Roundtrip, free-floating and peer-to-peer carsharing: A Bayesian behavioral analysis

Érika Martins Silva Ramos * David Issa Mattos†

Cecilia Jakobsson Bergstad ‡

Abstract

This study analyses behavioral psychological facilitators and barriers to using different carsharing business models. It identifies the most preferable carsharing business models for different trip purposes as well as the main motivators for using it. Users of carsharing services (N=1,121) in German cities completed a questionnaire distributed by five operators representing three different business models: free-floating (FF), round-trip station-based (RTSB), and peer-to-peer (P2P). All analyses are performed from a Bayesian perspective and further discussion of the statistical analyses is included. The main results indicate that there are different preferences for carsharing business models depending on the trip purpose, with a trade-off between free-floating and round-trip station-based business models. The peer-to-peer business model stood out for short holiday trips. Age, educational level, and income affected the probability of selecting different carsharing operators. Users of FF and RTSB differ regarding driving habits and trust in the services.

Keywords: carsharing; travel behavior; Bayesian modeling; Bradley-Terry model; carsharing business models

*erika.ramos@psy.gu.se Department of Psychology at the University of Gothenburg, Gothenburg, Sweden

†david.mattos@volvocars.com Volvo Cars, Gothenburg, Sweden

‡cecilia.bergstad@psy.gu.se Department of Psychology at the University of Gothenburg, Gothenburg, Sweden

1 Introduction

Sharing goods and services is an effective strategy to reduce greenhouse gas emissions and land use (Svenfelt et al., 2019). Therefore, shared mobility such as carsharing has the potential to offer environmental, social, and economic benefits as well as technological innovation for a more sustainable transition in the transport sector (Whittle et al., 2019).

The literature on social psychology and transport behavior has investigated to a great extent the travel mode choice in the context of public transport, active travel, and the use of the private car. But more research is needed to better understand the modern scenario of shared mobility in connection to psychological processes and how they influence travel behavior (Katsev et al., 2001). In this study, we investigate the effect of habits, social norms, trust, environmental concern; subjective and instrumental motivation on the use of carsharing services.

The objectives of this study are to estimate to what extent behavioral and psychological facilitators and barriers affect the use of different carsharing business models, to rank the most preferable carsharing business model according to different trip purposes, and to identify the main motivators for using carsharing. Previous research has identified that structural and subjective barriers affect the demand for carsharing services (Nansubuga and Kowalkowski, 2021). But these effects may not be homogeneous across different carsharing business models. Therefore, mapping these effects is an added value for the stakeholders.

The results from this study will help stakeholders to understand the patterns of travel behavior that each type of carsharing produces. For instance, this knowledge can be of importance for carsharing operators and to give support for planning sustainable cities, as proposed by the United Nations 2030 Development Agenda with the 17 Sustainable Development Goals (SDGs) in 2015.

Historically, carsharing started in the mid-1990s, sometimes as non-profit cooperatives, with further intensive development in metropolitan areas in North America (Martin et al., 2010). Today, many business models have emerged to address different market demands and mobility landscapes. In this study, the investigation is focused on the business-to-consumer (B2C) and peer-to-peer (P2P) models.

In the B2C business model, the cars are rented on demand by individual users from a company that owns the fleet, while in the P2P model, the cars are shared among individuals who own the vehicles and a company administrates the sharing platform. B2C carsharing is further divided into round-trip station-based (RTSB) (the cars need to be returned to a specific station or operational area) and free-floating (FF) (the cars can be parked anywhere within an operational area) (Münzel et al., 2018).

The business models have shown to produce different impacts on people's behavior. The impact on the reduction of car ownership is weaker for FF carsharing than for RTSB services (Becker et al., 2018). One reason for this may be that FF carsharing use is mostly for non-regular trips. Besides, different carsharing business models may attract attention from different profiles of users and their benefits may also facilitate different kinds of trips (Liao et al., 2020).

Different carsharing business models have spread across countries and cities in different manners, by interacting with the local transport scenarios and consequently generating different outcomes for traffic and travel behavior (Shaheen and Cohen, 2013). The different business models may generate more or less demand for parking in urban areas, for short inner-city trips (such as going out for dinner or social activities), or for sporadic trips (such as short holiday trips or bulk shopping).

In major metropolitan areas, the profile of people with positive attitudes towards carsharing is of young, employed, highly-educated men living in small households (Burghard and Dütschke, 2019). In the German context, this profile was one of the most car-oriented groups in the past and now turned into the opposite, the less car-oriented group, facilitating the spread of B2C carsharing services in the country (Kuhnimhof et al., 2013). In the Swedish context, carsharing is still a niche in big cities, with a dominant player owned by an incumbent car manufacturer. The FF model has not developed much, while RTSB services are prevalent (Bocken et al., 2020). In Italy, carsharing has consolidated as a recently increasing phenomenon, with a big fleet and a big market share of FF business models (Mugion et al., 2019). In the French scenario, P2P is especially popular if compared to other Western European countries such as Belgium, Germany, The Netherlands, and United Kingdom (Münzel et al., 2020).

As previously discussed, besides the different business models across countries, carsharing users also have different profiles (Baumgarte et al., 2021) and their motivation for using the service may be influenced by many structural factors (such as the ease of the booking system, price, convenience and accessibility of the vehicles) as well as behavioral and psychological aspects (such as travel habits, environmental attitudes, social norms, trust and the perception of control over their travel decisions) (Ramos et al., 2020). Therefore, this study is of importance to further investigate the motivators to use different carsharing business models.

The motives for driving a car or choosing another mode of transport are not merely driven by instrumental motives, such as cost, comfort, efficiency, parking availability, and so forth. A car also provides social visibility for the driver and allows them to comply with the social norms of their reference groups (Steg, 2005). In certain circumstances, people may be motivated for traveling by hedonic and social factors rather than merely utilitarian aspects, including aspects such as the sense of speed, motion, control, and enjoying the beauty of the surrounding environment (Mokhtarian et al., 2001).

The motivators to use a car, private or shared, are influenced by the perceived outcomes of its use. For instance, considering using fuel-efficient vehicles encompasses the perceived consequences of the comfort, performance, and environmental attributes of the car, as well as the symbolic aspects (such as receiving social approval from a reference group and sharing a certain social status) (Nayum and Klöckner, 2014; Noppers et al., 2014).

The perception of the social norms is formed by the evaluation that one makes of the expectations from their group of reference and their motivation to comply with these expectations (Davis et al., 1989), called the subjective norms. Subjective norms partially explain the choice of different modes of transportation, and it is an essential predictor of travel behavior because it provides information on the social influence of people's choices (Liu et al., 2017; Zahedi et al., 2019).

In connection to the social norms, carsharing users' profiles are partially explained by the connection of transport mode choice and environmental attitudes (Hoffmann et al., 2020). Climate morality was identified as the main factor to change motivation to reduce private car use (Andersson, 2020). However, transport-relevant attitudes can be ambivalent or complex, depending on the context. Environmental concern and awareness are not always relevant to users (Ramos and Bergstad, 2021), or they may be more relevant for certain segments, such as women (del Mar Alonso-Almeida, 2019). Environmental concern and awareness may also have the function of a secondary motivator, after extrinsic and economic ones (Böcker and Meelen, 2017).

