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Identifying and Quantifying Factors Determining Dynamic Vanpooling Use

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Abstract: Nowadays, the growth of traffic congestion and emissions has led to the emergence of an innovative and sustainable transportation service, called dynamic vanpooling. The main aim of this study is to identify factors affecting the travel behavior of passengers due to the introduction of dynamic vanpooling in the transportation system. A web-based mode choice survey was designed and implemented for this scope. The stated-preference experiments offered respondents binary hypothetical scenarios with an ordered choice between dynamic vanpool and the conventional modes of transport, private car and public transportation. In-vehicle travel time, total travel cost and walking and waiting time or searching time for parking varies across the choice scenarios. An ordered probit model, a multinomial logit model and two binary logit models were specified. The model estimation results indicate that respondents who are aged between 26 and 35 years old, commute with PT or are members of bike-sharing services were significantly more likely to choose dynamic vanpool or PT than private car. Moreover, respondents who are worried about climate change and are willing to spend more for environmentally friendly products are significantly more likely to use dynamic vanpool in comparison with private cars. Finally, to indicate the model estimation results for dynamic vanpool, the value of in-vehicle travel time is found to be 12.2€ per hour (13.4€ for Munich subsample).

Keywords: autonomous vehicles; dynamic vanpooling; emerging mobility

1. Introduction

Increasing urbanization (70% of people will live in cities by 2050) has pushed towards new European plans for smart cities, aiming to improve the efficiency of current systems and services using digital solutions. Smart city characteristics include smart mobility, environment and economy [1] While passenger transport is one of the main contributors in all three aspects, it causes problems for the environment (energy consumption and emissions [2]), the economy and, in general, the society [3]. The growth of car ownership has made the situation even worse, adding an increased necessity of more innovative and sustainable transportation services, especially in the context of future smart cities. For this, one of the promising solutions is ridesharing, referring to the concept of individuals sharing their ride and the generalized costs of a trip [4]. Ridesharing can improve the efficiency of existing transportation systems by increasing the vehicle occupancy and reducing the economic and environmental imprints of everyday travel.

Vanpooling, a variation of ridesharing using a van, was first introduced in the 1970s, due to the oil crisis in United States of America [5]. It is a transportation service in which groups of people who live in the same area and commute in the same directions choose to commute as a group in a van [6]. Over the last decade, smartphone-based vanpool services (also called dynamic van-pooling) have become more popular worldwide [7],

including Berlin (Door2door, Allygator Shuttle, BerlKönig), New York (ViaVan), London (Ford), Mexico City (Jetty) and Beijing (Didi Chuxing). It is worth mentioning that the total number of rides exceeds 30 million globally (www.viavan.com, accessed on 12 August 2021). To identify their unique characteristics against conventional modes of transport, ride-sharing services fill the gap between cheaper, but fixed route, public transport and the more expensive, flexible and private car or taxi [8]. In dynamic vanpooling services, passengers request a ride using their smartphones for a point-to-point pick-up and drop-off with their preferred time windows. The vans are dynamically routed with detours to serve different passengers by ride-sharing. Given higher capacity, commonly up to six passengers (www.berlkoenig.de; www.viavan.com, accessed on 12 August 2021), dynamic vanpooling is usually more economically affordable than a private car or taxi [9], but at the possible expense of a longer journey or waiting times due to ride-sharing.

While being similar to ridesharing using cars, van pooling also has differences in terms of operations, and also the sense that it creates for the passengers. As such, one of the major limitations of the existing literature is that dynamic vanpooling is not being included as a discrete alternative in mode choice (and stated preferences) studies. Note that, in discrete choice modeling, 'Stated Preference' (SP) is a survey-based method to estimate user choice preferences, while 'Revealed Preference' (RP) is a data-based method to estimate (reveal) peoples' decisions by actual choice data. Moreover, although the impact to the environment and traffic of such a mode of transport is much lower than conventional ridesharing, many of these services fail to become established (e.g., Bridj, Via, Kutsuplus, also others mentioned in [8]). As researchers move towards developing smarter and more efficient ways to assign vehicles to requests [10] and dynamically dispatch the vehicles (e.g., [11,12]), one missing element is insight into the specific factors that determine the use of these services by the potential customers. Some, for example, might choose a mode that guarantees a timely pick up at the desired point, putting a lower weight on the cost. Others, on the other hand, might prefer a cheaper service, even if they have to wait for a few minutes or walk a couple hundred meters. Therefore, the overarching goal of this paper is to investigate the factors affecting the travel preferences of individuals by the emergence of dynamic vanpool in the transportation system. To accommodate for this need, a novel stated preference experiment has been conducted, targeting the examination mode choice behavior for conventional modes of transport and vanpooling. The collected data have then been analysed using discrete choice models (Multinomial Logit and Ordered Probit models) to explore the factors that affect the use of vanpooling and the willingness to pay. The obtained factors provide insight into the identification of the potential users for this transportation service.

This paper is structured as follows: Section 2 provides a review of the literature and pertinent aspects related to vanpooling; Section 3 introduces the methods used, including survey design particularities and modelling aspects; Section 4 presents the analysis and modelling results; Section 5 presents an extensive discussion of results; Section 6 provides key insights and conclusions.

2. Literature Review

The literature on ride-sourcing is mostly dispersed among private and pooled ride hauling, ride matching and dynamic ridesharing services. It is worth mentioning that simulation studies show that on-demand ridesharing services would reduce both the Vehicle Miles Travelled (VMT) and the number of required vehicles even after allowing for extra distance due to involved detour [13,14]. The decision of individuals to choose shared ride services depends on the price discount, additional travel time and willingness to share the ride. Furthermore, in modeling travel choice behavior, Random Utility Models (RUM) is the most common demand method, where the user knows/considers mutually exclusive alternatives, each associated with its perceived utility and evaluated by the pre-trip choice probability. The literature shows a new class of Quantum utility models (QUM), where the user has an unclear sequence of decisions for his final choice, and it is possible to simulate

the decisions in the intermediate levels [15]. QUM has been implemented in many recent travel behavior studies mostly related with route choice modeling [16,17].

