Advanced Approach to Modelling Shared Automated Vehicles Users' Preferences

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Abstract

The flexibility of shared autonomous vehicles (SAVs) may engender a new mode of transportation that will be a cross between the public and private transportation available today. According to some estimates, car sharing and ride sharing services are two possibilities for automated vehicle (AV) traffic at the expense of private ownership. User preferences regarding car sharing, ride sharing, public transportation and their different attributes remain unclear. This study aims to fill the gap in this body of research and propose an advanced approach to SAV modelling using stated preferences (SP) and serious games.

1. Introduction

The ever increasing level of motorization and private vehicle ownership created a transportation reality that is inefficient. In modern western society, private cars are utilized for roughly 5% of their lifetime and waste tremendous amount of land while not in use (Borhhout, Rigole, & Andreasson, 2015). Shared automated vehicles (SAV) will merge some of the characteristics of private and public modes, thereby introducing a flexible, novel mode of transportation. According to some estimates, the possession of private cars could decrease substantially as (AVs) will penetrate the market, with the market share of car sharing increasing dramatically (Fagnant & Kockelman, 2013; Gruel & Stanford, 2016; Gurumurthy & Kockelman, 2018). Along with public transport and increased biking and walking, SAV could be the building blocks of a sustainable, efficient transportation system (Borhhout et al., 2015). The current study will focus on three different SAV services and their potential:

a. Sharing a ride in an AV (similarly to UberPool) (SR).
b. Renting an AV from a fleet of vehicles (similarly to Car2go) (SC).
c. Using automated public transport service (PT).

To the best of our knowledge to date, no user preferences research focused on the competition between these three services.

When dealing with a technology that is not yet accessible to the general public, aiming to predict users' reaction towards it can be challenging. Different studies use different methods to assess users' attitudes and preferences towards AVs. Using SP surveys in marketing research, travel demand and mode choice research is one of the most prevalent methods as it allows the exploration of potential of hypothetical modes or services (Yang, Choudhury, Ben-Akiva, Abreu e Silva, & Carvalho, 2009). This study utilizes and applies several experimental design techniques in the development of the presented SP surveys, including state of the art Bayesian D-efficient design.

2. Pilot Methodology

2.1 Survey Design

The first part of the survey included questions about travel habits, car ownership and occupational status, age, gender, area dial code and level of religiousness. The second part included a short explanatory video followed by six SP choice decisions where participants had to pick their preferred mode for their next trip to work. The SP choice contexts will be used to assess the influence of different costs, travel, walk and wait times and number of passengers traveling in the SR on the choice between SC, SR and PT. After each choice decision the participant was asked how sure is she in her answer and which of the other modes presented (if any), are acceptable to her beside the alternative she chose. The fourth part included psychological and attitudinal questions aimed to capture time style (Usunier & Valette-Florence, 2007), environmental concern, car sharing preferences and public transport attitude. The fourth and last part included socio- economic and demographic questions such as income and education.

The choice to present three different services at the expense of a vehicle ownership option was based on the flexibility afforded to the traveler when using these mobility service options. Furthermore, it is our expectation that these services will be cost and time competitive with ownership style modes. Ultimately, these service type services are expected to allow travelers to adjust their travel choices as their needs and plans change. For this purpose, an SP survey was designed, were respondents were asked to choose which service they would choose for their next trip to work.

Three choice alternatives in each choice decision were presented to respondents:

1. Private ride in an automated car (SC)- this option will allow you to call for an automated car from a fleet of cars that will be available to you exclusively for a limited period of time.

2. Shared ride in an autonomous car (SR)- This option will allow you to call for an automated car from a fleet of cars that is available to you, similar to Uber pool but with no driver. You will share your ride with other passengers to reduce costs, but this might cause additional pick up and drop off delays. You will share the ride with additional passengers. In some cases, you will be able to save time by riding on a high-occupancy vehicle lane.
3. Autonomous public transit (PT)- the service will be better than current public transportation in terms of frequencies and speed. Furthermore, it may include novel modes of transportation that are not yet available such as monorail. In some cases, you will be able to save time by riding on a high-occupancy or transit only lanes.