One reason frequently identified in transportation research to explain why people often cannot change their travel patterns to more environmental friendly travels is that habitual behaviors are strong barriers to behavioral change (Itzchakov et al., 2018; Lanzini and Khan, 2017; Ouellette and Wood, 1998).

Habit is a specific factor that changes the nature of behaviors; it refers to how people choose to behave to accomplish a specific goal. Habit is more than the frequency of a given behavior; after repeated occurrences, mediated by mental processes, the habit is then triggered by a cognitive structure that is learned, stored, and retrieved from memory when receiving stimulation from the environment (Aarts et al., 1998).

People with strong habits of commuting by private car are less likely to engage in obtaining new information about alternative travel modes (Sivasubramaniyam et al., 2020), such as carsharing services. However, a temporary structural change may unfreeze old habits and alter the choices of modes of transport (Verplanken et al., 1997). Offering trials and free of charge trips can change a habitual travel pattern, attitude, and travel mode choices (Fujii and Kitamura, 2003).

Habit has been claimed as one of the most important barriers to behavioral change (Gifford, 2011). To change habits, people need to take an active role to rethink their needs, seek alternative ways of traveling, and adapt to new services (Hazée et al., 2017). These adaptations require cognitive effort and may be perceived as a burden, making it difficult to start using new services such as carsharing.

To facilitate the breaking of old habits, trust and the perception of being able to change one's travel behavior are important factors to help people to change travel mode choices (Acheampong and Siiba, 2020; Derikx and Lierop, 2021; Zhang and Li, 2020).

Trust is a belief that contributes to reduce the social complexity and the perceived risk in the context of an exchange or transaction (Wu and Chen, 2005a). Trust in carsharing services is treated as the perception of risk and how much one can rely on the trusting party. The users expect that the operators will provide reliable services.

Lack of trust is one of the main deterrents of sharing a vehicle, and it is often associated with the effectiveness of carsharing services (Mugion et al., 2019). For instance, P2P platforms still need to increase their level of trust among users. Trust is an important aspect to build women's engagement in carsharing use, especially for the P2P business models (Prieto et al., 2017). It's an added value for women to have the information regarding the extent to which vehicles and evaluations of previous trips are trustworthy before deciding to use a car (del Mar Alonso-Almeida, 2019).

Feedback mechanisms, surge pricing, and payment security are important features of carsharing services to help users build their trust in the service and continue using it. Moreover, the social influence from the user's network is another aspect that helps to build trust (Shao and Yin, 2018). Previous research has shown that the levels of trust in other people are lower for users of P2P compared to B2C, while trust in the technology involved in the service is more important to users of P2P than to B2C users (Julsrud and Uteng, 2021).

The research questions for this study were formulated taking into account the variety of carsharing business models and the complexity of the psychological and behavioral aspects surrounding the use of carsharing services. Figure 1 summarizes the psychological factors covered in this study based on the literature previous discussed. The research questions are presented below:

RQ1 What are the car use patterns across the carsharing business models?

RQ2 To what extent does each motivator impact the probability of choosing a carsharing business model?

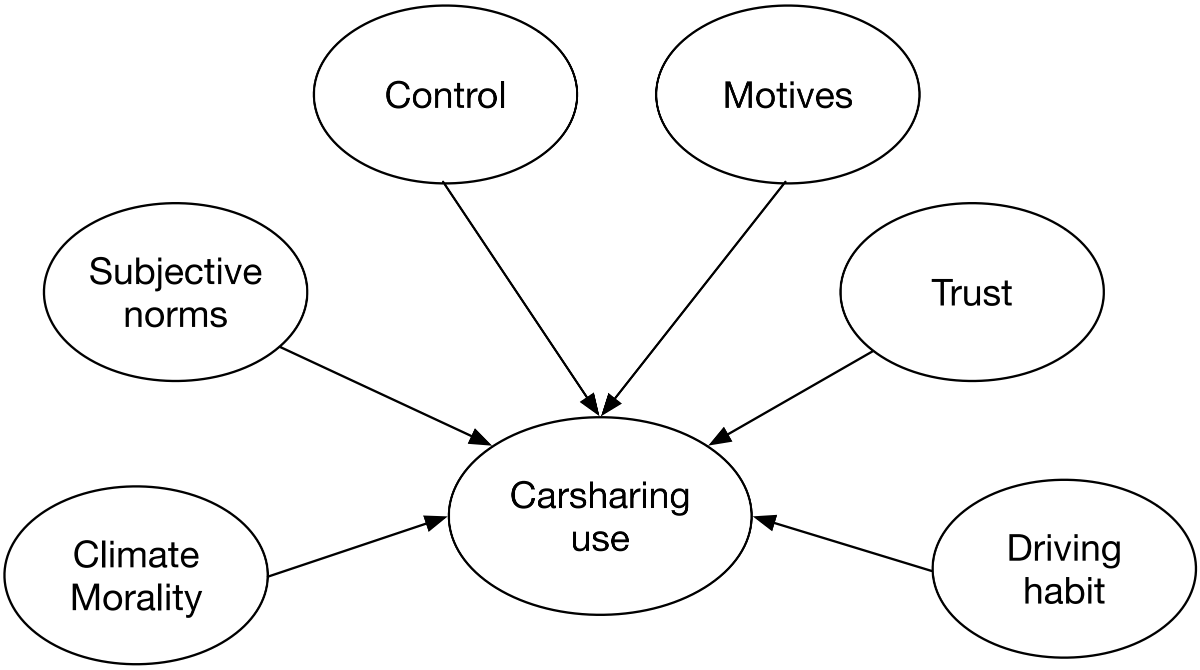

Figure 1: Psychological and behavioral predictive model of carsharing use.

RQ3 For each kind of trip purpose, what carsharing business model is preferred?

RQ4 For each business model, how do the different psychological predictors impact the frequency of use of carsharing?

2 Method

2.1 Sample

The sample consists of users of carsharing services (N=1,121) in the German cities of Frankfurt (N=465), Köln (N=136), Stuttgart (N=303), and nationwide for one of the operators (N=217). The mean age is 46 years and 49.2% of the respondents are male. Five operators representing four business models participated in the study. The operators are named based on their business models: free-floating (FF), round-trip station-based (RTSB_A and RTSB_B), peer-to-peer (P2P), and a combination of RTSB and FF (COMB).

Table 1: Socio-demographic descriptive statistics of the sample

	Overall
	(N=1121)
City	
Frankfurt	465 (41.5%)
Köln	136 (12.1%)
Stuttgart	303 (27.0%)
Others	217 (19.4%)
Age	
Mean (SD)	46.5 (12.9)
Median [Min, Max]	46.0 [20.0, 119]
Missing	135 (12.0%)
Gender	
Female	428 (38.2%)
Male	551 (49.2%)
Other	8.00 (0.7%)
Missing	134 (12.0%)
Education	
Secondary school 1	16.0 (1.4%)
Secondary school 2	87.0 (7.8%)
High school	164 (14.6%)
University	710 (63.3%)
Missing	144 (12.8%)
Household income before taxes (euro)	
< 1000	27.0 (2.4%)
1000 to 2000	127 (11.3%)
2000 to 3000	211 (18.8%)
3000 to 4000	163 (14.5%)
4000 to 5000	129 (11.5%)
> 5000	159 (14.2%)
Missing	305 (27.2%)
Household (number of persons cohabiting)	
1	359 (32.0%)
2	440 (39.3%)
3	160 (14.3%)
4	133 (11.9%)
> 5	29.0 (2.6%)
Presence of children in the household	
No	833 (74.3%)
Yes	288 (25.7%)

2.2 Instruments and procedures

The link to the survey was sent by the German carsharing association BCS (Bundesverband CarSharing) to the customers of four carsharing operators (named here RTSB_A, RTSB_B, P2P, and COMB). No economic benefit was linked to the participation and the respondents provided informed consent before answering the survey. The survey was open to the respondents from April to June 2018.

