Shared Autonomous Vehicle Services and User Taste Variations: Survey and Model Applications

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Abstract

This study provides insight into traveler-related attributes affecting the choice of future autonomous vehicles (AVs) and explores the importance of integrating those attributes into agent-based simulations and service optimization assessments. For this purpose, an online survey was carried out to collect data on travelers of the greater Paris region along with their behavior regarding autonomous vehicles. In addition, this paper identifies AV taste variations among individuals as well as the subjective criteria behind their willingness-to-use a shared autonomous vehicle (SAV) service depending on their current mode of transport. The paper shows how traveler-related attributes are relevant to studying a shared autonomous mobility system and how they can enhance the accuracy of agent-based models and the traveler preference dimension in optimization models.

Keywords: Shared Autonomous Vehicle; Multi-Agent Simulation; Taste Variations

1. Introduction

Autonomous vehicles (AVs) is an emerging technology that is expected to cause fundamental shifts in people transportation. AVs are expected to provide a sustainable solution that can enhance road safety levels and traffic flows, reduce fuel consumption, and thus, improve passenger mobility in general, especially that they can be used as a shared service. The potential deployment of AVs going in hand with the increasing need for shared mobility services have thus attracted the attention of the transportation research community especially after many large mobility providers have declared their plans for deploying new autonomous mobility services. In this study, we propose an analysis framework that aims at exploring taste variations of travelers who might be willing to use future shared autonomous vehicles (SAVs). The outputs of the proposed analysis are appropriate for two main study purposes: 1) estimating service demand using agent-based simulation, and 2) integrating travelers' profiles into a ridesharing optimization problem. The current research presents a first survey on SAVs user taste variations in France where the aim is to

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investigate the reasons behind travelers' willingness to use future SAVs depending on their explicit market segmentations. In addition, this survey is carried out to provide the essential inputs for integrating these variations into existing agent-based simulation and optimization models. This potential integration is evaluated through both simulation and optimization approaches for the transportation system of Paris.

This paper is organized as follows. In section 2, we provide an overview of the related literature. In section 3, we describe the methodology used for performing the survey and integrating its results in simulation and optimization models. The results obtained of this integration are detailed in section 4. Finally, in section 5, the key findings are summarized and some directions for future research are suggested.

2. Prior research

Large investigations are carried out on exploring traveler tendency toward using future SAV particularly in the last 5 years (see Becker and Axhausen (2017) and Gkartzonikas and Gkritza (2019) for a review). However, few studies have considered integrating user taste variations into SAV demand modeling and simulation. Chen and Kockelman (2016) employed a multinomial logit mode choice model in an agent-based simulation to investigate various dynamic pricing strategies on mode shares estimate of electric SAV in Austin, Texas. In their study, the SAV user preferences are assumed varied according to the traveler willingness-to-pay and value-of-travel-time (VOTT). Nonetheless, this study neglected user sociodemographic attributes in the SAV mode choice mechanism. Martinez and Viegas (2017) proposed another agent-based model in order to assess the impacts of deploying an SAV system in a mid-sized European city (Lisbon). In their study, the sociodemographic attributes (i.e. age and income) are represented in the model by applying a discrete choice approach. As their model is based on real trip-taking activity (i.e. all modes currently available), sociodemographic attributes are neglected for SAV mode and some hypothetical variation in terms of car ownership and holding public transport pass is used instead. Kamel et al. (2019) employed a widely used multi-agent simulator (MATSim) to explore the impact of user preferences on the modal share of SAVs integrating to the transportation system of Paris. The simulation was performed using the categorized scoring utility according to the individual sociodemographic attributes of the users. It is shown that ignoring user preferences could significantly affect the SAV modal share. Their work incorporated several optimization models, which are used to dynamically assign SAVs. However, the study considered SAV services only without ridesharing while the integrated user preferences are estimated from a non-local outsource sample.

