Applying Serious Games in Models of Preferences of Shared Automated Vehicles

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SHORT SUMMARY

Data obtained from a serious game was used to estimate a game-based model to better understand user preferences regarding shared automated vehicles (SAVs), while modeling how user experience and social interactions can shape decisions over time. Users' choice of three novel, fully automated transportations modes; shared ride, shared car, and automated transit, was studied with ten interacting players engaged in a competitive mode choice game. The players aimed to maximize their overall score, which was affected by their mode choice, their punctuality, and the choices of all the other players. Each game had 50 rounds to allow implicit learning and provide insight on how choices are shaped with experience. Results showed a strong shift to shared rides over shared cars and transit with road users reaching a state of equilibrium in terms of scores. The implications of game-based methods on formation of user preferences and mode choice is discussed.

Keywords: Autonomous and connected vehicles, Game Based Models, Discrete choice modeling.

1. INTRODUCTION

Serious games (SGs) are designed for study purposes rather than pure pleasure. SG is a virtual system where players engage in artificial conflict, defined by the game rules and constraints (Salen & Zimmerman, 2004). They are different from an agent-based simulation, as the agent is not governed by a software code but rather by the choices and actions of a human player. In transportation, SGs allow a flexible research environment and abstract the travel experience into concrete choices and allow inference of travel behaviors in a dynamic and realistic context. A multiplayer game setting allows social interaction and the social consequences can be shown to the players as additional feedback. The repeated choice nature of the game is used to show how implicit learning can be used to facilitate cooperation and shape preferences over time. While using games for behavioral economics research is not a new practice, utilizing SGs for studying decision-making in the transportation field is much scarcer. Such research will likely expand considering persuasive Information and Communication Technologies (ICT) and Advanced Travel Information Services (ATIS), which now allow travelers to communicate and receive online information regarding the state of the transportation system and traffic (Klein and Ben-Elia, 2016).

2. METHODOLOGY

Game design and administration

One hundred students from Ben-Gurion University of the Negev were recruited during the COVID19 lockdown period necessitating only virtual participation. In each session, ten players joined the virtual computer lab using a Zoom link they received by email. All players were required to use a computer and not a phone, sit in a quiet room, have a stable internet connection, have a webcam turned on, the computer's sound turned on, or a headset. The game instructions were presented and read aloud by the experimenter. The games had 50 consecutive rounds to simulate 50 days. This number of rounds was found sufficient for convergence of the results in a series of ten-player pilots. The players were shown a short explanatory animated video especially procured for this study to establish a basic level of knowledge regarding automated vehicles (AVs) and SAVs among the respondents and to present them with the three available alternatives. The players were asked to simulate a daily commute choice, from home to work or college. They were told that each day begins at 8:00 AM and that the goal is to arrive at 9:30 AM and to maximize their score in each day/round. They were informed that being too late or too early will decrease their total payoff while the penalty for being late is greater than for being too early, to simulate real-life consequences; Being too early may be considered as a time of idleness and being too late may have negative consequences on work productivity. The players were instructed each morning to choose their preferred mode to commute out of the three alternatives. After completing the task, each player was compensated with 40-100 ILS, depending on performance, compared to other co-players. In addition to the video, the players were presented with the following verbal descriptions of the three alternatives:

1. Private ride in an automated vehicle (SC)- This vehicle will be available to you exclusively for the duration of your ride to work. This vehicle can take you to your destination at your preferred time. However, if many players choose this option, it may result in congestion that will increase travel times.
2. Shared ride in an autonomous car (SR)- With this option, you will be able to share your ride with another passenger and split the cost, but your travel time may increase due to picking up or dropping off the other passenger. The vehicle departs when there are two passengers on board. If you chose this option while no one else did, the car will depart just with you in it, but you will pay the same cost as if the ride was shared.
3. Automated public transit (PT)- This service will be better than the public transit familiar to you in terms of modes, frequencies, travel time and reliability. This service departure every 30 minutes. The duration of the trip is one hour, independent of the number of players who choose it. This mode will operate on a designated route unaffected by road traffic.