2.2 Orthogonal design

In order to evaluate each variable level, the levels were designed in a perfectly orthogonal design. The design uses five attributes and 10 variables. The orthogonal design was generated using SPSS version 20 (IBM, 2011). Ten variables with 2-5 attribute levels each, yielded 64*2 scenarios representing 128 choice situations.

To account for heterogeneity in the population, two different designs are used, one for users commuting 40 km or less, and one for those over 40 km (one way). The reason for this class differentiation is that longer trips naturally have lower marginal cost per km whereas short trips have a 'drop charge' minimal cost that is independent of the trip's length. The values shown in the SP table were based, in part, on values that the respondents entered at an earlier stage of the survey. All respondents, including those who do not use private car as their main mode, were asked:

"Please estimate, how long is your commute distance by car, one way?" The per kilometer price was set to 2 shekels/km. This value is based on well-established vehicle operating cost calculations (Heshev Information Systems Ltd, 2016) and includes capital recovery, gasoline, insurance fees, depreciation and maintenance costs.

The participants were also asked "Please estimate your one-way commute time to work by car".

The answers to both this question were pivoted around the design values. Other attributes were number of passengers in the SR, waiting and walking time to the PT station.

The levels were varied according to the experimental design presented in Tables 1-2:

Table 1 - Design for commute distance of under 40 km

	Automated Shared Car (SC)	Automated Shared Ride (SR)	Automated Public Transit (PT)
Cost (nis)	0.8*CommuteDistance (D)*2 1*D*2 1.3*D*2 1.6*D*2	0.5*D*2 0.7*D*2 0.9*D*2 1*D*2	0.2*D*2 0.3*D*2 0.4*D*2 0.5*D*2
Time (min)	0.7* CommuteTime (T) 1* T 1.3* T	0.7*T 1* T 1.3*T	0.7* T 1* T 1.3* T
Passengers in SR (except you)	-	1 2 3-5 Van (up to 10)	-
Waiting time (min) for SC and SR	1 5 10	1 5 10	-
Waiting and Walking for PT (min)	Home pick up	Home pick up	5 10 15

Table 2 - Design for commute distance of over 40 km

	Automated Shared Car (SC)	Automated Shared Ride (SR)	Automated Public Transit (PT)
Cost (nis)	0.7*D*2 0.9*D*2 1*D*2 1.2*D*2	0.3*D*2 0.4*D*2 0.6*D*2 0.7*D*2	0.1*D*2 0.2*D*2 0.3*D*2 0.4*D*2

All other levels except cost were the same as the under 40 km design.

The design originally had 64 scenarios. Dominant or unreasonable scenarios were manually removed from both classes. Scenarios that met the following criteria were mostly eliminated:

- Shared ride is more expensive than a private ride.

- Public transport is more expensive than a share ride.
- Waiting time for a private car is significantly higher than for a shared ride.

Post scenario elimination, the design for under 40 km included 47 scenarios, while the design for 40 km or over, included 50 scenarios. Finally, the survey and scenarios were generated using Qualtrics platform (Qualtrics, Provo, UT) and the respondents were classified according to their average commute distance to work (one way), to one of the two survey designs.

3. Pilot Results

3.1 Pilot Data Collection and Model Estimation

In order to validate the survey and the orthogonal design, a pilot study was conducted. A representative sample of 297 Israeli respondents completed an online survey generated by Qualtrics. The participants were recruited through I Panel (ipanel.co.il., 2019) a survey company that operates an online panel. Participants needed to have at least a part time job, be over the age of 18, not have in their possession a company car and travel for at least 10 minutes to work each way. The participants were compensated by I-Panel with 4.5 NIS (about 1.2$). Each respondent was presented with six choice scenarios, yielding 1782 choice decisions. The choice probabilities are presented in Table 3.

Table 3- Choice Probabilities

SC	SR	PT	Total
340	486	956	1782
19%	27%	54%	100%

This distribution is over represented by PT choices which indicates that the SP design of this mode was too attractive.