Although dynamic vanpooling has gained attention, studies related to it, dynamic ridesharing, flexible transit or micro transit are still scarce, e.g., the authors of [18] evaluated the potential demand of a flexible transit using stated preference experiments and identified the potential users of this mode of transportation. The stated-preference (SP) experiments included choices between public transportation, private car and a flexible transit mode and estimated value of time from the obtained parameters of the choice models (16.3$ per hour for the car mode and 21.1$ for the flexible transit). It was found that respondents who commute with public transportation and have a bikeshare membership are more likely to choose a more flexible transit mode. In [19], user preferences towards pooled on-demand services for time–reliability–cost trade-offs is analyzed by stated preference experiments. They evaluated the value of time (VOT) and value of reliability (VOR) of different trip stages, reporting in-vehicle VOT (7.88–10.80 €/h), waiting VOT (9.27–16.50 €/h), waiting to in-vehicle VOT ratio (between 1–1.5) and VOR/VOT ratio for both the waiting and in-vehicle stage to be around 0.5. In [20], a joint revealed-stated preference model for choice between pooled and private ride-hailing is developed from a 2019 survey of Austin, Texas residents, reporting value of travel time and willing to pay extra to not pool as $27.80, $19.40 and $10.70 per hour and $0.62, $1.70 and $1.32 per hour for commute, shopping, and leisure travels. It was also found that women and older adults have a lower propensity to do pooled rides while individuals who are employed, highly educated and live-in high-density areas have a high propensity. Regarding preferences towards social aspects, authors in [21] reported that user attraction is the ease and speed of service compared to walking and public transport, safety is an important concern (women preferring same sex passengers), social interactions are relevant but not as much as traditional factors of time and cost and that negative experience is more deterrent than a positive social interaction experience. In [22], it is also reported that a stranger presence is less critical than added detour time towards using a shared service. In [23], it is found out that less than one third of respondents have strong preferences against sharing their rides.

Further, to understand the effect of individual's demographics, authors in [24] stated that gender, car ownership and education can significantly affect the preference to use shared mobility services. Specifically, considering their perceived value of time, authors in [25] stated that attributes referred to attitudes influence the travel behavior of individuals. Based on a qualitative survey, revealed preferences (RP) survey and stated preference (SP) survey, they concluded that middle-aged users with high income and an active social life have a higher value of time. Then, considering the future of on-demand mobility with autonomous vehicles, [26] investigated the effect of autonomous vehicles on the value of travel time savings (VTTS) and mode choice for commuting trips, comparing privately owned autonomous vehicles and shared autonomous vehicles in stated preference experiments. The study indicated that the attributes of the alternatives such as in-vehicle travel time and cost significantly affect the mode choice and the sociodemographic characteristics play an important role in the modal split. In [27], the value of time for autonomous vehicles using revealed and stated preference methods is estimated. Specifically, stated preference (SP) experiments were conducted, comparing autonomous vehicles, public transportation and private cars. The results show that in-vehicle travel time and travel cost play an important role on the mode decision. On the contrary, gender and age do not influence the preference of the users on the adoption of autonomous vehicles. Also, Ref. [28] examined the travel behavior of the respondents from the introduction of shared autonomous vehicles (SAV) by stated preference experiments comparing SAVs (with or without ride-sharing) and public transportation. The model showed that waiting time plays a significant role in the choice of SAVs and young users are more likely to use the share service.

3. Methods

3.1. Survey Design

One of the main objectives of this research is to quantify the trade-offs between different components of the decision to choose a faster and more expensive mode of transport and to estimate the independent influence of attributes on the adoption of a new mode of transport, called dynamic vanpool.

To perform the above, a stated-preference survey was designed and conducted using a three-part questionnaire. In the first part, respondents were asked about their current travel characteristics, such as the most frequently used mode of transport, average commuting time (both ways), car availability, possession of driver's license and their satisfaction with the current way of travelling. Moreover, respondents were asked to express their attitudes regarding their affinity to new technology, their environmental concerns and their affinity to social media.

In the second part, nine hypothetical choice scenarios were presented to the respondents, in which respondents were asked to state their preference in a 5-point rating scale (ranging from the strong preference for the first alternative to the strong preference for the second alternative). The alternatives considered in this study were private car, public transport and dynamic vanpool. Each scenario included two alternatives (three scenarios involved choices between private car and dynamic vanpool, three scenarios involved choices between public transport and dynamic vanpool and three scenarios involved only dynamic vanpools). The choice alternatives were defined by three attributes (in-vehicle travel time, total travel cost and walking/waiting time or searching time for parking), varying on three levels. The values of attribute levels are summarized in Table 1 and an example of a stated preference scenario is presented in Figure 1. Note that the respondents indicate their preference level for the choice alternative by answering among 5 different levels.

Table 1. Summary table of alternatives, attributes and attribute levels.

Alternative	Attribute	Attribute Levels
Private car	In vehicle travel time	12, 20, 28 min
	Total travel cost	5.00€, 7.00€, 9.00€
	Walking time and searching time for parking	2, 6, 10 min
Public Transportation	In-vehicle travel time	16, 26, 36 min
	Total travel cost	1.50€, 2.20€, 2.90€
	Walking and waiting time	7, 12, 17 min
Dynamic Vanpool	In-vehicle travel time	14, 24, 34 min
	Total travel cost	4.00€, 6.00€, 8.00€
	Walking and waiting time	5, 10, 15 min

The last part of the survey included standard demographic questions regarding gender, age, education level, main occupation and income. Finally, respondents were asked to indicate their choice on a 5-point rating scale (ranging from strongly disagree to strongly agree), regarding general personality traits [29].

The full factorial design of each pair of alternatives includes 729 choice sets. Due to the large number of choice sets, an efficient design was applied to eliminate the choice situations. In this study, Federov's exchange algorithm was applied, which calculates an exact optimal design, fulfilling one of three criteria [30]. Applying this algorithm in R statistical software [31] for each set of two choice alternatives, 9 choice sets were generated and, then, were divided into 3 blocks (versions) randomly. This procedure was repeated for the remaining pairs of alternatives. In the end, three blocks of nine hypothetical scenarios were generated, including three scenarios which involved choices between private car and dynamic vanpool, three scenarios which involved choices between public transport and dynamic vanpool and three scenarios which involved only dynamic vanpools.

3.2. Behavioral Model

Two types of econometric models were specified and estimated: ordered probit models and multinomial logit models. In the sections below, the application of these two models for dynamic vanpooling is presented.

Scenario 2:

Please imagine that **only the following options** are available for a certain trip of approximately 8km.

Which transportation mode would you choose?

	Private Car (A)	Vanpool (B)
In-vehicle travel time	12 min	14 min
Total travel cost*	7.00 €	4.00 €
Walking + waiting / parking time**	6 min	15 min

ⓘ Choose one of the following answers

| Certainly A | Probably A | Indifferent | Probably B | Certainly B | None |

* Total travel cost for car is a combination of fuel cost, fixed (car ownership including insurance and tax) and variable (maintenance and repair) costs and parking costs. The parking fee is 3.00 €

** For vanpool is the waiting and walking time and for car is the walking and searching time for parking.

Figure 1. Stated preference experiment scenario for a car/vanpool scenario (example).