The survey was designed by the authors, based on pre-existing literature. It assessed sociodemographic variables and five latent psychological predictors of carsharing use, namely driving habits, climate morality, subjective norms, trust, and control. All items across the psychological predictors had a 5-point Likert scale, in which 1 corresponds to the lowest valence of the measurement and 5 to the strongest. The average duration to answer the survey was 15 minutes.

Below, each subscale is presented, together with an example of an item and the reference to the literature on which the subscale was based.

Habit is assessed by eight items that intend to capture the automaticity and the psychological need to use a car (e.g. 'I use the car without planning ahead') (Klöckner and Friedrichsmeier, 2011).

Climate morality is assessed by five items that involve the individual's perception of the negative effects to the environment due to the use of a private car (e.g. 'I feel morally obliged to reduce the environmental impact due to my travel patterns') (Klöckner and Friedrichsmeier, 2011). The concept of climate morality is in this study treated as a combination of personal norms and environmental concerns.

Subjective norms are assessed by three items that involve the individual's perception of their peers' evaluation when it comes to the use of carsharing (e.g. 'People who are important to me like that I use carsharing') (Bamberg et al., 2003; Thøgersen, 2006).

Trust is assessed by three items that involve the perception of the quality and trustworthiness of carsharing services (e.g. 'Based on my previous experience with carsharing, I know that it is trustworthy') (Zhang et al., 2019).

Control is assessed by six items that involve the individual's perception of control, usefulness, and ability to accomplish their needs by using carsharing services (e.g. 'Carsharing helps me to accomplish activities that are important to me') (Bamberg et al., 2003; Wu and Chen, 2005b). The concept of control is treated as a combination of the concepts of perceived behavior control, ease of use, and perceived usefulness (see the supplementary material).

Participants were asked to indicate which of the carsharing operators they were most likely to choose for six trip purposes (work-related, going out for dinner, daily shopping, bulk shopping, recreational activities on the weekends, and short holidays), based on a 5-point Likert scale, in which 1 corresponded to "very unlikely" and 5 corresponded to "very likely". They were also asked to indicate how often they used a given operator's cars in the past 12 months, based on an ordinal scale in which 1 = "not at all", 2 = "at least once a year", 3 = "at least once every six months", 4 = "at least once a month" and 5 = "at least once a week".

2.3 Data analysis

This section provides an overview of the data analysis plan, including a description and justification of each statistical model.

The analyses were conducted within the Bayesian framework. The main reasons for choosing the Bayesian frameworks, as opposed to the frequentist, are: the Bayesian approach (a) provides better control of type I error (Kelter, 2020), (b) provides more robust evidence towards the null hypothesis (Kruschke, 2013), (c) provides stables estimates for models with many parameters and latent variables (Kucukelbir et al., 2015), (d) makes explicit representation of the model assumptions (McElreath, 2020), (e) obtains a full posterior distribution which allows a probabilistic interpretation of parameter intervals, as opposed to the repeated sampling interpretation and approximations of the standard errors (Kruschke, 2013; McElreath, 2020) and (f) allow the use of extensions such as monotonic effects in generalized linear models (Bürkner and Charpentier, 2020).

2.3.1 To what extent does each motivator impact the probability of choosing a carsharing business model?

This research question analyses how different motivators impact the probability of choosing a specific carsharing business model (represented by the operator) as the main operator. This question is modeled with a Bayesian multinomial regression with a logistic link function utilizing the `brms` R package (Agresti, 2003; Bürkner, 2018). In the multinomial regression, the response variable is categorical. The probability of selecting a specific category (a carsharing business model) is based on a generalized linear model that takes into account multiple predictors.

The predictors in the generalized linear model are the motivators for the use of carsharing (accessibility, reduction of expenses, not owning a car, sustainability, avoiding maintenance, not worrying about parking and convenience) and socio-economic variables (gender, income, age, and education). The motivators are binary variables that represent whether it is important for the user or not; gender is a categorical variable; age is normalized on a numerical scale; education and income are ordinal variables. The ordinal predictors (income and education) were modeled considering monotonic effects (Bürkner and Charpentier, 2020).

A mathematical formulation of the model (that includes both socio-economic variables and motivators) is represented below. The model utilises the following notation:

- i indicates each subject
- j indicates the category (the business model of the main operator)
- Y_i indicates the observation (the reported main operator) for subject i
- $x_{\text{var},i}$ indicates the response subject i gave to the predictor variable
- a_j is the intercept for the business model j
- $\beta_{\text{var},j}$ is the slope coefficient for predictor variable in business model j
- $mo(\text{var})$ indicates that predictor variable is treated as a monotonic predictor

- The simplex parameters for the monotonic effects are represented by $\mu_{\text{var},j,k}$, where var is the predictor, j the business model, and k the ordered value of the predictor.

- The scale parameter is represented by the slope coefficient β of the variable.

Monotonic effects is a technique proposed by Bürkner and Charpentier (2020) to parametrize ordinal independent variables in a regression framework. This technique utilizes a scale parameter that represents the direction and size of the effect in the scale and simplex parameters that represent the differences between each category in this ordinal scale.

As is common in the Bayesian framework, the model is divided in terms of the likelihood and the priors.

Likelihood (the multinomial regression):

$$
\begin{aligned}
Y_i &\sim \text{Multinomial}(\pi_{ij}) \\
\pi_{ij} &= \Pr(Y_i = j) = \frac{\exp f_{ij}}{\sum_j \exp f_{ij}} \\
f_{ij} &= a_j + \beta_{\text{accessibility},j} \cdot x_{\text{accessibility},i} + \beta_{\text{expenses},j} \cdot x_{\text{expenses},i} \\
&\quad + \beta_{\text{not owning a car},j} \cdot x_{\text{not owning a car},i} + \beta_{\text{sustainability},j} \cdot x_{\text{sustainability},i} \\
&\quad + \beta_{\text{gender},j} \cdot x_{\text{gender},i} + \beta_{\text{age},j} \cdot x_{\text{age},i} + \beta_{mo(\text{income}),j} \cdot x_{\text{income},i} \\
&\quad + \beta_{mo(\text{education}),j} \cdot x_{\text{education},i}
\end{aligned}
$$

Priors of the parameters (for all predictor):

$$
\begin{aligned}
\beta_j &\sim \text{Normal}(0, 5) \\
a_j &\sim \text{Student-T}(3, 0, 2.5) \\
\mu_{j,k} &\sim \text{Dirichlet}(1)
\end{aligned}
$$

The priors were chosen to be weakly-informative priors. Weakly-informative priors are proper priors (they are a valid probability distribution) that allow the model parameters to be estimated without bias. In other terms, weakly-informative priors have a very low impact on the parameter estimation when compared to the evidence provided by the data.