Following the instructions and the description of the modes, a choice screen was presented, in which the player had to choose one of the three modes as well as the departure time using a time-slider. The first five rounds were training rounds aimed to allow the players to experiment with the game's interface and the feedback mechanism. In addition, after the 5^{th} round players were provided pre-trip information on the expected travel time on the road and the average number of travelers sharing rides.

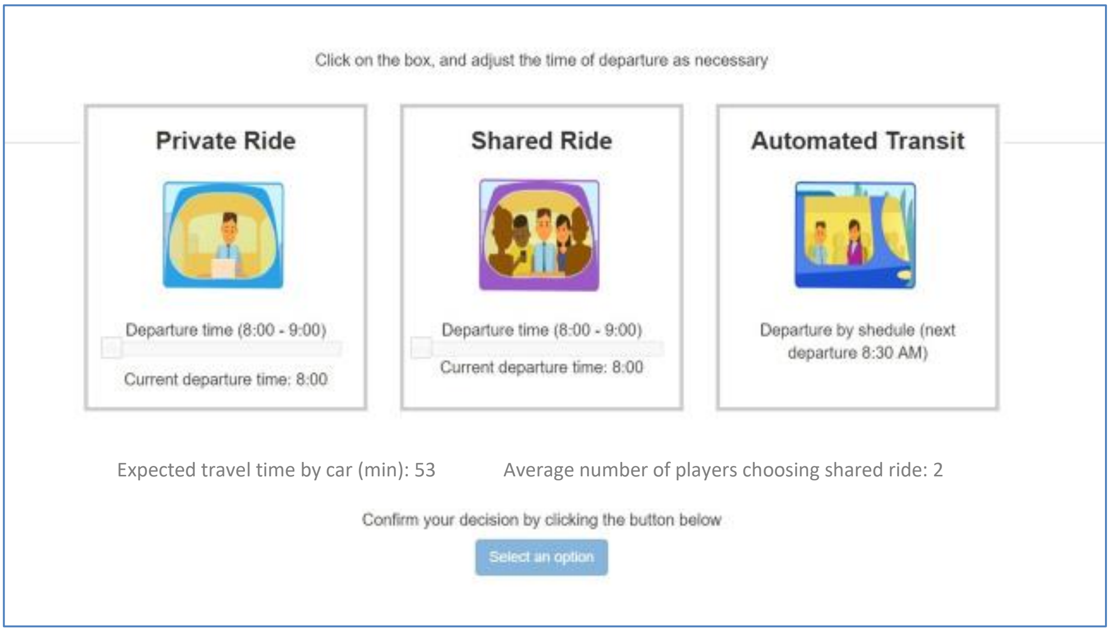

Figure 1- Screen Shot of the mode choice game (after the 5th round)

Following the choice screen, a feedback screen was presented.
The feedback screen showed the outcomes of the choices, including the actual travel time and the player's score for that round. Actual travel time for road users was based on a cost function accounting for the choices of all players (volume-delay). The score function was based on a schedule-delay specification with early, late arrival and travel time delay penalties. The expected travel time previously shown on the choice screen was also presented for reference. Then, the players continued to the next round.

3. RESULTS AND DISCUSSION

Choice probabilities

One hundred players faced 50 “daily” choice decisions, yielding to a total of 5000 mode choices. Each player chose both the departure time and the mode. Leaving aside the departure time choice, the reported mode shares in all 50 rounds were 59% SR, 30% SC and 11% PT.

Game-based model

A Cross-nesting LK type model for panel data was chosen to capture the repeated choice nature of the game, which had 50 rounds, and to account for the cross-nested choice structure of the departure time and the mode.
A random parameter (RNP) was defined to capture unobserved taste heterogeneity persistent over time (Joan Leslie Walker, 2001). In addition, the cross-nesting structure is introduced by five cross-nesting parameters (CN) to capture correlation across the different alternatives: CN_SR, CN_SC and different departure times that correspond with early, intermediate, and late departure time in SR or SC: CN_E, CN_M, CN_L. In a cross-nesting structure, the alternatives belong to more than one group (Joan Leslie Walker, 2001). For example, Early SR belongs both in the “SR” group and the “Early departure” group. As PT runs on a fixed schedule

with one departure time, it did not belong in any of the nesting structure groups. The model was estimated using Pandas Biogeme (Bierlaire, 2018).