3.2.1. Ordered Probit Model

As explained above, since respondents were asked to state their preferences on a 5-point rating scale, multinomial logit models would have to be built upon a reduced amount of information and with assumptions made by the researchers to overcome the fact that the ordered responses violate the Independence for Irrelevant Alternatives assumption of the logit model [32]. Therefore, ordered probit models were developed to estimate the ordered choices as the dependent variable. It is noteworthy that each choice variable takes numerical values between 1 and 5, which means that choice "1" corresponds to the respondents that state certainly alternative A and choice "5" corresponds to the respondents that state certainly alternative B.

Figure 2 illustrates the distribution of the choice probability P as a function of the utility U. Considering a rating scale with 5 levels ("Certainly A", "Probably A", "Indifferent", "Probably B", "Certainly B"), there are 4 thresholds (k1 to k4) that separate the 5 choices. This means that respondents choose the alternative "Certainly A" if the utility is lower than k1, alternative "Probably A" if the utility is between k1 and k2, alternative "Indifferent" if the utility is between k2 and k3, alternative "Probably B" if the utility is between k3 and k4 and alternative "Certainly B" if the utility is greater than k4.
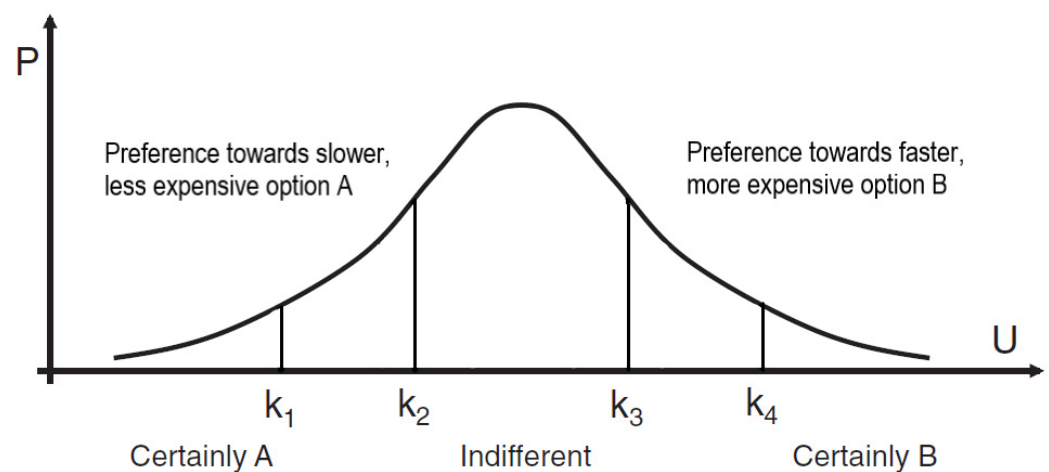
Figure 2. Choice probability distribution of the respondents' preference; adapted from [32].

As noted above, three alternatives (private car, public transportation and dynamic vanpool) and three attributes (in-vehicle travel time, travel cost and waiting/walking time) were considered in the stated-preference experiments. The values of the attributes differ among the alternatives and, therefore, responses should be rearranged so that the fastest (and more expensive) option is always second. Figure 2 indicates that option A refers to a slower and less expensive mode of transportation and, on the contrary, option B refers to a faster and more expensive mode of transportation; implying that an increase in that attribute corresponds to a higher preference for the faster alternative. The general formulation of the deterministic part of the utility function can be specified as per Equation (1).

3.2.2. Multinomial Logit Model (MNL)

As multinomial logit models could not be specified directly due to the violation of the Independence for Irrelevant Alternatives (IIA), the 5-point scale of the response was transformed to a binary choice [33]. Therefore, responses with varying preferences for option alternative A (or B) were categorized as having a preference for choice A (or B, respectively). Responses with no preference between two options and responses gathered from the experiments which consider the same mode (dynamic vanpool) were excluded from the model.

The general formulation of the deterministic part of the utility function can be expressed by the following equation:

$$V_{iq} = \sum_{k} \beta_{iq} x_{ikq} \tag{1}$$

where:

V_{iq}: deterministic or systematic element of alternative *i* for the individual *q*;
β_{iq}: parameters of exploratory variables;
x_{ikq}: independent variable.

3.2.3. Willingness-to-Pay

The estimated coefficients of the cost and travel time can be applied to calculate the willingness-to-pay of the respondents to use a faster and more expensive mode of transport and the willingness-to-pay to use private car, public transportation and dynamic vanpool. The utility is, in general, unitless and can be expressed as an imaginary unit of "utils". Taking into account that the travel time is measured in minutes and travel cost in Euro (€), the units of the coefficients would be utils/min and utils/€, respectively. Therefore, the

ratio of the coefficient for the travel time over the coefficient for the travel cost would have units of €/min, which is the expected unit for a value-of-time (*VOT*) measure:

$$VOT = \frac{\beta_{\text{time}}}{\beta_{\text{cost}}} * 60 \left(\frac{\text{utils/min}}{\text{utils/€}} * 60 = \frac{€}{\text{h}} \right) \tag{2}$$

where:

β_{time}: estimated coefficient of travel time;
β_{cost}: estimated coefficient of travel cost.

4. Model Estimation and Analysis

4.1. Data Collection and Sample Identity

A pilot survey was conducted and a sample of 25 responses was collected. The main objective of the pilot survey was to verify the structure and efficiency of the survey and revise it based on the comments by the respondents. Initial models were also specified and estimated to test the applicability of the choice modelling methodology used, in terms of coefficient signs and anticipated statistical significance. These responses were not used in the final data collection and analysis reported next.

The data collection of the final survey started in March 2019 and concluded in May 2019. Two methods were used for the distribution of the survey. The survey was distributed using mailing lists and various social media platforms, such as Facebook and LinkedIn. The drawback of this method is that the survey was not distributed randomly to the population and potential biases may have occurred. Therefore, it was decided to also distribute the survey via printed flyers: 2000 flyers were distributed in chosen neighborhoods within the city of Munich, in both the English and German languages. The main advantage of this method is that the target population would include people who are not on social media or are on different social networks.

Some general characteristics of the respondents' responses are presented in the following section. The total number of the participants in the survey was 240. After an initial analysis of the data, 32 responses were excluded due to missing values or unsuccessful submission of the survey. Therefore, the remaining 208 responses were analyzed, resulting in 1872 choice observations. Considering that the survey was distributed online, it is necessary to examine the origin of the responses, namely the current residence of the responses. The outcome of this analysis indicated that a major subsample is from the Munich region (102 responses). Table 2 shows detailed characteristics for the survey participants.

Table 2. General characteristics for survey participants.