2.3.2 For each kind of trip purpose, what carsharing business model is preferred?

This research question aims to analyze the preferences for one carsharing business model compared to another, given the kind of trip purpose. When the same subjects rate multiple operators, these operators can be compared in pairs using the Bradley-Terry model. The Bradley-Terry model is a statistical model which can be used to evaluate the probability of a user selecting between two carsharing operators. The model assumes that a carsharing operator has a latent strength variable that influences the probability of selecting it over another operator. This estimated latent strength parameter can be used to rank the different operators. This preference assessment is made with users that are registered with at least two carsharing operators ($N = 447$).

The model assumes that the latent strength parameters λ are independent for each type of trip. The model utilizes the following notation:

- k represents the subject
- i and j represent two distinct carsharing operators
- λ_i represents the latent strength variable that influences the probability of selecting it over another operator
- $Y_{i,j,k}$ indicates the observation (the preferred carsharing operator) among operators i and j for subject k. If carsharing operator i is preferred for a specific type of trip, then $Y_{i,j,k,\text{trip}} = 1$. Otherwise, if j is preferred then $Y_{i,j,k,\text{trip}} = 0$
- $\mathcal{P}[i \text{ beats } j|\text{trip}, k]$ is the probability of carsharing operator i being preferred (beating) carsharing operator j for a specific type of trip

As is common in the Bayesian framework, the model is divided in terms of the likelihood and the priors.

Likelihood (Bradley-Terry model per trip):

$$\mathcal{P}[i \text{ beats } j|\text{trip}, k] = \frac{\exp \lambda_i}{\exp \lambda_i + \exp \lambda_j}$$
$$Y_{i,j,k,\text{trip}} \sim \text{Bernoulli}(\mathcal{P}[i \text{ beats } j|\text{trip}])$$

Priors:

$$\lambda_{i,\text{trip}} \sim \mathcal{N}(0, 3)$$

The model utilizes a normal prior distribution with a variance of 3.0. This variance was set to be weakly-informative, i.e. to reduce the influence of the prior in the model convergence, while providing some level of regularisation to the model (Mattos and Ramos, 2021). This prior allows probabilities to be of i beating j to be in the range of 0.0001 to 0.9998.

After obtaining the posterior distribution of the latent strength parameter, this posterior distribution can be sampled multiple times (in this case 1,000) and ranked. This process results in a distribution of the ranks of the operators, which includes the uncertainty in the rank estimation.

2.3.3 For each business model, how do the different psychological predictors impact the frequency of use of carsharing?

To answer this research question, the data is analyzed with a Bayesian cumulative ordered regression for each kind of carsharing business model (Bürkner and Vuorre, 2019). The response variable is ordinal and corresponds to the frequency of use. In this model, the predictors correspond to psychological and socio-economic variables. The socio-economic predictors are gender (categorical variable), age (normalized in a numerical scale), education, and income (ordinal variables). The ordinal predictors (education and income) are modeled considering monotonic effects. The psychological predictors of the second model are the scores (numerical) obtained from the factor analysis of the latent variables habit, climate morality, subjective norm, trust, and control.

The model (including both the socio-economic and psychological predictors) is represented below, following the notation used by McElreath (2020). This notation utilizes the ordered-logit distribution to simplify writing the probabilities of each category in the scale order used in a more formal description (Bürkner and Vuorre, 2019).

The model for each business operator utilises the following notation:

- i indicates each subject
- Y_i indicates the observation (the reported frequency of use of the main operator in an ordinal scale)
- $x_{\text{var},i}$ indicates the response subject i gave to the predictor variable
- ϕ_i is the predicted value of the linear model for subject i
- κ_m is the intercept for the category m of the response variable
- β_{var} is the slope coefficient for the predictor variable
- $mo(\text{var})$ indicates that the predictor variable is treated as a monotonic predictor
- $\mu_{\text{var},k}$ are the simplex parameters for the monotonic effects where var is the predictor and k the ordered value of that predictor. The scale parameter is represented by the slope coefficient β of the predictor

As is common in the Bayesian framework, the model is divided in terms of the likelihood and the priors.

Likelihood (the cumulative ordered logit regression):

$$
\begin{aligned}
&Y_i \sim \text{Ordered-Logit}(\phi_i, \kappa) \\
&\phi_i = \beta_{\text{habits}} \cdot x_{\text{habits},i} + \beta_{\text{climate}} \cdot x_{\text{climate},i} \\
&\quad + \beta_{\text{subj}} \cdot x_{\text{subj},i} + \beta_{\text{trust}} \cdot x_{\text{trust},i} + \beta_{\text{control}} \cdot x_{\text{control},i} \\
&\quad + \beta_{\text{gender}} \cdot x_{\text{gender},i} + \beta_{\text{age}} \cdot x_{\text{age},i} + \beta_{mo(\text{income})} \cdot x_{\text{income},i} \\
&\quad + \beta_{mo(\text{education})} \cdot x_{\text{education},i}
\end{aligned}
$$

Table 2: Summary of the analysis models

Independent variable	Model	Dependent variables
Reported main operator	Bayesian multinomial regression	Motivators (accessibility, expenses, not owning a car, and sustainability) and socio-demographic (gender, age, income, and education)
Preferred carsharing operator	Bayesian Bradley-Terry model	Paired comparison between two operators
Frequency of use in ordinal scale	Bayesian cumulative ordered logit regression	Psychological factors (habits, climate, subjective norms, perceived control, and trust) and socio-demographic (gender, age, income, and education)

Note 1: Ordered dependent variables such as age, income and education were modelled using monotonic effects
Note 2: Categorical predictors and binary were modelled using dummy variables

Priors of the parameters (for all predictor):

$$\beta_j \sim \text{Normal}(0, 5)$$

$$\kappa_m \sim \text{Student-T}(3, 0, 2.5)$$

$$\mu_{j,k} \sim \text{Dirichlet}(1)$$

The first model is easily obtained by removing the motivators from the linear model in ϕ_i.

For both models, the priors were chosen to be weakly-informative priors. Weakly-informative priors are proper priors (they are a valid probability distribution) that allow the model parameters to be estimated without bias. In other terms, weakly-informative priors have a very low impact on the parameter estimation when compared to the evidence provided by the data.

2.3.4 Summary of the analysis

Table 2 provides a summary of the analysis with the independent variable, the statistical model, and the dependent variables.

2.4 Computational implementation and reproducible appendix

The data was analysed using the statistical software R version 4.0.3. The statistical models were developed using the `brms` package for Bayesian regression modelling (Bürkner, 2018), including the multinomial and cumulative ordered logit regression; the `bpcs` package for the Bayesian Bradley-Terry model (Mattos and Ramos, 2021); and the `psych` package for factorial analysis (Revelle and Revelle, 2015).

A reproducible workflow for the statistical analysis as well as full information regarding the session, including the version of all the used packages and the code used to generate the models, plots, and tables, as well as the data, are available in the online appendix: `https://erikamsramos.github.io/carsharing/`.