Regarding optimization models for SAVs, a considerable amount of research has been directed towards studying the impacts of introducing them on existing transportation systems. However, the development of new optimization approaches for planning and operating SAV systems has received less attention from the operations research community. First, this is because most of scientific and technological advances have been made by AV manufacturers and service providers who do not always reveal the details of their methods and techniques due to commercial sensitivity aspects. Another reason is that many studies have suggested that the same methods that are used for operating shared conventional vehicles can still be applied for SAVs (Mourad et al., 2019). Reviewing the available literature on modeling SAV systems, we observe that traveler requests are usually represented as randomly generated or real-life demand through time and space. In both cases, this demand is often considered homogenous in terms of traveler preferences and behavior. Traveler requests are usually characterized by their origins, destinations and time constraints but with no other profiling criteria. This is because these systems are associated with complex optimization problems (with many complicating features, e.g. time windows) that are hard to be solved even without introducing traveler profiles. In addition, most studies have focused on evaluating the system from the point of view of service operators rather than taking into account the preferences of their users. For example, Levin et al. (2017) proposed a system that dynamically builds shared rides between travelers using SAVs. Their system checks whether there is already any SAV which is located, or en route, to where traveler request has appeared and assign it to serve that request. In addition, Alonso-Mora et al. (2017) considered a real-time ridesharing system where traveler demands are served using a fleet of SAVs that dynamically considers their actual locations and time restrictions. Relatively, Pimenta et al. (2017) considered a system in which small SAVs operate between different sections in a closed industrial site. While transported workers have the same travel behavior, the system aims at building routes for SAVs at minimized operational costs. To conclude, most of SAV models have focused on optimizing system-wide operational costs (e.g. vehicle mileage, travel time, fleet size, etc.) while less attention has been directed towards considering more traveler-centered aspects, such as; comfort, privacy, waiting time and others. This research gap represents an opportunity that we aim to tackle in this paper, as we will see in the following sections.

3. Methodology

This research study is organized around two major parts: 1) SAVs survey model, and 2) demand estimation and evaluation across multi-agent simulation and service optimization.

3.1. SAVs survey model

In order to explore user taste variations, a local survey was conducted in the greater Paris area. The first part of the designed survey was organized into three blocks. First, sociodemographic attributes (i.e. age, gender, socio-professional category, and income). Second, typical daily one-way journeys including origin-destination regions, mode of transport, monthly cost and travel-related times (depending on mode: waiting, parking availability, etc.). Third, evaluation of the current journey (on a 5-point Likert scale) in terms of safety, security, comfort, freedom during travel. At the end of these blocks, participants are asked if they would rather, or not (Yes/No), use an AV instead of their current mode of transport (answer a priori).

Employing above information, an alternative travel using SAVs was simulated for the same participants' travel attributes. The cost was estimated from the prices of Lyft USD 300/30 rides subscription plan (Lyft, 2018). The total travel times were calculated using the total travel time (x) given by the participants (Table 1). The values of x multipliers were deduced from the travel patterns in V-Traffic (2014, p: 6), Le Monde (2014), Wesawit (2013), and the French global transport survey of 2010 in the greater Paris (EGT2010).

Table 1. SAVS alternative calculation of total travel time.

Total travel time	PT	car	Bike	Walk
Paris-Paris	$x \times 0.79$	$x - (t_p + t_w)$	$x \times 0.85$	
Paris-Suburbs	$x \times 0.8$	t_p : $parking - time$	$x \times 0.34$	$x \times 0.125$
Suburb-Suburb	$x \times 0.4$	t_w : $walking - time$	$x \times 0.25$	

The second part of the survey exposes the simulated travel to participants and asks them if they would use (Yes/No) the SAVs in the future as a replacement of their current mode of transport (a posteriori answer). Depending on their answer, they are asked to give a score (5-point Likert scale) to tell how important each of the criteria behind their decision is. The list of the criteria is generated depending on the mode (as for second block of the first part of the survey, i.e. typical daily one-way journey). If participants answer with Yes, they are asked if they would pay extra 20% to have a private ride, as VIP travelers.