Characteristic	Attribute	Percentage (%)
Gender	Male	48.7%
	Female	49.3%
	Prefer not to answer	1.0%
Age	18–25	16.6%
	26–35	48.8%
	36–45	20.5%
	46–55	8.8%
	55–65	3.9%
	>65	0.5%
	Prefer not to answer	1.0%
Education level	High school	5.9%
	Vocational school	6.8%
	Bachelor	30.2%
	Master	44.9%
	Doctorate	11.2%
	Prefer not to answer	0.9%

Table 2. *Cont.*

Characteristic	Attribute	Percentage (%)
Main occupation	Full-time employed	61.0%
	Part-time employed	8.3%
	Student	26.3%
	Currently unemployed	2.9%
	Housewife or houseman	1.5%
Household size	1	29.8%
	2	35.1%
	3	20.0%
	4+	15.1%
Driver's license	Yes	81.2%
	No	18.8%
Car availability	0	38.2%
	1	30.0%
	2	28.0%
	3+	3.9%
Income	Up to 500€	3.9%
	500–1000€	12.7%
	1000–2000€	21.0%
	2000–3000€	13.7%
	3000–4000€	9.3%
	4000–5000€	10.2%
	5000–6000€	6.8%
	6000–7000€	4.9%
	7000–8000€	3.4%
	8000–9000€	0.5%
	More than 9000€	3.4%
	Prefer not to answer	10.2%
Main commute mode	Car as a driver	34.1%
	Car as a passenger	3.4%
	Public transportation	48.8%
	Bicycle	9.8%
	Walk	2.0%
	Other	1.5%
Commuting time	Up to 30 min	22.2%
	30 min to less than 60 min	44.0%
	60 min to less than 90 min	22.2%
	More than 90 min	11.6%

4.2. Model Estimation Results

The following discrete choice models have been specified and estimated within this research using the PandasBiogeme software [34], for which detailed information and tutorials are available [35]. Prior to the estimation of the models, a priori expectations of the estimated coefficient signs and magnitudes were presumed, based on similar studies on mode choice (e.g., [36]), and used to verify their estimated counterparts.

4.2.1. Ordered Probit Model

In order to take advantage of the ordered responses (Certainly A, Probably A, Indifferent, Probably B, Certainly B) as dependent variables, ordered probit models have been estimated first [37]. In each model, the utility function of the system is represented as the difference in the utilities of the two considered alternatives. Option B refers to a faster and more expensive mode of transportation, whereas option A refers to a slower and less expensive mode of transportation. Therefore, the collected data were rearranged when needed, to comply to this convention. It is clarified that this is not strictly needed but is only performed to simplify the interpretation of the estimated model coefficients.

The model specification started with a simple model with the main variables (in-vehicle travel time, travel cost and waiting/walking time); then, meaningful variables were added progressively. Variables with low significance were removed and variables with high significance (significance level above 95%) were retained. Naturally, this process was not blindly following the significance levels, but the interpretation of the coefficients was examined at each step, to ensure that the estimated coefficients had meaningful signs and magnitudes. After evaluating different specifications, the final ordered probit model was estimated (Table 3). A random effect component was also considered in the model specification in order to capture the sample heterogeneity. However, in this selected final model specification, the estimated coefficient for the standard deviation of the random effect was statistically insignificant and thus was not retained. This indicates that the heterogeneity of the sample has been adequately captured by the variables. The resulting model is presented in Table 3.

Table 3. Ordered Probit estimation results.

Variables	Coeff. Estimate	Robust Asympt. Std. Error	Robust t-Stat	Robust p-Value
In-vehicle travel time	−0.0673	0.00575	−11.7	0.00
Total travel cost	−0.335	0.0228	−14.7	0.00
Waiting/Walking time	−0.0448	0.00607	−7.38	0.00
PT	0.189	0.0563	3.36	0.00
Age: 18–25	−0.195	0.082	−2.36	0.00
Age: 46–65	−0.255	0.0935	−2.73	0.01
Car as commute mode	0.211	0.0684	3.08	0.01
60 < Commuting time < 90	0.246	0.0632	3.89	0.00
Employee	−0.437	0.116	−3.76	0.00
Income < 3000€	−0.11	0.057	−1.90	0.03
Student	−0.562	0.12	−4.63	0.00
Household size: 2	−0.127	0.0594	−2.15	0.01
Household size > 4	−0.272	0.0835	−3.56	0.02
Commute satisfaction	−0.083	0.0311	−2.68	0.01
Number of cars in household: 3	0.558	0.1425	3.92	0.00
Driving License	0.461	0.0784	5.88	0.00
Carsharing membership	0.183	0.070	2.63	0.02
Bike-sharing membership	−0.265	0.0775	−3.41	0.00
Real-time information services	0.0652	0.0222	2.94	0.00
Affinity to technology	0.0686	0.0355	1.93	0.03
Social media	−0.048	0.0234	−2.05	0.04
Extraverted, enthusiastic	0.065	0.0314	2.07	0.04
Sympathetic, warm	−0.110	0.0358	−3.07	0.00
Threshold parameters for index model				
k1	−1.775	0.272	−6.56	0.00
k2	−0.821	0.2688	−3.05	0.00
k3	−0.659	0.2687	−2.45	0.00
k4	0.224	0.2687	0.83	0.00
Summary statistics				
Number of observations: 1845				
Number of estimated parameters: 27				
Initial log-likelihood: −2780.77				
Final Log-likelihood: −2507.13				
Likelihood ratio test: 547.30				
Rho-square for the final model: 0.10				

The signs and magnitudes of the coefficients were found to be reasonable and consistent with the respective a priori expectations. As expected, the estimated coefficients of the main attributes (in-vehicle travel time, travel cost and waiting/walking time) were negative. Furthermore, it is worth mentioning that the coefficient of the dummy variable for PT indicates that ceteris paribus respondents have a higher propensity to use PT instead of dynamic vanpool. Conversely, the coefficient of the dummy variable for car was statistically insignificant and, therefore, was not retained in the final model.

In terms of sociodemographic characteristics, it is observed that respondents who are young (between 18 and 25 years old) and middle-aged (between 46 and 65 years old) are more likely to choose a slower and less expensive mode of transport. Moreover, it is noted that respondents who are employed (full- or part-time) and have a low income (less than 3000€) have a higher tendency to use a dynamic vanpool or PT. Last but not least, it is

noteworthy that students or those living in a household with at least two people have a tendency of choosing a less quick and cheaper mode of transport.

Regarding the travel characteristics of the participants, respondents who commute daily with a private car and whose commuting time is between 60 and 90 min (both ways) have a higher tendency to use a faster and more expensive option. As well, car ownership and possession of a driving license significantly affect travel behavior. According to the model estimation results, the possession of a driving license along with more than two cars in the household leads to higher likelihood of choosing a faster, more expensive option. Concerning the membership of innovative transportation services, respondents who are members of a bike-sharing service have a higher propensity to use a more affordable option, while the opposite effect is observed for respondents who are members of a carsharing service.