3 Results

Descriptive statistics were used to investigate the use of private cars across the different carsharing business models. The results are presented in Table 3.

Overall, 68.1% of the sample reported not having a private car in their households, and 29.6% of the sample expected that their household would be car-free if they were not members of a carsharing service, while 42.1% believed that they would have at least one car. Among those who own a private car, 6.2% use it daily. The users of FF present the highest percentage of daily use of a private car (11.5%) relative to the other operators. Users of COMB and RTSB_B have a higher percentage of ownership of monthly public transport passes, 57.1% and 69.3%, respectively.

To investigate the extent each motivator impacts the probability of choosing a carsharing business model, two Bayesian multinomial regression models were created. The first contains only the socio-economic variables in the linear regression, while the second contains both the socio-economic variables and the motivators. Both models utilize normal weakly-informative priors for the coefficients of the generalized linear model. These models were compared using the widely applicable information criterion (WAIC) (Gelman et al., 2014; McElreath, 2020). The first model has a WAIC of 2296.6 and the second of

Table 3: Descriptive statistics of private car use across carsharing business models

	COMB	FF	P2P	RTSB_A	RTSB_B	Overall
	(N=226)	(N=253)	(N=214)	(N=72)	(N=316)	(N=1121)
Current number of cars in the household with carsharing membership						
No car	180 (79.6%)	107 (42.3%)	147 (68.7%)	55 (76.4%)	255 (80.7%)	763 (68.1%)
One car	45 (19.9%)	104 (41.1%)	46 (21.5%)	15 (20.8%)	55 (17.4%)	279 (24.9%)
Two cars	1 (0.4%)	30 (11.9%)	14 (6.5%)	1 (1.4%)	5 (1.6%)	56 (5.0%)
Three or more cars	0 (0%)	12 (4.7%)	7 (3.3%)	1 (1.4%)	1 (0.3%)	23 (2.1%)
Expected number of cars in the household without carsharing membership						
No car	69 (30.5%)	46 (18.2%)	71 (33.2%)	18 (25.0%)	124 (39.2%)	332 (29.6%)
One car	106 (46.9%)	114 (45.1%)	84 (39.3%)	42 (58.3%)	124 (39.2%)	472 (42.1%)
Two cars	10 (4.4%)	41 (16.2%)	20 (9.3%)	4 (5.6%)	16 (5.1%)	91 (8.1%)
Three or more cars	0 (0%)	10 (4.0%)	5 (2.3%)	0 (0%)	0 (0%)	15 (1.3%)
Do not know	34 (15.0%)	23 (9.1%)	19 (8.9%)	6 (8.3%)	40 (12.7%)	123 (11.0%)
Missing	7 (3.1%)	19 (7.5%)	15 (7.0%)	2 (2.8%)	12 (3.8%)	88 (7.9%)
Frequency of use of private car						
Daily	8 (3.5%)	29 (11.5%)	19 (8.9%)	2 (2.8%)	8 (2.5%)	72 (6.4%)
4-6 days a week	2 (0.9%)	33 (13.0%)	16 (7.5%)	3 (4.2%)	8 (2.5%)	68 (6.1%)
1-3 days a week	14 (6.2%)	63 (24.9%)	27 (12.6%)	5 (6.9%)	14 (4.4%)	129 (11.5%)
Do not know	54 (23.9%)	55 (21.7%)	68 (31.8%)	20 (27.8%)	91 (28.8%)	298 (26.6%)
Missing	148 (65.5%)	73 (28.9%)	84 (39.3%)	42 (58.3%)	195 (61.7%)	554 (49.4%)
Ownership of monthly PT ticket						
No	97 (42.9%)	113 (44.7%)	103 (48.1%)	37 (51.4%)	97 (30.7%)	468 (41.7%)
Yes	129 (57.1%)	140 (55.3%)	111 (51.9%)	35 (48.6%)	219 (69.3%)	653 (58.3%)

2216.3. This shows that the motivators increase the model fitness compared to only the socio-demographic model.

Figures 2 and 3 show the conditional effects of the socio-demographic and the motivator variables. The conditional effects show how the probability of selecting a particular carsharing business model changes when one of the predictor variables changes. The summary statistics of the posterior distribution of every parameter for both models are presented in the online appendix.

The results show no variation between genders. An increase in age presented a reduction of probability for P2P and FF, and an increase for RTSB_B. An increase in income and education presented a reduction in probability for P2P and an increase for FF. Regarding the motivators, P2P and FF were the business models that presented higher variation in the probabilities given that the motivator was selected by the user. However, overall, the results do not show a relevant variation in the probabilities of choosing a carsharing operator for different motivators.

To investigate the preference for carsharing business model, five distinct Bayesian Bradley-Terry models were created, one for each trip purpose. The trip purposes were work-related, going out for dinner, daily shopping, bulk shopping, recreational activities

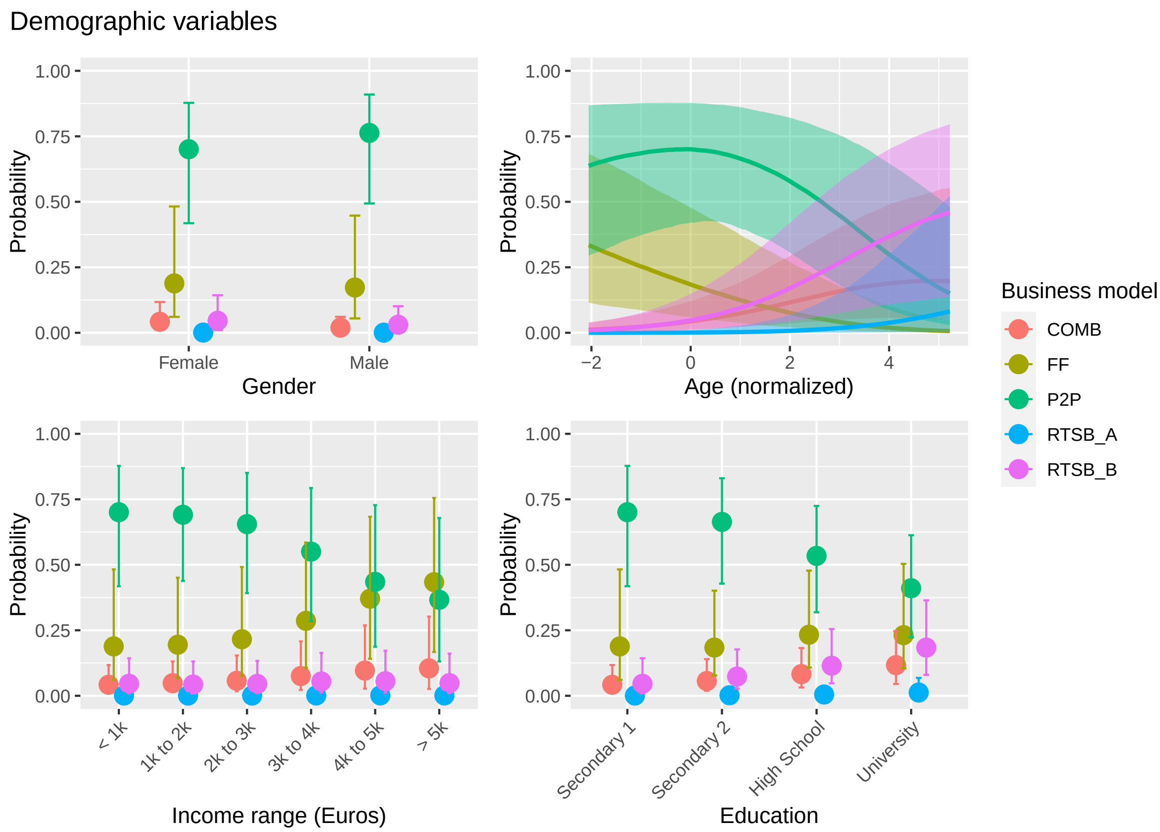

Figure 2: Conditional effects for the demographic variables. The line in the categorical and ordered predictors represents the 90% credible intervals while the dots represent the median value of the posterior distribution. For age, which is a continuous predictor, the central line corresponds to the median and the filled area corresponds to the 90% credible intervals.