3.2. Demand estimation and evaluation across multi-agent simulation and service optimization

First, the SAV demand is estimated using a multi-agent transport simulation platform MATSim (Axhausen, 2016) and its Dynamic Vehicle Routing Problem (DVRP) extension (Maciejewski, 2016). This simulation allows us to investigate dynamic demand that is responsive to traffic and network. To reply to the existing needs in the simulation and analysis, some features related to traveler behavior are developed beforehand. As an essential input, the synthetic population of the case study area has been generated employing an open source generator, previously developed by authors (Kamel et al., 2018), which applies fitness-based synthesizing with multilevel controls. The activity chains with specific individualized time frames have been allocated to each synthetic agent according to the sociodemographic and socio-professional attributes along with the probability that we have found in Paris global transport survey (EGT2010). The utility scoring of MATSim is modified based on our previous work in order to integrate user taste variations (Vosooghi et al., 2019). These functions have been set according to the analysis of the conducted survey and the utility of actual modes. The simulations are performed for individual-ride and ridesharing SAV services with and without considering user taste variations. The service performance and transportation system indicators are then analyzed.

Furthermore, we introduce traveler profiles into an existing optimization model, which operate a fleet of SAVs to serve traveler demands. More precisely, we take the original model, where traveler demands were assumed to be homogenous, and we introduce the concept of “VIP” travelers (i.e. who are willing to pay extra 20% of their travel expenses in order to have a private on-demand AV) into it. We then analyze the potential impact of introducing these profiles and highlight their effects from system-wide and traveler-centered perspectives (i.e. overall operational cost, waiting and detour time). For this purpose, the output of ridesharing SAV service in a multi-agent simulation is used as the input of the optimization model.

4. Results

4.1. The survey

The survey had 457 participants. More than 50% of the participants were young people under 24 years old where most of them were men (67%). The socio-professional category distribution was composed mostly of active and students (94%) while the real proportion of active categories of the greater Paris region was 88% (INSEE, 2018). The incomes were fairly distributed with a higher proportion (35%) of the [1000€, 2000€] segment. The trips outside Paris city were 87% of the total number of the whole region trips, while the real proportion was 70% (OMNIL, 2017).

The first part of the survey shows that 67% of participants would accept to use an AV as an alternative of their current mode of transport (Fig. 1). Car users had the largest potential to change their transport mode, followed by public transport users (60% conversion rate for car users and 58% for PT users). Travelers biking or walking did not score that high with 20% together. In the second part of the survey, after that participants were informed how the use of SAVs would be like for their current typical journey, it was found that 30% of them would use SAVs as a replacement of their current mode of transport. In this later case, car users had the largest potential to change mode (27%), followed by public transport users (17%). Travelers that use biking or walking did not state that they would be ready to change their mode (8% together). Compared to the acceptance of AVs, the percentage of PT and car users who state their willingness-to-use SAV service decreased by 41% and 33% respectively, where biking and walking only decreased by 12% each.

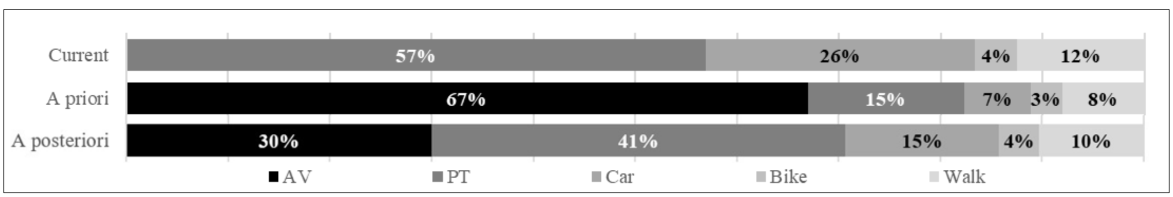

Fig. 1. AV acceptance rates vs. SAVs willingness-to-use regarding current modal split of Paris greater region.