The LK model with cross-nesting structure and RNP is written as:

$$
\begin{aligned}
U_{1SR} &= (Intercept + RNP) + \beta_1 * X_1 ... + CN\_SR + CN\_E \\
U_{2SR} &= (Intercept + RNP) + \beta_1 * X_1 ... + CN\_SR + CN\_M \\
U_{3SR} &= (Intercept + RNP) + \beta_1 * X_1 ... + CN\_SR + CN\_L \\
U_{1SC} &= (Intercept + RNP) + \beta_1 * X_1 ... + CN\_SC + CN\_E \\
U_{2SC} &= (Intercept + RNP) + \beta_1 * X_1 ... + CN\_SC + CN\_M \\
U_{3SC} &= (Intercept + RNP) + \beta_1 * X_1 ... + CN\_SC + CN\_L \\
U_{pt} &= (0 + RNP) + \beta_1 * X_1 ...
\end{aligned}
\tag{1}
$$

Game-based model parameters

Aside from the cross-nesting structure and the RNP, five other variables were included in the final models.

- Expected travel time by car: At the end of each round (after the fifth round), the average time it takes to go by SR or SC was shown to respondents.
- Avg Share: This parameter is the average number of players choosing SR since the game began.
- Experience: This is a dummy parameter of experience with the game. Equals one if the round number > 20, or 0 otherwise.
- Late: This is a dummy parameter that indicates whether the player was over 10 minutes late in arriving at work in the previous round (lagged). (1=yes, 0=no).
- Score: This parameter used the final score from the previous round as shown to the player on the feedback screen.

Alternatives and choice proportions

For the sake of the GBMs, the departure time of SR and SC, originally recorded as a continuous variable (1-60 minutes), was converted to a categorical variable. The continuous values were grouped based on three time slots and classified as Early, Intermediate or Late. Departures before the 39th minutes were classified as Early, departures between the 39th and the 43rd minute were classified as Intermediate (Mid), and departures made after the 43rd minute were classified as Late. This classification was based on the distribution of the departure time data so that each time slot includes approximately one-third of the departures.

Overall, there were seven alternatives based on the alternative and departure time chosen.

Table 1- List of alternatives and choice proportions for the game-based model

#	Alterna-tives	Departure time	Mode	Choice proportion
1	E_SC	Early	SC	2%
2	M_SC	Mid	SC	3%
3	L_SC	Late	SC	25%
4	E_SR	Early	SR	6%
5	M_SR	Mid	SR	45%
6	L_SR	Late	SR	8%
7	PT	One scheduled depar-ture at 08:30	PT	11%

Game-based model estimates and inference

All parameters are significant at the 5% level except for the intercepts of Early SR and Mid SR, which are non-significant (t-tests are shown in parenthesis; see Table 2). The first five trial rounds were excluded from the model. The model used 2,500 Modified Latin Hypercube Sampling (MLHS) draws, which were found empirically sufficient for parameter convergence.

Table 2- Game-based model estimates

Parameter	**SR**			**SC**			**PT**
	Early	Mid	Late	Early	Mid	Late	-
Intercept	-0.852 (-1.01)	-0.249 (-1.26)	2.880 (5.40)	-0.852 (-2.28)	-1.040 (-2.74)	2.880 (10.7)	0-fixed
RNP Intercept	0.811 (15.40)						
Expected travel Time by car	-0.219 (-3.11)	-	-0.508 (-8.59)	-0.284 (-4.40)		-0.711 (-17.00)	0-fixed
Experience	-	1.250 (9.37)	-		0.771 (5.64)		0-fixed
Late	0.835 (1.99)	-	-	0.961 (3.68)			0-fixed
Avg Shared	1.120 (3.83)	1.780 (6.70)	-	-	1.520 (4.25)	0.980 (3.55)	0-fixed
Score	0-fixed	3.970 (5.89)	-	-3.350 (-2.23)	-	-	-3.120 (-3.36)
CN Early	0.801 (5.41)	-	-	0.801 (5.41)	-	-	-
CN Late			1.260 (8.50)			1.260 (8.50)	
CN Mid		1.140 (7.76)			1.140 (7.76)		
CN SC	-			0.304 (2.18)			-
CN SR	0.346 (2.74)			-			
Sample size	100						
observations	4500						
Excluded observa-tions	500						
Initial log-likelihood	-4929						
Final log-likelihood	-4703						
Draws	2500						

"-" non-significant parameter that was fixed to 0.00.

