WILLINGNESS TO PAY FOR CONNECTED VEHICLES: AN ALTERNATIVE-SPECIFIC MIXED LOGIT REGRESSION APPROACH

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Abstract: The study of connected vehicles (CVs) has become a hot topic in recent years. Understanding the characteristics that lead consumers to relate to CVs motivates researchers to conduct market analysis studies. The current research investigated the socio-demographic attributes that may contribute to the individual preferences for purchasing CVs. Researchers constructed a series of Alternative-Specific Mixed Logit models to examine the associations between individual preferences of respondents and their willingness to pay for CV features in their future vehicle. The results indicate that hours spent driving play a privileged role among sociodemographic characteristics and driving behavior attributes of respondents. People who drive longer hours tended to purchase CV features. Also, the factor of age had a noticeable effect as the results showed that older people are more likely to purchase CV features.

Keywords: automated mobility, connected autonomous vehicle, willingness to pay, adoption, mixed Logit model.

1. Introduction

Both scholars and transit operators are concentrating on the development of connected vehicles (CVs), along with rapid technological developments and emerging innovative mobility methods. CVs' most expected advantages are improving traffic safety levels and the performance of the transportation network (Arvin *et al.*, 2019; Dowling *et al.*, 2016; Ghiasi *et al.*, 2019; Kidando *et al.*, 2018; Li *et al.*, 2016). The Internet of Things (IoT), as one of the most remarkable technological developments in the recent decade, provides connectivity for all mobile applicants and fixed infrastructures at any time and any location. The automotive industry can take advantage of this revolutionary technological innovation to design the next generation of vehicles. The connectivity of transportation elements, through sharing the real-time information, will dramatically improve the performance, efficiency and safety of whole transportation systems (Andorka and Rambow-Hoeschele, 2020). The connectivity and ability to transmit data in the real environment can be established between a vehicle and other vehicles (V2V) and vehicle to infrastructures (V2I) through the IoT. The IoT introduces a new feature of "V2X" that enables communications between the CV and other features that potentially can change the vehicle guidance (i.e., vehicles, infrastructures, pedestrians, etc.) (Guerrero-ibanez *et al.*, 2015).

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A remarkable trend of investing in the connected vehicles' market has occurred in recent years. Estimations show that revenue from the monetization of car data will be over $400 billion by 2030 (Van Themsche, 2016). In the United States, the U.S. Department of Transportation (USDOT) and all state DOTs have shown extreme interest in developing CV technology and its infrastructures (Bertini et al., 2016). The USDOT in collaboration with the Society of Automotive Engineers (SAE) has already began determining V2V and V2I communication regulations and standards while previous estimations showed over 100 million vehicles in the US will be embedded with telematics by 2025 (Bock et al., 2016). The National Highway Traffic Safety Administration (NHTSA) categorized connected automated vehicles (CAVs) into five levels from level 0 to level 4 in which level 0 represents vehicles that are controlled by drivers and level 4 reflects vehicles that are fully automated and the vehicle itself can manage all driving tasks. The NHTSA, recently, stated that the V2V and V2I connectivity features can potentially eliminate 80% of all unimpaired crashes' scenarios (Narla, 2013). This emphasis on CV technology has motivated many researchers to conduct analytical studies to measure the readiness of the automotive market to embrace these emerging vehicles. Several studies in recent years have been conducted to understand the demographic characteristics of people that relate to their preferences for purchasing and using advanced features in their future vehicles. Since information transmission and safety assistance are the main pillars of CV technology, it would very helpful to better understand the possible relationship between sociodemographic characteristics of potential users of CVs and their willingness-to-use (WTU) preferences for CV features. Moreover, this knowledge will help us understand penetration levels of these features in the future markets (Kopelias et al., 2019).