Furthermore, respondents who frequently use real-time transport information services and are interested in new technology and willing to spend more for innovative technological products are more likely to use a faster and more expensive transportation mode. On the other hand, participants who use often social media platforms, such as Facebook and Instagram, have a tendency of choosing a slower and less expensive mode of transport.

Finally, the final ordered probit model specification included variables associated with the personality traits of the respondents. It is noteworthy that respondents who self-characterised as extroverted and enthusiastic were more likely to choose a faster and more expensive mode of transportation. On the other hand, those who viewed themselves as sympathetic and warm tended to choose a slower and cheaper option.

4.2.2. Multinomial Logit Model

Further to the Ordered Logit models, MNL models [38] were also estimated to be able to directly extract values of time and be able to provide comparability with other studies' results. MNL models were also implemented and estimated using PandasBiogeme software. The iterative forward selection process followed, included the derivation of an initial model, which consisted of the alternative specific constant and the main attributes of the alternatives. Subsequently, additional parameters were added and the ones with a very low significance level were removed immediately. This process was carried out until all coefficients of the parameters were significant. It should be noted that the specification of the model and the number of observations used were different. Thus, a direct comparison of the Rho-square between the Ordered Probit and the MNL model could not yield any meaningful conclusion with regard to which model performs better.

Table 4 presents the estimated coefficients and robust statistical tests of the selected MNL model specification. As before, the criterion for inclusion of all coefficients was that they were consistent with prior expectations, in terms of sign and magnitude, and statistically significant at a 95% significance level (naturally, this is not a rigid threshold, therefore a variable fulfilling the other criteria at 94% significance level was retained).

Table 4. MNL estimation results.

Variables	Coeff. Estimate	Robust Asympt. Std. Error	Robust t-Stat	Robust *p*-Value
In-vehicle travel time (Car)	−0.137	0.0258	−5.20	0.00
Total travel cost (Car)	−0.445	0.112	−4.14	0.00
Walking/Parking time (Car)	−0.0938	0.0352	−2.65	0.01
In-vehicle travel time (Dynamic vanpool)	−0.147	0.0203	−7.33	0.00
Total travel cost (Dynamic vanpool)	−0.722	0.0769	−9.15	0.00
Waiting/Walking time (Dynamic vanpool)	−0.0755	0.0253	−3.03	0.00
In-vehicle travel time (PT)	−0.104	0.0206	−4.79	0.00
Total travel cost (PT)	−0.811	0.193	−4.00	0.00
Waiting/Walking time (PT)	−0.133	0.0316	−3.96	0.00
Age: 26–45 (PT)	−0.616	0.26	−2.42	0.02
Age: 56–65 (Car)	−1.25	0.524	−2.73	0.01
Monthly income > 7000€ (PT)	−0.946	0.447	−2.10	0.04

Table 4. *Cont.*

Variables	Coeff. Estimate	Robust Asympt. Std. Error	Robust t-Stat	Robust *p*-Value
Bachelor's or Master's degree (PT)	0.571	0.241	2.36	0.02
Student (PT)	0.582	0.294	2.00	0.05
PT as commute mode (PT)	1.31	0.312	4.05	0.00
Bike as commute mode (Car)	−0.817	0.409	−2.04	0.04
30 < Commuting time < 60 (Car)	−0.591	0.217	−2.75	0.01
30 < Commuting time < 60 (PT)	−0.816	0.249	−3.33	0.00
60 < Commuting time < 90 (PT)	−0.946	0.289	−3.39	0.00
Commuting time > 90 (Car)	−0.656	0.333	−1.88	0.06
Driving license (Car)	0.968	0.274	3.55	0.00
Driving license (PT)	−1.42	0.364	−3.82	0.00
Available cars in household: 3 (PT)	−1.45	0.615	−2.18	0.03
Carsharing membership (PT)	−0.546	0.267	−1.99	0.05
Bike-sharing membership (Car)	−0.73	0.314	−2.14	0.03
Bike-sharing membership (PT)	0.797	0.343	2.13	0.03
PT seasonal ticket (Car)	−0.578	0.234	−2.54	0.01
PT seasonal ticket (PT)	−0.946	0.313	−2.94	0.00
Carsharing familiarity (Car)	−0.186	0.0939	−2.07	0.04
Uber familiarity (Car)	0.191	0.0942	2.05	0.04
Real-time information services (Car)	0.204	0.0857	2.48	0.01
Environmental awareness (Car)	−0.302	0.117	−2.56	0.01
Anxious, easily upset (PT)	−0.316	0.102	−3.14	0.00
Disorganized, careless (PT)	0.233	0.124	2.02	0.04
Conventional, uncreative (PT)	0.279	0.11	2.78	0.01
Sympathetic, warm (Car)	−0.298	0.12	−2.61	0.01
Sympathetic, warm (PT)	0.273	0.131	2.31	0.02

Summary statistics

Number of observations: 1182	Number of estimated parameters: 37
Initial log-likelihood: −819.30	Final Log-likelihood: −600.11
Likelihood ratio test: 438.38	
Rho-square for the final model: 0.268	Rho-square-bar for the final model: 0.222

In terms of sociodemographic characteristics, model estimation results indicated that respondents aged between 26 and 45 years old and between 56 and 65 years old are more likely to choose dynamic vanpooling instead of PT and private car, respectively. Furthermore, participants with high monthly income (more than 7000€) have a clear preference to use dynamic vanpooling compared to PT. On the other hand, students and those who hold a bachelor's or master's degree are more likely to choose PT in comparison with dynamic vanpooling.

Regarding the travel characteristics of the participants, it is noted that the participants who commute with PT have a propensity to use PT instead of dynamic vanpool. In terms of daily commuting time, it is observed that respondents who commute more than 30 and less than 60 min have a tendency to use dynamic vanpooling instead of a private car. Besides, respondents who commute more than 30 and less than 90 min are significantly more likely to choose dynamic vanpooling in comparison with PT. Possession of driving license affects the travel behavior of the users. Specifically, respondents who possess a driving license have a propensity to use a private car and dynamic vanpooling instead of PT. Finally, a significant propensity to use dynamic vanpooling and a private car was identified by those whose household has at least three available cars.

It is noteworthy that membership in a bike sharing service, as well as a car sharing service, significantly affects the travel behavior of the respondents. Model estimation results showed that respondents who are members of a bike sharing service are less likely to use a private car and dynamic vanpooling. On the other hand, it is obvious that respondents who are members of a car sharing service or have a seasonal ticket of PT service are more likely to choose dynamic vanpooling. Finally, users who are familiar with the Uber service and frequently use real-time transport information services have a clear propensity to use a private car instead of PT.