As the scores of different criteria were close, we use regression trees to demonstrate the hierarchy of criteria. Fig.2 shows that the main three influencing criteria on SAVs willingness-to-use are comfort, travel time, and freedom (represented by positive answers in the figure). In Fig.3 (a), comfort is quite discriminating given the fact that people who give it a score of 5, have a probability of 0.8 to accept the use of SAVs. Travel time and freedom are less discriminating given their lower probabilities. For negative answers, the most influencing criteria on SAVs unwillingness-to-use are cost, security, and the current mode of transport. Indeed, the most reluctant participants give higher importance to cost (≥3.8 average) with a probability of 0.97. Meanwhile, those who do not use car as a current mode (with a potentially small transport budget) have a probability of 0.84. Finally, participants giving less importance to cost (>2.8 average) and higher importance to security (≥4.7 average) have a probability of 0.78 of not using SAVs.

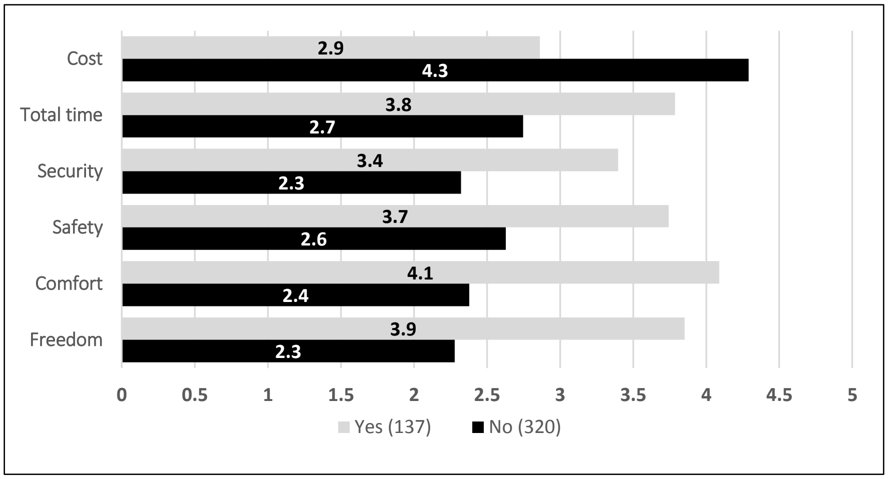

Fig. 2. Willingness-to-use criteria average scores.

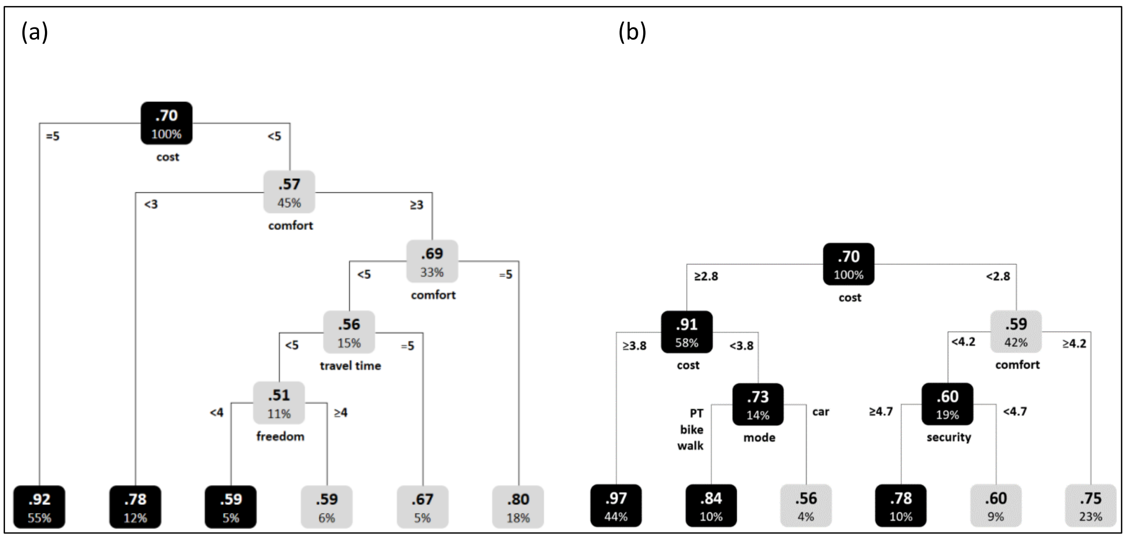

Fig. 3. SAVs regression trees of (a) willingness-to-use, and (b) unwillingness-to-use.