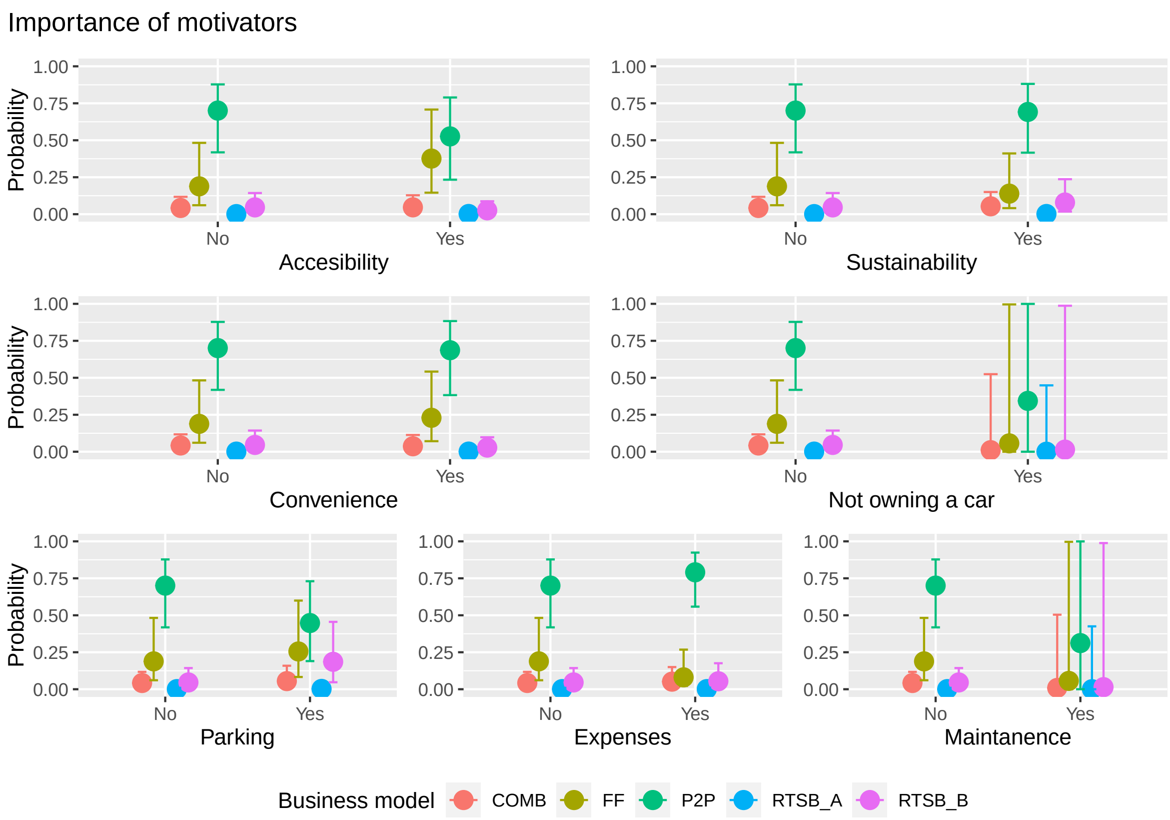

Figure 3: Conditional effects for the motivator variables. The line represents the 90% credible intervals while the dots represent the median value of the posterior distribution.

on the weekends, and short holidays.

Table 4 shows the median rank of every carsharing business model ranked by trip purpose. The uncertainty in this rank is represented by the mean and standard deviation of the rank. The summary statistics of the posterior distribution of every parameter for all models are presented in the online appendix.

For work-related trips, the rank of preferences is FF, RTSB_A, COMB, P2P, and RTSB_B. For going out for dinner, the rank of preferences is FF, COMB, RTSB_A, RTSB_B, and P2P. For daily shopping trips, the rank of preferences is COMB, FF, RTSB_A, RTSB_B, and P2P. For bulk shopping trips, the rank of preferences is RTSB_B, COMB, RTSB_A, P2P, and FF. For trips to recreational activities on weekends, the rank of preferences is RTSB_B, COMB, RTSB_A, P2P, and FF. For short holiday trips, the rank of preferences is P2P, RTSB_A, RTSB_B, COMB, and FF.

To assess the impact of different psychological predictors on the frequency of use of carsharing, two cumulative ordered logit regression models were fitted. The first model contains only the socio-economic predictors and the second model contains both the psychological and the socio-economic predictors. The psychological predictors of the second model are the scores (numerical) obtained from the factor analysis of the latent variables habit, climate morality, subjective norm, trust, and control.

Table 5 shows the Guttman coefficients of reliability, Lambda 3 and Lambda 4, for the factor analysis of the psychological factors. The covariance matrix was based on a polychoric correlation matrix since the items were in an ordinal scale (Gadermann et al., 2012; Holgado-Tello et al., 2010).

The models were compared using the widely applicable information criterion (WAIC) (Gelman et al., 2014; McElreath, 2020). The WAIC for each model is shown in Table 6. This table shows that while for all models adding psychological predictors resulted in a better fit, for the COMB and P2P models this improvement was smaller.

The conditional effects plots in Figure 4 show how the probability of selecting a specific operator changes with changes in the psychological predictors. Due to a large number of model parameters, the estimated socio-demographic plots and the all-parameter values

Table 4: Rank of the types of carsharing

Carsharing	Median	Mean	sd
Work trips			
FF	1	1.05	0.23
RTSB_A	2	2.77	1.07
COMB	3	3.03	0.96
P2P	4	4.04	0.96
RTSB_B	4	4.10	0.89
Dinner trips			
FF	1	1.00	0.07
COMB	2	2.16	0.45
RTSB_A	4	3.60	0.92
RTSB_B	4	3.68	0.75
P2P	5	4.55	0.70
Daily shopping trips			
COMB	1	1.38	0.71
FF	3	2.69	0.77
RTSB_A	3	2.83	1.16
RTSB_B	3	3.10	0.89
P2P	5	5.00	0.03
Bulk shopping trips			
RTSB_B	1	1.04	0.22
COMB	2	2.45	0.52
RTSB_A	3	2.51	0.57
P2P	4	4.31	0.47
FF	5	4.69	0.46
Recreational trips			
RTSB_B	1	1.39	0.63
COMB	2	2.23	0.86
RTSB_A	3	3.01	1.01
P2P	4	3.37	0.73
FF	5	5.00	0.00
Holiday trips			
P2P	1	1.40	0.57
RTSB_A	2	1.93	0.73
RTSB_B	3	2.69	0.57
COMB	4	3.99	0.13
FF	5	5.00	0.00

Table 5: Values of the Lambda 3 and Lambda 4 of Guttman for the psychological predictors

Lambda	Habits	Climate	Subj. norms	Trust	Control
Chronbach's Alpha (Lambda3)	0.87	0.87	0.69	0.94	0.58
Lambda4	0.91	0.90	0.80	0.84	0.89

Table 6: WAIC comparing the models with only socio-economic predictors (Model 1) against with both socio-economic and psychological predictors (Model 2) for each carsharing business model.