3.2 Estimation of Mixed Logit Model for Panel Data

The collected data is used to estimate a mixed multinomial logit heteroskedastic error component type model. The paramter estimates from this model are used as the priors for the Bayesian D-Efficient design presented in the next section. Table 4 presents the results of the estimated model. The t-test for each significant parameter is presented in parentheses. All parameters are significant at the 95% level and their signs are logical:

Table 4 - Mixed Logit Model Results

Utility Parameters	Automated Shared Car (SC)	Automated Shared Ride (SR)	Automated Public Transit (PT)
Number of Halton draws	2000		
Number of observations	1782		
Number of estimated parameters	24		
Null log-likelihood	-1957.727		
Final log-likelihood	-1256.621		
Adjusted rho-square	0.346		
Alternative specific constant	-10.3 (-5.99)	-12.1 (-8.20)	Base case
Standard deviation of the constant	-1.65 (-7.80)	1.30 (7.48)	Base case (fixed to 1)
Number of cars per household	Insignificant	Base case	0.696 (2.39)
Cost	-0.0590 (-10.21)	-0.0527 (-8.78)	-0.0734 (-7.92)
Time	-0.0538 (-5.41)	-0.0520 (-7.27)	-0.0673 (-9.34)
Walk and wait 10 min for PT (dummy- 0=no, 1=yes)	-	-	-0.542 (-3.02)
Walk and wait 15 min for PT (dummy- 0=no, 1=yes)	-	-	-0.788 (-4.64)
ln(wait time) for SR and SC	-0.123 (-2.05)	-0.123 (-2.05)	-
Usually drive	Insignificant	Base case	-0.954 (-3.07)
Frequents stop for errands	Base case	Insignificant	-0.315 (-2.71)
Working full time	Insignificant	Base case	-0.996(-3.11)
Age- over 65 (dummy, 0=no, 1=yes)	Insignificant	1.21 (2.23)	Base case
Environmental concern	Base case	Insignificant	-0.541 (-2.74)
Public transit attitude	-	-	-1.67 (-8.76)
Obedience to time (time style sub scale)	Base case	0.491 (2.32)	0.491 (2.32)
Linearity and economicity of time (time style sub scale)	Base case	Insignificant	-0.416 (-2.38)
License (dummy, 0=no, 1=yes)	1.55 (1.87)	0.935 (1.37)	Base case

4. Extended Survey Methodology

4.1 Bayesian D-Efficient Design

Pilot results demonstrated over attractiveness of PT which can be attributed to the design levels chosen for the pilot study. In order to rebalance the choice probabilities, a new design is proposed. D-efficient design can be generated when sufficient priors are available. Since the final model configuration was not yet finalized, Bayesian MNL D-efficient was chosen as it better accounts for incorrect priors (Walker, Wang, Thorhauge, & Ben-Akiva, 2018). In order to conduct the Bayesian D-efficient design, the error component panel MMNL model presented above was estimated and used. Two different designs are used, one for users travelling 20 km or less, and one for users travelling over 20 km for their commute trip. As the pilot results showed that the median commute distance is 19 km, the 40 km break point used in the pilot design was altered. Both designs showed reasonable design parameters (balance, D-error, S-estimates). In order to control for attribute balalnce, each attribute is represented an equal number of times as each design has 12 scenarios divided into two blocks.

Table 5 - Design for commute distance of under 20 km

	Automated Shared Car (SC)	**Automated Shared Ride (SR)**	**Automated Public Transit (PT)**
Cost (nis)	0.8*D*2 1.2*D*2 1.6*D*2	0.5*D*2 0.8*D*2 1.1*D*2	0.2*D*2 0.5*D*2 0.8*D*2
Time (min)	0.7* T 1* T 1.3* T	0.7* T 1.05* T 1.4* T	0.7* T 1.1* T 1.5* T
Passengers in SR (except you)	-	Front seat Window seat Middle seat	-
Waiting time (min) for SC and SR	1 5 10	1 5 10	-
Waiting and Walking for PT (min)	Home pick up	Home pick up	5 10 15

Table 6 - Design for commute distance of over 20 km

	Automated Shared Car (SC)	**Automated Shared Ride (SR)**	**Automated Public Transit (PT)**

Cost (nis)	0.85*D*2 1.05*D*2 1.25*D*2	0.65*D*2 0.85*D*2 1.05*D*2	0.3*D*2 0.5*D*2 0.7*D*2

All other levels except cost were the same as the under 40 km design.