Last but not least, factors related to environmental awareness, as well as personality traits, were examined in this model. According to model estimation results, respondents who are worried about the environment are significantly less likely to use a private car. Concerning the personality traits, it is observed that anxious and easily upset users have

a clear preference for dynamic vanpooling. Conversely, conventional and uncreative, as well as sympathetic and warm respondents, are significantly more likely to use PT in comparison with dynamic vanpooling.

4.2.3. Value of Time

One of the main objectives of this study is the estimation of value-of-time for the chosen alternatives using econometrical models. It is noteworthy that the total travel time was divided into in-vehicle travel time and walking/waiting or parking time. The value of in-vehicle travel time can be denoted as VOT_{iv} and the value of walking/waiting or parking time can be denoted as $VOT_{w/pt}$. As discussed previously, the willingness-to-pay can be calculated by the following equations:

$$VOT_{iv} = \frac{\beta_{\text{time}}}{\beta_{\text{cost}}} * 60 \tag{3}$$

$$VOT_{w/pt} = \frac{\beta_{\text{wtime}}}{\beta_{\text{cost}}} * 60 \tag{4}$$

where:

VOT_{iv}: Value of in-vehicle travel time;
$VOT_{w/pt}$: Value of walking/waiting or parking time;
β_{time}: estimated coefficient of in-vehicle travel time;
β_{cost}: estimated coefficient of travel cost;
β_{wtime}: estimated coefficient of walking/waiting or parking time.

Table 5 summarizes the *VOT* obtained from the ordered probit and MNL models. For the OP models, generalized *VOT* was calculated because the coefficients of travel time and travel cost were common.

Table 5. Summary table of *VOT* obtained from OP and MNL models.

	OP Model	MNL Model
Generalized VOT_{iv}	12.05 €/h	-
Generalized $VOT_{w/pt}$	8.02 €/h	-
VOT_{iv} (Car)	-	18.47 €/h
$VOT_{w/pt}$ (Car)	-	12.65 €/h
VOT_{iv} (Vanpool)	-	12.22 €/h
$VOT_{w/pt}$ (Vanpool)	-	6.27 €/h
VOT_{iv} (PT)	-	7.69 €/h
$VOT_{w/pt}$ (PT)	-	9.84 €/h

According to the obtained results, the generalized value of in-vehicle travel time of the system (12.05 €/h) is greater than the value of walking/waiting time savings (8.02 €/h), which is a counterintuitive finding. According to [39], the disutility related to walking is 1.85 times higher than the disutility related to in-vehicle time savings [18]. One potential consideration of this result is that the combination of waiting and walking time in the experimental design may affect the influence of these attributes in respondents' choice decision.

In this study, an MNL model was estimated in order to estimate the *VOT* for each alternative, taking into account the travel cost as a mode-specific variable. According to the summary table of *VOT*, it is observed that people are willing to pay more to use private cars compared to dynamic vanpooling, as the *VOT* for private cars (18.47 €/h) is significantly higher than the *VOT* for dynamic vanpooling (12.22 €/h). Furthermore, it is noteworthy that the *VOT* for PT (7.69 €/h) is the lowest among the other alternatives, as expected. Concerning about the value of walking/waiting time is that respondents were observed to be more willing to pay more to reduce this time for PT compared to dynamic vanpooling.

Moreover, the validity of the obtained values was investigated according to the literature. Authors in [39] reported values obtained by national studies and EIB (European Investment Bank) and meta-analysis models. These values indicate that there is a differentiation in *VOT* based on trip purpose.

In this study, it is worth mentioning that the trip purpose was not included in the experimental design due to its dimensionality. Therefore, the magnitude of the obtained values from the models is within the estimated values by [39].

5. Discussion

In this research, respondents were asked about their sociodemographic characteristics, including gender, age, household size, education level, main occupation, income and personality traits. According to the obtained results from the estimated models, young people (18–25 years old) and middle-aged people (46–65 years old) are less likely to use a faster and more expensive mode of transport. Respondents aged between 26 and 45 years old and between 56 and 65 years old have a higher propensity to choose dynamic vanpooling instead of PT and private cars, respectively. In terms of monthly income, respondents with low income (less than 3000€) tend to use a slower and less expensive option. On the contrary, there is a clear preference for dynamic vanpooling by the respondents whose monthly income exceeds 7000€. Regarding the main occupation of the respondents, students are significantly more likely to use PT compared to a private car or dynamic vanpooling. Moreover, it is indicated that respondents with a Bachelor's or Master's degree have a clear preference for PT, instead of private car and dynamic vanpool. Concerning about the household size is that people who live in a household with two or more than four members were observed to be relatively more likely to use a slower and less expensive mode. Last but not least, the personality traits were included in the estimated models. Results indicated that extraverted and enthusiastic people are more likely to use a faster and more expensive mode. Furthermore, anxious and easily upset people have a preference for private dynamic vanpooling, instead of PT. Besides, the disorganized and careless, as well as the conventional and uncreative respondents, have a higher propensity to use PT compared to dynamic vanpooling. Moreover, it is observed that sympathetic and warm, as well as conventional and uncreative people, have a clear affinity to a slower and cheaper option, namely PT or dynamic vanpooling.

5.1. Commute Habits

It is worth mentioning that the first part of the survey consisted of questions about the commute habits of respondents. These variables were included in the estimated models. Concerning the most frequently used mode of transport, it is indicated that respondents who commute daily with PT are significantly more likely to use PT. Besides, it is noted that respondents who commute frequently with a private car have a certain propensity to use a faster and more expensive mode of transport. Conversely, people who commute with a bicycle have a tendency to use dynamic vanpooling instead of a private car. An interesting outcome was that the commuting time plays a significant role in the adoption of dynamic vanpooling. According to the model estimation results, there is a clear preference for dynamic vanpooling by respondents whose commuting time (both ways) ranges between 30 and 90 min. In addition, the possession of driving license significantly affects the travel behavior of the users. As a result, respondents who have a driving license have a significant preference for using a private car or dynamic vanpooling compared to PT. Furthermore, another factor that influences the travel behavior is whether people are members of innovative transportation services, such as bike-sharing and carsharing. According to the model estimation results, people who are members of a bike-sharing transportation service have a significantly propensity to use PT rather than private cars or dynamic vanpooling. On the other hand, respondents who have membership of a carsharing service are relatively more likely to use dynamic vanpooling. Finally, it is

observed that the familiarity with the Uber service and real-time transport information services positively influences the choice of private car.