Model	FF	RTSB_A	RTSB_B	COMB	P2P
Model 1	1533.7	379.5	1044.1	712.3	896.1
Model 2	1475.6	353.3	1021.6	711.0	893.9

are presented only in the online appendix.

Overall, the probability of answering on the highest extreme of the scale (which is labeled as Response 5 in Figure 4 and represents the highest frequency of use, e.g. daily) was the main response affected by the psychological variables. For Response 5, an increase in the strength of driving habits reduced the probabilities for FF and P2P, increased the probabilities for RTSB_A and RTSB_B, and had no effect on COMB. An increase in climate morality had a small effect of decreasing the probabilities for RTSB_B and COMB. An increase in subjective norms had a small effect of decreasing the probabilities for RTSB_A, RTSB_B, and P2P. An increase in trust reduced the probabilities for RTSB_B and COMB and increased the probabilities for FF. An increase in control reduced the probabilities for FF, RTSB_A, RTSB_B, and COMB, and increased the probabilities for P2P.

4 Discussion

The main contributions of this article are that it provides information on the behavioral aspects that underlie the choices of carsharing business models. This information can be used to better understand the impact of shared mobility in society from a sustainable perspective. It has methodological contributions by discussing the importance of considering the limitations of frequentist statistics and it proposes a Bayesian analysis for an applied research topic.

This article has the unique contribution of using Bayesian models, considering monotonic effects, using the Bradley-Terry model, and using ordinal and multinomial regressions. It also includes fully reproducible extra material that facilitates replication by any other researcher. This is an important approach to minimize the issues surrounding the so-called "replication crisis" and to promote an open dialogue among researchers in transportation research (Vuong, 2017).

The results provide an overview of the patterns of private car use and public transport pass ownership among the five groups of users, based on their membership in different

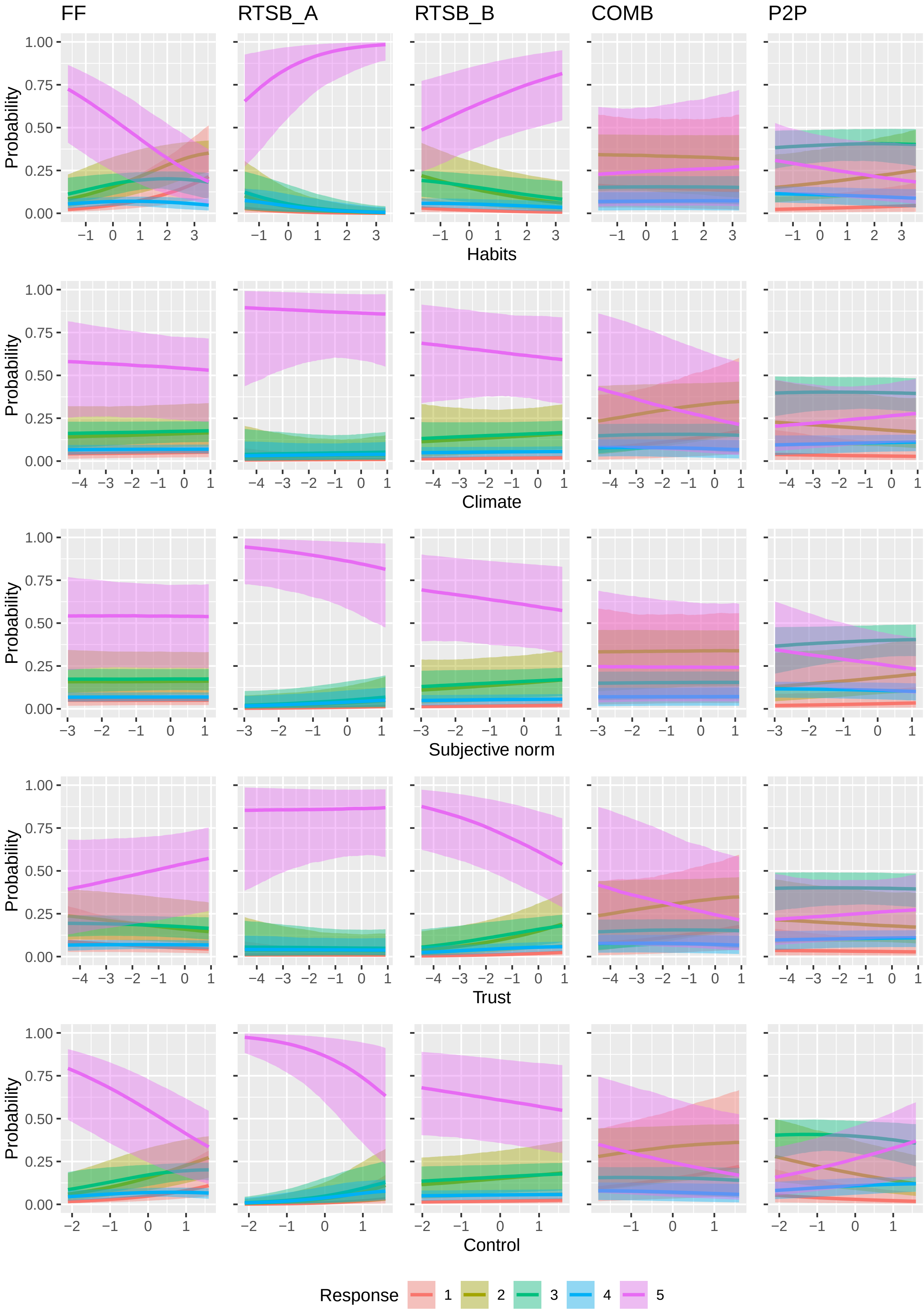

Figure 4: Conditional effects for the psychological variables. The line represent the median and the area represents the 90% credible intervals of the posterior distribution.

carsharing operators. Overall, all users believe that they would have more cars in their households if they were not members of a carsharing service. There is some variation within the three operators of the RTSB business model (COMB, RTSB_A, and RTSB_B), with the users of RTSB_B owning monthly public transport pass to a greater degree. The users of FF were the ones with higher percentages of private car ownership and private car use. These results are an important source of information to better understand how carsharing can be integrated into public transportation and help to develop policies aiming for more integration (Hull, 2008). Further research could investigate why this difference emerged and whether it is statistically robust.