A few more design alternations were made in order to improve the Bayesian D-efficient design:

4.2 Modifications in the New Design

In order to simplify the design, the number of attribute levels was reduced to a maximum of three levels. The differences between the cost and time levels were set to 0.2, in opposed to larger differences of 0.3-0.4 for the under 20 km design. Larger differences yielded highly unbalanced scenarios as they were multiplied by the average travel time and travel distance, creating a higher variance in levels for the over 20 km design than in the under 20 km.

The attribute of number of passengers traveling with you in the SR yielded no significant results in the pilot model. Therefore, we decided to focus on different seating configurations and how they may affect utility. Also, we decided to present this attribute in a more visual manner to simplify explanatory texts and to improve participants' situation simulation. The seating configurations are presented in Figure 1:

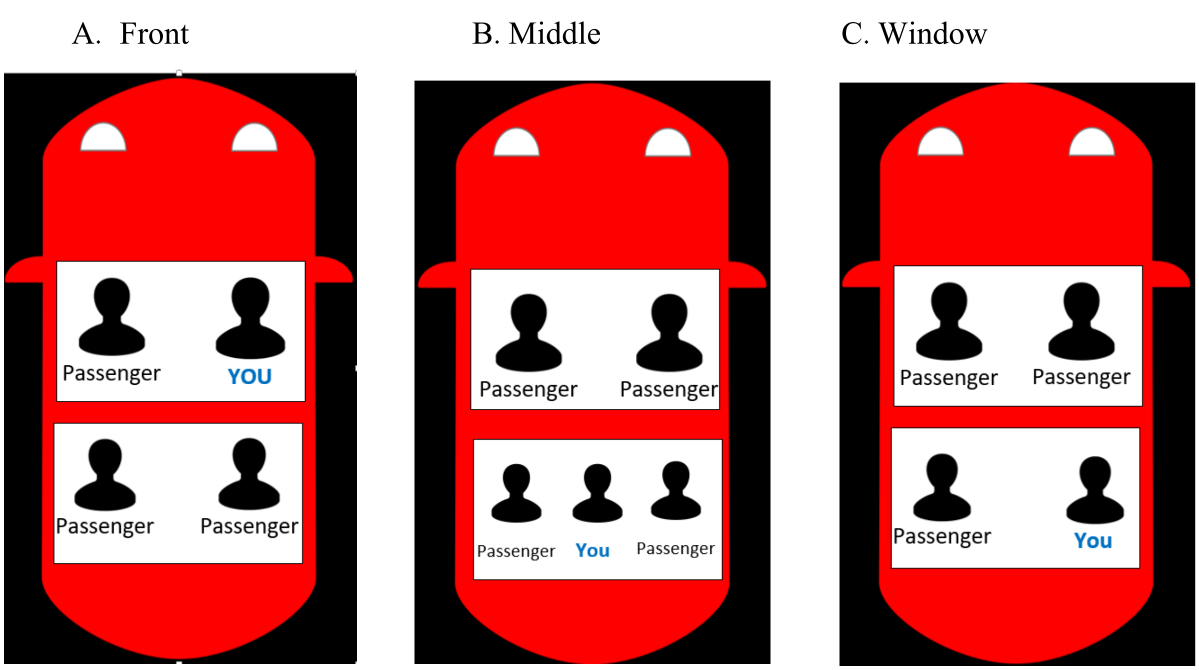

Figure 1- Suggested SR Seating Configuration Attribute

5. Future work

By the end of March 2019, an extended survey of 700 Israeli respondents will be run. Post data collection, the model will be improved and extended. The Bayesian MNL D- efficient model results will be ready before September, for the hEART 2019 symposium.

Scholars argue that relying solely on SP experiments can be problematic as they suffer from hypothetical bias. Namely, saying isn’t the same as doing (Fifer et al. 2014; Hensher 2010).

Therefore, we propose a novel multi methodology that will also build on serious games. Participants will take part in a serious game designed especially for this study. Participants will face computerized social choice dilemmas with alternatives similar to the survey. The MMNL model results will be used to plug in initial utility function values for the game as demonstrated by Zellner, Massey, Shiftan, Levine and Arquero (2016). Comparing estimates from both methods will improve the understanding of how experience shapes preferences over time.

Bibliography

Borhhout, W., Rigole, P.-J., & Andreasson, I. (2015). IMPACTS OF SHARED AUTONOMOUS TAXIS IN A METROPOLITAN AREA.

