a larger percentage of the population would be willing to rent a car when needed instead of owning a car. We found that in this scenario the P2PCS would be used by 11% of the population at a rental rate of 5.5 €/h. We also tested the impact of three sets of transport policy packages, including favorable parking pricing, supportive regulation, and reduced taxes on car ownership and car use, differing with reference to their effectiveness in supporting the P2PCS. In the best-case scenario, we found that the

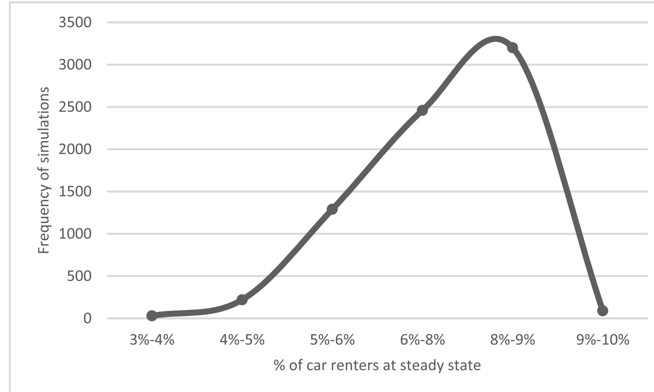

Fig. 11. Frequency (vertical axis) of simulations obtaining the percentage of car renters (horizontal axis) as a function of the sensitivity analysis with respect to the innovation and imitation effect
Note: total number of simulations 7290.

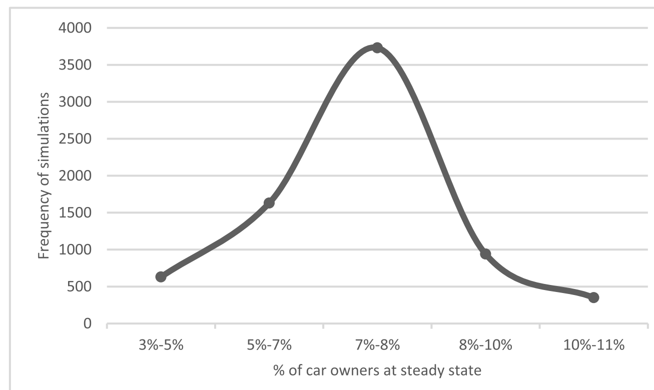

Fig. 12. Frequency (vertical axis) of simulations obtaining the percentage of car owners (horizontal axis) as a function of the sensitivity analysis with respect to the innovation and imitation effect
Note: total number of simulations 7290.

percentage of the population that would use the service would rise up to 42%.

Actually, also due to the COVID-19 pandemic, in the geographical area we have studied, the demand and the supply of peers-shared cars are not significant yet, the main problem being triggering both sides of the market and overcoming the skepticism currently characterizing the potential users. However, P2PCS would be a cheaper service than the standard B2C one, and it would be accessible even in less-densely populated areas. In addition, car owners could amortize the cost of vehicle purchase and ownership taxes, while car renters could dispose of a car when needed without incurring purchase and ownership costs, including the cost of the garage, and would be able to choose from a wide range of vehicles. The problem is essentially due to the lack of knowledge of the service, currently used mainly in some large Italian cities (Milan, Bologna).

This study allowed us to detect the research areas that need to be further investigated with reference to the P2PCS market. From a methodological point of view, we proved that integrating agent-based and discrete choice modelling could enhance the capability of performing informative scenario analysis while increasing the robustness of the forecasts obtained. Although this approach has not been used yet to estimate the evolution of the P2PCS market, it is a promising methodology that should be further explored.

From an empirical point of view, three important topics still need to be analyzed. Indeed, several papers have been devoted to identify the most promising policies to be implemented in order to foster B2CCS (e.g., Balac et al., 2017; Dowling & Kent, 2015; Shaheen, Martin, & Hoffman-Stapleton, 2021; Shaheen et al., 2010). Akyelken et al. (2018) suggested developing multi-modal networks within towns and cities, having the Municipalities provide carsharing schemes that are coordinated at the regional level with the public transport system, and subsidizing public transport services as carsharing is viewed as complementary to public transport. They also proposed parking allowances and differentiated parking fees for car sharing vehicles, city zoning with car traffic restrictions/bans for non-car sharing vehicles, and differentiated value added tax for carsharing services. However, there are no studies specifically analyzing what would be the most effective policies to support the uptake of a P2PCS scheme. They might differ according to the side of the market taken into account, car owners versus car renters, and the type of area where the service is provided, urban versus rural. Therefore, future research should be focused on the analysis of which policies would be more effective in stimulating the demand and the supply side of the market.

An important research area that should be further investigated is also the role that the innovation effect and the imitation effect play in the P2PCS market. Currently, there are very few papers shedding light on the magnitude of the coefficient of innovation, the coefficient of imitation, and the contact rate, and they refer specifically to the B2CCS, while there are no estimates for the P2PCS market.

The methodology we used in our study has a few limitations. With reference to the data we collected to estimate the preferences of the demand and supply side of the P2PCS market, we gathered them in November–December 2019 before COVID-19 started, however, the health emergency might have reduced the safety perception of sharing a car with strangers. Moreover, we collected stated preference data potentially affected by the hypothetical bias issue. Finally, we surveyed 449 individuals, a sample that underrepresents the low-income segment of the population and might be too small compared with the 1.2 million people living in the Friuli-Venezia Giulia region. To overcome these limitations and to check the robustness of our results, it would be advisable to perform a new survey involving a larger sample and collecting both revealed and stated preference data specifically controlling for the pandemic effect. With reference to the simulation model, which is based on the Bass Diffusion model, the main drawback is the assumption that the innovation and the imitation coefficients do not change over time. Moreover, we have found only two studies estimating the value of these two critical coefficients with reference to the carsharing market. In the future, it would be advisable to further empirically study the magnitude of the innovation and imitation effect within the carsharing market and to account for the fact that the evolution of the ICTs might dynamically significantly change the value of the imitation effect.

CRediT authorship contribution statement

Lucia Rotaris: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Software, Supervision, Validation, Writing – original draft. **Mariangela Scorrano:** Conceptualization, Methodology, Software, Validation, Writing – review & editing.

Appendix

Table 8
Socio-demographic characteristics of the sample of car owners and car renters and of the population living in Friuli-Venezia Giulia

	Sample of car owners	Sample of car renters	FVG population*
Gender			
male; female	52%; 48%	52%; 49%	49%; 51%
Age			
21-24; 25–44; 45–64; >64	6%; 41%; 39%; 14%	9%; 35%; 39%; 17%	7%; 34%; 41%; 17%
Education			
middle school; high school; bachelor; master	2%; 49%; 13%; 36%	18%; 35%; 30%; 18%	
middle school or high school; bachelor or master			79%; 21%
Occupational status			
employee; self-employed; student; retired/housewife; unemployed	55%; 23%; 5%; 15%; 2%	48%; 9%; 19%; 18%; 7%	
employee; self-employed; not working; unemployed			38%; 26%; 29%; 7%
Income			
<€30,000; €30,000-€70,000; >€70,000	29%; 45%; 26%	22%; 68%; 10%	
<€15,000; €15,000–26,000; €26,000–55,000; >€55,000			37%; 34%; 24%; 5%

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