We identified that the preferences for different carsharing operators were not affected by gender and that the preferences for P2P and FF are lower for older age groups and higher for RTSB_B. P2P and FF presented opposite patterns of preferences, given income and education levels; as these increase, the preference's probability for P2P decreases, and increases for FF.

The motivators sustainability, convenience, and reduction of expenses did not have a substantial effect on the preferences for different CS business models. The motivators of not owning a car and avoiding maintenance leveled the probabilities of preferences for all CS business models. This means that when these motivators are valued by the users, all CS business models are equally preferred.

When the motivators accessibility and parking are relevant for the users, there is an increase in the probability of selecting FF and a decrease in the probability of selecting P2P. The motivational effect on the CS preferences was relatively small. Possible explanations are that the model is not sensitive to the typical users' demands and/or that some of the subsamples were relatively smaller. We suggest that future research take this into account and further explore what the motivators behind the choice of different carsharing business models are, apart from the ones explored in this study.

The results show that there are different preferences for carsharing business models depending on the trip purpose, with a trade-off between FF and RTSB. The FF model is the least preferred for more sporadic trips and possibly for longer distances (bulk shopping, recreational activities on weekends, and short holidays), while RTSB is the most preferred.

For recurrent trips in the inner city (work-related trips, daily shopping, and going out for dinner), FF is amongst the most preferable and RTSTB the least preferred. The P2P business model stood out for short holiday trips as the most preferred carsharing business model.

The FF carsharing showed to be the business model that has the higher potential to demand more parking areas in the city as well as to generate more short inner-city trips. This result poses a question to policymakers of to what extent this business model is a challenge for the goal of sustainable cities and how to regulate it in a way to guarantee a sustainable transport system.

It would be interesting for future research to incorporate other alternatives of transportation for each trip purpose into the trade-off of FF and RTSB, such as taxis and public transportation, that we did not include in this study.

Regarding the behavioral patterns, we identified that users of FF and RTSB differ substantially in terms of driving habits and trust in the service. Stronger driving habits positively affected the probability of answering on the highest level of the scale (e.g. highest frequency of use) for RTSB operators, while higher levels of trust in the service positively impacted the probability of high frequency of use of FF services. Previous research has shown that the levels of trust of other people are lower for users of P2P compared to B2C, while trust in the technology involved in the service is more important to users of P2P than to B2C users (Julsrud and Uteng, 2021).

While previous research has identified a relevant impact of normative aspects on travel mode choice, including carsharing (Derikx and Lierop, 2021), in this study, a small negative effect was detected, and only for the RTSB_A, RTSB_B, and P2P. One interpretation could be that the variation among the business models is not robust enough as the variation among modes of transportation (e.g. car, public transport, active transportation). Further research could look in more detail at the effect of using different business models on social norms.

Previous research has identified a positive predictive effect of perceived behavioral control on the intention to use carsharing (Derikx and Lierop, 2021; Zhang and Li, 2020). In this study, we add value to the literature on this topic by showing that this effect is not stable across all points of the response scale. With the increase in perceived behavior control, there is a decrease in the higher frequency of carsharing use (Response 5) for FF, RTSB_A, RTSB_B. While for P2P users; with an increase in perceived behavior control there was an increase in Response 5.

It is difficult to discuss this difference in normative aspects between business models, once other covariates may be explaining this difference. This is a cross-sectional study and, therefore, causal claims are out of the scope of this research. However, one may speculate if the increase in the perception of control over their trips could lead to users of carsharing to have a better planning of their trips and therefore reduce the extreme levels of frequency of travel. While for P2P business models, which tend to be less expensive than FF and RTSB, the planning and control over trips are less relevant since there is no big variation in the costs.

Corroborating with previous literature (Ramos and Bergstad, 2021; Yoon et al., 2017; Zhang and Li, 2020), the climate morality latent variable did not present a relevant effect on the participants' frequency of use of any operator. This result gives one more piece of evidence that the choice to use carsharing services is rather motivated by other factors than sustainability motivations.

When it comes to methodological discussions, we identified that the highest frequency of use (Response 5 on the scales) was the main affected response on the scale, meaning that the frequent behaviors were more sensitive to variations in the behavioral and psychological latent variables.

This result is important to communicate with other researchers. In some areas of research, including social sciences and psychology, the Likert scales are often treated as continuum scales (metric assessment), rather than as ordinal data and to avoid using it as a metric assessment, (Liddell and Kruschke, 2018).

There are many problems in statistical analysis surrounding the use of Likert scales, mainly due to the common practice of analyzing ordinal data as if they were a continuous scale. Among these problems, inflated Type I and Type II errors, misses and inversions of main and interaction effects are in the list of detractions (Liddell and Kruschke, 2018) when opting for this practice.

The psychological predictors modeled had low variation between the operators COMB and P2P, limiting the possibilities of interpretation of these predictors. This low variation together with the fit indexes indicates that the models had a better fit for the FF and RTSB business models. Further research could investigate in more detail what are the most relevant individual factors that explain the preferences of the users of these business models.

5 Conclusions

Research on shared mobility, such as carsharing services, is important to produce knowledge that can be used for governance that aims for equity and sustainability. The multifaceted nature and uncertainty linked to smart mobility make it difficult for practitioners and urban planners to foresee the consequences of future mobility systems (Wallsten et al., 2021). Previous studies have shown that carsharing users may present positive environmental attitudes, though that is not the main motivation to use carsharing (Münzel et al., 2019), as it we have identified in this study as well. Users that are more oriented to public transport tend to choose B2C services and include them in their routines as an alternative form of transportation. They, therefore, tend to use carsharing more frequently than those who only use P2P carsharing, which is used primarily for sporadic trip purposes (Münzel et al., 2019). We also identified that the users of FF may be a niche that demands more parking areas in the urban centers, and they may increase the demand for short inner-city trips. This pattern of behavior generated by FF business models may pose a challenge to urban planners in terms of land use and traffic planning.

The advent of shared mobility has claimed to be a more economical alternative to traveling compared to owning a personal car. However, most of its users have higher average educational and income levels (Machado et al., 2018), representing only a share of the population. It is important to remember that the affordability of transport systems for low-income earners should be highlighted in transport policy and that carsharing may still be quite expensive for economically and socially disadvantaged groups. This share of the population faces difficulties even affording public transportation and the costs of traveling lead to social exclusion (Bondemark et al., 2020).

To conclude, our final remarks for practitioners aiming to promote sustainable solutions in urban mobility are that preferences for carsharing business models vary depending on the trip purpose, age, and income levels. The use of different business models may also affect the frequency of use of other modes of transportation, such as public transportation. And finally, psychological aspects, such as trust in the service and driving habits are important sources of information to plan the feasibility of specific carsharing business models. The results of this study show how much variation exists among the different carsharing business models in the market and that careful planning regarding this topic is necessary to address urban mobility needs sustainably.

Author contributions

Érika Martins Silva Ramos: conceptualization, methodology, validation, investigation, data curation, writing original draft, writing review & editing, visualization, project administration. **David Issa Mattos**: methodology, formal analysis, investigation, data curation, writing original draft, writing review & editing, visualization. **Cecilia Jakobsson Bergstad**: conceptualization, methodology, validation, writing review & editing, supervision, fund acquisition.

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Declarations of interest

Declarations of conflict of interest: none.

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