5.2. Environmental Awareness and Affinity to Technology

Respondents were asked about environmental concerns, technological innovation and affinity to social media. The factor analysis process was followed to extract the factors based on participants responses. According to the results, respondents who are worried about climate change and are willing to spend more for environmentally friendly products are significantly more likely to use dynamic vanpooling in comparison with private cars. On the other hand, people who are extremely interested in new technology and are willing to spend more for new technological products have a higher propensity to use private cars and dynamic vanpooling, instead of PT. Finally, respondents who have an affinity to social media have a tendency to use cheaper and less expensive modes of transport, namely affordable dynamic vanpooling or PT.

5.3. Limitations and Future Work

The COVID-19 pandemic has impacted the acceptance and adoptability of all modes of shared transport, which includes both traditional and emerging modes of public transport [40,41]. Since the current study was conducted before the pandemic, it would not reflect the current perception and attitude towards public transport. Still, the study can target the necessity of understanding the factors that influence the adoption of these modes of transport and, hence, is still pertinent or will be moreso as we go past the pandemic years. Further, the sample size of the study (208 responses) is relatively small to capture the population heterogeneity and it is suggested for future studies to increase the survey sample data.

In the environmental prospective, the future studies could examine more detailed inclusion of environmental aspects in the experimental design to better highlight the impacts of environmental information, while keeping in mind the risk of inducing data collection sources of bias. Also, since advancements in vehicle automation have emerged different self-driving mobility service concepts, future studies can focus on understanding user perception on acceptance and adoption of autonomous vehicles as an alternative shared mobility transport.

6. Conclusions

The emergence of dynamic vanpooling as an innovative transportation mode signifies the need to carefully explore factors influencing the travel behavior of individuals in relation to it and identify the characteristics of its potential users. Due to the lack of RP data, an SP survey is a practical and widely used option. The SP experiment performed caters to the exploration of choice, as well as the trading behavior of individuals with the use of a five-point scale for choice (certainly mode a to certainly mode b). Model estimation results indicate that males with high income are more likely to use a faster and more expensive mode of transport. On the other hand, young people and students have a higher propensity to use a less expensive mode of transport. Value of Travel Time results show that the respondents are likely to pay more for using a private car; however, they may be willing to pay more for using dynamic vanpooling instead of PT, indicating a preference towards more demand responsive services.

Regarding future work, the experiment could benefit from an extended experimental setup with a larger number of alternatives and attributes, such as comfort, safety and trip purpose, as well as from the combination of RP and SP methods to cater to a more realistic trips representation. Considering the impact of automation on offered services in public transport [42] and shared autonomous vehicles [4], or investigating the impact that route selection might have, could be other promising research directions. In addition, although its initially targeted market segment was commuters, van pooling could be further explored for touristic purposes, especially in regions with high tourist traffic. Additionally, issues of

heterogeneity and data collection biases should be addressed, e.g., by focusing on specific groups, such as young people or students and conducting market segmentation. On the modelling side, discrete choice model variations (e.g., Mixed Logit or hybrid latent class models) should be examined to incorporate taste heterogeneity.

References

1. Research Institute for Housing, Urban and Mobility Studies (OTB). Smart Cities Ranking of European Medium-Sized Cities. 2018. Available online: http://www.smart-cities.eu/download/smart_cities_final_report.pdf (accessed on 12 August 2021).
2. Zhou, Y.; Huang, Y.; McGlynn, J., III; Han, A. Who Will You Share a Ride with: Factors that Influence Trust of Potential Rideshare Partners. In Proceedings of the 6th International Workshop on Urban Computing UrbComp'17, Halifax, NS, Canada, 14 August 2017.
3. Schreieck, M.; Wiesche, M.; Krcmar, H. Design and Governance of Platform Ecosystems—Key Concepts and Issues for Future Research. In Proceedings of the 24th European Conference on Information Systems (ECIS), Istanbul, Turkey, 12–15 June 2016.
4. Narayanan, S.; Chaniotakis, E.; Antoniou, C. Shared Autonomous Vehicle Services: A Comprehensive Review. *Transp. Res. Part C Emerg. Technol.* **2020**, *111*, 255–293. [CrossRef]
5. Kircher, D.; Wapensky, L. *Vanpooling: An Overview*; Publication EPA-908/1–78-001; US Environmental Protection Agency, Region VIII: Denver, CO, USA, 1978.
6. Ditmore, C.; Deming, D.A. Comparative Analysis of Vanpool and Single Occupant Commuters' Self-reported Stress Level Before and After the Commute. ICoMaaS 2017 Proceedings. pp. 83–135. Available online: https://scholarworks.alaska.edu/handle/11122/6529 (accessed on 12 August 2021).
7. Tirachini, A.; Chaniotakis, E.; Abouelela, M.; Antoniou, C. The sustainability of shared mobility: Can a platform for shared rides reduce motorized traffic in cities? *Transp. Res. Part C* **2020**, *117*, 102707. [CrossRef]
8. Currie, G.; Fournier, N. Why most DRT/Micro-Transits fail–What the survivors tell us about progress. *Res. Transp. Econ.* **2020**, *83*, 100895. [CrossRef]
9. Dong, Y.; Wang, S.; Li, L.; Zhang, Z. An empirical study on travel patterns of internet based ride-sharing. *Transp. Res. Part C Emerg. Technol.* **2018**, *86*, 1–22. [CrossRef]
10. Su, S.; Chaniotakis, E.; Narayanan, S.; Jiang, H.; Antoniou, C. Clustered Tabu Search Optimization for Reservation—Based Shared Autonomous Vehicles. Transp. *Lett. Int. J. Transp. Res.* **2020**. [CrossRef]
11. Li, D.; Antoniou, C.; Jiang, H.; Shen, W.; Zhang, L.; Han, W. How Scheduling Advances Affect Level of Service, Fleeting, and Critical Mass in Smartphone-Based Vanpooling. In Proceedings of the 99th Annual Meeting of the Transportation Research Board, Washington, DC, USA, 9–13 January 2020.
12. Li, D.; Antoniou, C.; Jiang, H.; Xie, Q.; Shen, W.; Han, W. The value of prepositioning in smartphone-based vanpool services under stochastic requests and time-dependent travel times. *Transp. Res. Rec.* **2019**, *2673*, 26–37. [CrossRef]
13. Bischoff, J.; Maciejewski, M.; Nagel, K. City-wide shared taxis: A simulation study in Berlin. In Proceedings of the 2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC), Yokohama, Japan, 16–19 October 2017; pp. 275–280.
14. Tirachini, A.; Gomez-Lobo, A. Does ride-hailing increase or decrease vehicle kilometers traveled (VKT)? A simulation approach for Santiago de Chile. *Int. J. Sustain. Transp.* **2020**, *14*, 187–204. [CrossRef]
15. Vitetta, A. A quantum utility model for route choice in transport systems. *Travel Behav. Soc.* **2016**, *3*, 29–37. [CrossRef]
16. Hancock, T.O.; Broekaert, J.; Hess, S.; Choudhury, C.F. Quantum probability: A new method for modelling travel behaviour. *Transp. Res. Part B Methodol.* **2020**, *139*, 165–198. [CrossRef]
17. Di Gangi, M.; Vitetta, A. Quantum utility and random utility model for path choice modelling: Specification and aggregate calibration from traffic counts. *J. Choice Model.* **2021**, *40*, 100290. [CrossRef]