4.2. Multi-agent simulation

The multi-agent simulation was carried out for the transportation system of Paris area. The simulations incorporate two types of SAV services: 1) individual-rides, and 2) ridesharing. In both services, 2000 standard 4-seats SAVs have been integrated into the simulations. The service cost is considered to be 0.48 €/km for individual-rides and 0.4 €/km for ridesharing. By integrating the explored user taste variations into the agent-based simulations, the significant changes are observed in both proposed services. As Table 2 shows, the modal shares of both individual-ride and ridesharing scenarios increase after introducing user taste variations. The average wait time of users slightly increases as more requests are served using the same fleet size. The in-vehicle time remains almost unchanged. The revenue distance, which is the total passenger kilometer travelled (and illustrates the amount of profits that operator get from the service based on the mileage pricing) increases significantly, particularly for the ridesharing scenario. Similarly, the vehicle-empty distance increases in both scenarios. The share of different number of passengers being simultaneously on-board (for ridesharing scenario) change after introducing user taste variations. This occurs since the travelers with different trip patterns use the service. Given the average SAV travel distance (~6 kilometers) and the service price, travelers rather chose SAVs without ridesharing.

Table 2. Summary of SAV service and traveller related metrics.

Scenario	Individual-ride		Ridesharing	
	No user taste variation	With user taste variation	No user taste variation	With user taste variation
SAV modal share (%)	1.06	1.28	0.60	0.94
Average waiting time (min)	3.1	3.5	3.2	3.5
Average travel time (min)	7.6	7.7	8.3	8.9
Revenue distance (km)	0.23 M	0.28 M	0.13 M	0.21 M
Empty distance (km)	0.12 M	0.14 M	0.07 M	0.10
1 PAX ratio (%)	100	100	88	83
2 PAX ratio (%)	N/A	N/A	11	16
3 PAX ratio (%)	N/A	N/A	<1	<1
4 PAX ratio (%)	N/A	N/A	0	0

The aforementioned changes on service and traveler related indicators can be explained by the fact that different users with different trip patterns choose SAV services. Table 3 shows the share of SAV users by socio-professional categories. When user taste variations are considered, it is observed that employed people use less the SAV service in both scenarios. There is no change on the share of unemployed people among users of individual-ride SAVs. The latter slightly increases in ridesharing scenario as the service price is lower and the travel time is less important for the corresponding category of people. Noticeably, young people, such as students and persons under 14 years old, consist a higher share of users compared to the scenarios where user taste variations are neglected. Meanwhile, as it was expected, it is observed that less retired people choose SAVs when their taste variations are considered.

These results indicate that estimating demand of SAVs service, and relatively its configuration and design must take into account the demographic structure of the city or region of interest as well as the taste variations of its inhabitants.

Table 3. Summary of SAV users by socio-professional categories.

Scenario	Individual-ride		Ridesharing	
	No user taste variation	With user taste variation	No user taste variation	With user taste variation
Employed	56	42	59	44
Unemployed	11	11	10	14
Retired or pre-retired	23	19	24	17
Students >14 years	8	22	5	21
< 14 years of age	0	2	0	3
Homemakers	2	4	2	2

4.3. Service optimization

As aforementioned, we also introduce traveler profiles into an optimization model that is used to operate SAVs. In order to match travelers in shared trips, the model uses the concept of meeting points. Riders can be picked up at their origin locations or at a pickup meeting point, and dropped off at their destination locations or at a drop-off meeting point. These meeting points are usually located at feasible walking distances from traveler origin and destination locations. The main advantage of using meeting points is that they can lead to shorter detour distances compared to the case where travelers are only picked up or dropped off at their origins and destinations (Stiglic et al., 2015).