ChoiceMetrics (2014) Ngene 1.1.2 user manual: The Cutting Edge in Experimental Design, Choice Metrics, http://www.choice-metrics.com/.

Fagnant, D. J., & Kockelman, K. M. (2013). The travel and environmental implications of shared autonomous vehicles, using agent-based model scenarios. *Transportation Research Part C: Emerging Technologies*, *40*, 1–13. https://doi.org/10.1016/j.trc.2013.12.001

Fifer, S., Rose, J. & Greaves, S., 2014. Hypothetical bias in Stated Choice Experiments: Is it a problem? And if so, how do we deal with it? Transportation Research Part A: Policy and Practice, 61, pp.164–177. Available at: http://dx.doi.org/10.1016/j.tra.2013.12.010.

Gruel, W., & Stanford, J. M. (2016). Assessing the Long-term Effects of Autonomous Vehicles: A Speculative Approach. *Transportation Research Procedia*, *13*, 18–29. https://doi.org/10.1016/j.trpro.2016.05.003

Gurumurthy, K. M., & Kockelman, K. M. (2018). ANALYZING THE DYNAMIC RIDE-SHARING POTENTIAL FOR SHARED AUTONOMOUS VEHICLE FLEETS USING CELLPHONE DATA FROM ORLANDO, FLORIDA Krishna. *Computers, Environment and Urban Systems*. https://doi.org/10.1016/J.COMPENVURBSYS.2018.05.008

Hensher, D. a., 2010. Hypothetical bias, choice experiments and willingness to pay. Transportation Research Part B: Methodological, 44(6), pp.735–752. Available at: http://dx.doi.org/10.1016/j.trb.2009.12.012.

Iacobucci, R., Mclellan, B., & Tezuka, T. (2018). evaluating a Shared Autonomous Electric Vehicle system interacting with. *Energy*. https://doi.org/10.1016/j.energy.2018.06.024

Krueger, R., Rashidi, T. H., & Rose, J. M. (2016). Adoption of Shared Autonomous Vehicles-A Hybrid Choice Modeling Approach Based on a Stated-Choice Survey. *TRB 95th Annual Meeting Compendium of Papers*, 20 pages.

Lavieri, P. S., Garikapati, V., Bhat, C., Pendyala, R., Astroza, S., & Dias, F. (2016). MODELING INDIVIDUAL PREFERENCES FOR OWNERSHIP AND SHARING OF AUTONOMOUS VEHICLE TECHNOLOGIES, (November).

Levin, M. W., Li, T., Boyles, S. D., & Kockelman, K. M. (2016). A general framework for modeling shared autonomous vehicles. *95th Annual Meeting of the Transportation Research Board*, *64*(January), 1–23. https://doi.org/10.1016/j.compenvurbsys.2017.04.006

Litman, T. (2018). Autonomous Vehicle Implementation Predictions: Implications for Transport Planning. *Transportation Research Board Annual Meeting*, (2018), 36–42. https://doi.org/10.1613/jair.301

Qualtrics LLC. (2015). Qualtrics. Retrieved from http://www.qualtrics.com/

Usunier, J. C., & Valette-Florence, P. (2007). The Time Styles Scale: A review of developments and replications over 15 years. *Time & Society*, *16*(3), 333–366. https://doi.org/10.1177/0961463X07080272

Walker, J. L., Wang, Y., Thorhauge, M., & Ben-Akiva, M. (2018). D-efficient or deficient? A robustness analysis of stated choice experimental designs. *Theory and Decision*, *84*(2), 215–238. https://doi.org/10.1007/s11238-017-9647-3

Yang, L., Choudhury, C. F., Ben-Akiva, M., Abreu e Silva, J., & Carvalho, D. (2009). *Stated Preference Survey for New Smart Transport Modes and Services: Design, Pilot Study and New Revision*.

Zellner, M., Massey, D., Shiftan, Y., Levine, J., & Arquero, M. J. (2016). Overcoming the Last-Mile Problem with Transportation and Land-Use Improvements: An Agent-Based Approach. *International Journal of Transportation*, *44*(11), 1–26. https://doi.org/10.14257/ijt.2016.4.1.01