18. Frei, C.; Hyland, M.; Mahmassani, H. Flexing service schedules: Assessing the potential for demand-adaptive hybrid transit via a stated preference approach. *Transp. Res. Part C Emerg. Technol.* **2017**, *76*, 71–89. [CrossRef]

19. Alonso-González, M.J.; van Oort, N.; Cats, O.; Hoogendoorn-Lanser, S.; Hoogendoorn, S. Value of time and reliability for urban pooled on-demand services. *Transp. Res. Part C Emerg. Technol.* **2020**, *115*, 102621. [CrossRef]

20. Kang, S.; Mondal, A.; Bhat, A.C.; Bhat, C.R. *Pooled Versus Private Ride-Hailing: A Joint Revealed and Stated Preference Analysis Recognizing Psycho-Social Factors*; Technical Paper; Department of Civil, Architectural, and Environmental Engineering, The University of Texas at Austin: Austin, TX, USA, 2020; Volume 124, p. 102906.

21. Sarriera, J.M.; Álvarez, G.E.; Blynn, K.; Alesbury, A.; Scully, T.; Zhao, J. To share or not to share: Investigating the social aspects of dynamic ridesharing. *Transp. Res. Rec.* **2017**, *2605*, 109–117. [CrossRef]

22. Lavieri, P.S.; Bhat, C.R. Modeling individuals' willingness to share trips with strangers in an autonomous vehicle future. *Transp. Res. Part A Policy Pract.* **2019**, *124*, 242–261. [CrossRef]

23. Alonso-González, M.J.; Cats, O.; van Oort, N.; Hoogendoorn-Lanser, S.; Hoogendoorn, S. What are the determinants of the willingness to share rides in pooled on-demand services? *Transportation* **2021**, *48*, 1733–1765. [CrossRef]

24. Ko, E.; Kim, H.; Lee, J. Survey Data Analysis on Intention to Use Shared Mobility Services. *J. Adv. Transp.* **2021**, *2021*, 5585542. [CrossRef]

25. Atasoy, B.; Glerum, A.; Bierlaire, M. Mode choice with attitudinal latent class: A Swiss case-study. In Proceedings of the Second International Choice Modeling Conference, Leeds, UK, 4–6 July 2006; pp. 1–16. Available online: https://infoscience.epfl.ch/record/167866 (accessed on 12 August 2021).

26. Steck, F.; Kolarova, V.; Bahamonde-Birke, F.; Trommer, S.; Lenz, B. How Autonomous Driving May Affect the Value of Travel Time Savings for Commuting. *Transp. Res. Rec. J. Transp. Res. Board* **2018**, *2672*, 11–20. [CrossRef]

27. Kolarova, V.; Steck, F.; Cyganski, R.; Trommer, S. Estimation of the value of time for automated driving using revealed and stated preference methods. *Transp. Res. Procedia* **2018**, *31*, 35–46. [CrossRef]

28. Krueger, R.; Rashidi, H.T.; Rose, M.J. Preferences for shared autonomous vehicles. *Transp. Res. Part C Emerg. Technol.* **2016**, *69*, 343–355. [CrossRef]

29. Gosling, D.S.; Rentfrow, J.P.; Swann, B.W. A very brief measure of the Big-Five personality domains. *J. Res. Personal.* **2003**, *37*, 504–528. [CrossRef]

30. Wheeler, R.E. optFederov. AlgDesign. The R Project for Statistical Computing. 2004. Available online: http://www.r-project.org/ (accessed on 12 August 2021).

31. R Core Team. *R: A Language and Environment for Statistical Computing*; R Foundation for Statistical Computing: Vienna, Austria, 2020; Available online: http://www.R-project.org/ (accessed on 12 August 2021).

32. Antoniou, C.; Polydoropoulou, A. The value of privacy. Evidence from the use of mobile devices for traveler information systems. *J. Intell. Transp. Syst. Technol. Plan. Oper.* **2015**, *19*, 167–180. [CrossRef]

33. Antoniou, C.; Matsoukis, E.; Roussi, P. A methodology for the Estimation of Value-of-Time Using State-of-the-Art Econometrics Models. *J. Public Transp.* **2007**, *10*, 3. [CrossRef]

34. Bierlaire, M. PandasBiogeme: A Short Introduction. 2018. Available online: https://transp-or.epfl.ch/documents/technicalReports/Bier18.pdf (accessed on 13 April 2020).

35. Bierlaire, M. PandasBiogeme Documentation. 2021. Available online: https://biogeme.epfl.ch/documents.html (accessed on 3 September 2021).

36. Kuppam, A.R.; Pendyala, R.M.; Rahman, S. Analysis of the Role of Traveler Attitudes and Perceptions in Explaining Mode-Choice Behavior. *Transp. Res. Rec.* **1999**, *1676*, 68–76. [CrossRef]

37. Train, K.E. *Discrete Choice Methods with Simulation*; Cambridge University Press: Cambridge, UK, 2003.

38. Mcfadden, D. Conditional logit analysis of qualitative choice behavior. In *Frontiers in Econometrics*; Academic Press: Cambridge, MA, USA, 1973; pp. 105–142, ISBN 0-12-776150-0.

39. Wardman, M.; Chintakayala, V.P.K.; de Jong, G. Values of travel time in Europe: Review and meta-analysis. *Transp. Res. Part A Policy Pract.* **2016**, *94*, 93–111. [CrossRef]

40. Parady, G.; Taniguchi, A.; Takami, K. Travel behavior changes during the COVID-19 pandemic in Japan: Analyzing the effects of risk perception and social influence on going-out self-restriction. *Transp. Res. Interdiscip. Perspect.* **2020**, *7*, 100181. [CrossRef]

41. Shamshiripour, A.; Rahimi, E.; Shabanpour, R.; Mohammadian, A.K. How is COVID-19 reshaping activity-travel behavior? Evidence from a comprehensive survey in Chicago. *Transp. Res. Interdiscip. Perspect.* **2020**, *7*, 100216. [PubMed]

42. Tirachini, A.; Antoniou, C. The economics of automated public transport: Effects on operator cost, travel time, fare and subsidy. *Res. Transp. Econ.* **2020**, *21*, 100151. [CrossRef]