We start by defining the set of feasible matches (shared rides) between different travelers (phase-1). A feasible match respects the time constraints of its participants (i.e. time windows), the capacity of the vehicle, and achieves a distance saving. The distance saving is obtained by comparing the distance of the shared trip with the sum of distances of individual trips (i.e. when no sharing is done and every traveler travels alone from origin to destination). A matching optimization problem then selects the best matches among the ones generated in phase-1 such that the number of matched travelers and the corresponding distance savings are maximized.

In the original model, all traveler demands are assumed to be homogeneous (i.e. no traveler profiles are considered). Now, we introduce the concept of VIP travelers into the model and we analyze its impact on the operator revenues as well as the quality of the service provided. VIP travelers are those who are willing to pay extra 20% of their travel expenses in order to have an individual SAV ride (no sharing with others). Our survey showed that 40% of participants who are willing to use the SAVs are ready to pay extra 20% of the ridesharing price.

In order to test the proposed model, we consider the SAV trip records that were generated by the simulation model in the previous section. These trips correspond to short trips around city center with an average travel time of 11.5 minutes. SAVs are assumed to be homogeneous with a capacity of 4 places and 24 km/h speed. The maximum walking distance that travelers can accept to reach a meeting point is set to be 500 m. The AV transport cost per kilometer is set to be 0.2 €/km (Cortright, 2017). In addition, the travel cost per km for non-VIP travelers is considered to be 0.2 €/km and for VIP travelers 0.24 €/km (20% more than the normal fee, reference to our survey) (Table 4). The 0.2 €/km fee is calculated using the same average monthly subscription price (220€) as presented to the surveys' participants. The average daily mileage is assumed at 36 km.

Table 4. Instance characteristics and parameters.

Trip pattern: short trips around city center	
Parameter	Value
Average number of travelers	2200
Average trip distance for traveler	~6 km
Average trip time for traveler	11.5 min
Max walking distance to a meeting point	0.5 km
Walking speed	1.2 m/s
Vehicle speed	24 km/h
SAV capacity	4
SAV cost per km	0.2 €/km
Traveler fee per km	0.2 €/km
VIP traveler fee per km	0.24 €/km

We consider different instances with 2200 travelers on average, which represent 10% of the initial demand for SAV service with ridesharing and without considering user taste variations, based on the multi-agent simulation. The results indicate that the general benefit of the service operator might decrease by up to 4.5% when 40% of travelers are assumed to be subscribed to the VIP service. Although VIP travelers pay extra charges for the service, the operator will also have some additional costs, which are related to the higher number of individual-ride SAVs needed to operate the service. More precisely, an SAV that was able to serve 2 or 3 travelers in the original case, might have to serve only an VIP traveler in the second case which might increase the system-wide vehicle-mileage and thus increase the operational cost of the service.

From travelers' point of view, results indicate that introducing traveler profiles into the system has the potential to enhance the quality of the service provided. On the one hand, VIP travelers will have a more comfortable, and relatively shorter travel times, as they will be transported directly from their origins to their destinations. On the other hand, the average detour time and the average waiting time (at meeting points) for non-VIP travelers will decrease by 13.3% (~0.38 min) and 6.5% (~0.32 min) respectively. To conclude, introducing traveler profiles to the system can increase the overall satisfaction of VIP travelers as well as having a positive effect on non-VIP travelers in terms of their detour and waiting times. However, this means that service operators might need to invest some of their benefits in order to provide an enhanced travel experience for their travelers.

5. Conclusion

In this paper, some insights on the different attributes that affect travelers choice of using future autonomous vehicles are given. First, a survey to collect data from travelers of the greater Paris area is presented. Then, the impacts of integrating these attributes into existing multi-agent simulation and optimization service are investigated. As most of research studies do not take traveler taste variations into account, this paper highlights the importance of considering them when building multi-agent simulation and optimization models. We thus believe that this paper will encourage more research towards a more traveler-centered design of future transportation systems.

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