- The **RNP Intercept,** which captures the correlation across time associated with different agents caused by the panel data, was significant. This confirms that the taste heterogeneity of the individual is persistent over time, as expected.
- **Avg travel time by car.** The negative sign indicates that longer travel time in SR and SC negatively affected their utilities, as expected. The effect for late departures is stronger than the effect for early departures, indicating that longer expected travel time facilitates earlier departures. A likelihood ratio test confirmed that there were no statistical differences between the parameters of Early and Mid SC, so the same parameter was used for both.
- **Experience.** Positive significant parameters for Mid/Late SC and Mid SR indicate that experienced players preferred to choose these alternatives, which resulted in high scores and supporting the idea that experience with new modes can facilitate behavioral changes. A likelihood ratio test confirmed that there were no statistical differences between the parameters of Mid and Late SC, so the same parameter was used for both.
- **AVG Share.** The larger this parameter (meaning more players choose to share), the probability of choosing Mid/ Early SR increased, which supports the hypothesis that social interaction can encourage sharing. As more players chose to share, the probability of Early/Mid departure time increased, to avoid late arrival penalties. The probability of choosing Mid/Late SC also increased, with Mid departures being more favorable than Late departures. This can be explained by increased travel time caused by the SR detour penalty (SD) game parameter, which pushed players towards SC when the demand for SR was too high.
- **Late.** Being late in the previous round increased the probability of choosing Early SR and SC (Early, Mid and Late) in the following round. Being late increased the probability of choosing earlier departures in SR and avoid the penalty associated with late arrivals, which is higher than the penalty for early arrival. It also increased the probability of SC, which does not have the sharing delay (SD) parameter, hence is perceived as more predictable.
- **Score.** A positive parameter for Mid SR, and a negative parameter for Early SC and PT, indicated that the higher the score in the previous round, the more likely the players are to choose Mid SR, and the least likely to choose PT or Early SC in the following round. This supports the idea that players implicitly learn which modes result in the highest score through the feedback system and adjust their choices accordingly.
- **Cross-Nesting (CN) parameters.** The positive parameters confirm the hypothesis that an unobserved correlation among different modes and departure times exists. SR choices and Late departures are the most strongly correlated.

4. CONCLUSIONS

The way policy makers and transportation planners plan for the possible introduction of AVs and SAVs is crucial to what impact their deployment will have on society and wider sustainability goals. Results from the GBM show how virtual experience combined with ex-ante and ex-post information encouraged travelers to switch to this mode, modify their departure time and eventually create a global effect that improved overall road traffic. As more players chose ride sharing, the probability of choosing SR with an early or intermediate departure increased. With apps already widely used for trip planning (e.g., Moovit) (Haque, Chin, & Debnath, 2013), these findings provide valuable insights on how real-time information regarding modal shares, can be used in policy making to encourage ride sharing and to regulate its demand. The results also show how this information can be used to control mode choice and departure time in the direction of a system optimum. The more players chose to share, the higher the detour time penalty was, encouraging other players to choose a private ride. Furthermore, the GBM showed that as travel time increased, earlier departures were encouraged, especially if the player ended up being late. In addition, a disturbing result is the near abandonment of PT, a phenomenon that even without AVs, is already evident in North American cities where ride sourcing is displacing PT services already weakened by COVID19 social distancing (Schaller, 2021).

The game setting also allowed to study the underlying implicit learning process of the players by modeling the effect of experience with different modes. The results showed that experienced players learn to choose a combination of travel mode and departure time that will result in a better score, such as a shared ride with an intermediate departure time. These results support the results of Klein & Ben-Elia (2018), which showed how facilitating cooperation in route choice can be used to maintain a stable and fair system optimum. As the possible outcomes of AVs on traffic and congestion remain unclear, policy makers must think of creative ways to mitigate congestion. Coordination between travelers' choices, including mode and departure time, is a key element for efficient transportation systems. Such cooperation can be encouraged through the use of Advanced Travel Information Services (ATIS) that will advise travelers on the optimal route, mode and departure time safeguarding the system's efficiency.

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