This study aims to identify individuals' preferences for CV features using an appropriate statistical approach. Therefore, this study attempts to answer this question: What are the demographic characteristics and travel behavior attributes related to people's preferences and WTP for CVs? To undertake this analysis, an online survey has been conducted in the United States from September 2013 to April 2014 to collect socioeconomic attributes and choice behaviors of drivers for purchasing a CV. The contribution of this study is to find possible relationships between sociodemographic characteristics of participants and their WTP when purchasing connected vehicles in the future by using an appropriate and sophisticated statistical analysis method. The organization of the paper is as follows. Section 2 provides an overview of past related studies and proposes shortcomings in the background research that will be addressed in the current study. Section 3 presents an analysis methodology of the study and overall results of the conducted survey. Section 4 provides results of the statistical analysis, and, finally, discussion and conclusions are presented in Section 5. The results of this study could be utilized by auto market analysts, transportation economists, transportation authorities, transport investment agencies, and collaborators in emerging and advanced transportation systems.

2. Literature Review

As discussed in the introduction section, CV focus on increasing safety levels and assisting drivers by providing real-time information. In recent years many studies covered the issues of

willingness-to-pay (WTP) and willingness-to-use (WTU) for vehicles with automated and advanced features. This section tries to cover past studies related to sociodemographic characteristics' factors that may influence WTP and WTU for such vehicles.

According to the past studies, various attributes of people may influence WTP and WTU for advanced features in a vehicle. Level of risk taking, social trust, convenience and satisfaction issues, price, environmental concerns, incentives or discounts, luxury, and efficiency are the most important attributes revealed in the past studies as motivating factors for purchasing and using a new advanced feature in the vehicle (Choi and Koo, 2019; Jiang *et al*., 2018; Kyriakidis *et al*., 2015; Liu *et al*., 2019a, Motamedi *et al*., 2018; Sahebi and Nassiri, 2017; Schoettle and Sivak, 2014; Shabanpour *et al*., 2018). A study by Bansal and Kockelman (2017) showed that almost half of the people in the United States are willing to pay extra money for automated features in their next vehicle and obviously people with higher income levels have a greater tendency to do so. Among other characteristics of people willing to use advanced features in their next vehicle, age and gender showed significant relationships. People who are early adopters (Zmud *et al*., 2016b), male (Bansal *et al*., 2016; Jiang *et al*., 2018) and younger (Abraham *et al*., 2017; Payre *et al*., 2014; Wang *et al*., 2019) have shown more WTU for advanced and automated vehicles. Also, some studies proved that eagerness to purchase and use automation technologies has a direct relationship with the education attainment and the level of knowledge about emerging vehicles (Daziano *et al*., 2017; Ebnali *et al*., 2019; Shin *et al*., 2015; Zmud *et al*., 2016a). Purchasing and using automated and emerging features in the vehicle may also impact travel behavior and commuting patterns of the drivers, causing them to increase vehicle mile traveled (VMT) or, inversely, forcing drivers to take shorter distances (Gkartzonikas and Gkritza, 2019; Shin *et al*., 2019).

Among those mentioned motivating attributes for purchasing and using advanced features in the vehicle, the price of the feature may play a more critical role (Shabanpour *et al*., 2017). Daziano *et al*. (2017) explored that people generally are willing to use automated electric vehicles if the vehicle is able to drive a longer range; however, they are concerned about the price of the vehicle and fuel costs. The safety level of the CV's features is the other important attribute that influences people's decision in purchasing and using them. Basically, two main factors of optimal design and reliability determine the effectiveness of safety features in CVs. The design of safety features meets the driver's need for an automated feature that warns of and reacts to a hazard in a timely manner, and the reliability of the feature increases the driver's comfort because they are confident, they have control over unpredicted conditions (Medenica, 2019). However, the various connectivity features that will be introduced in the automotive market will have issues such as privacy and security sensitivity, data transmission approaches, and ethical frameworks, which also will be subject to competition (Outay *et al*., 2017).

Regarding implemented methodologies, stated preference methods were the main approaches for measuring WTP for CVs. Discrete choice modeling using Logit models and a fixed-response forced-choice method were the main approaches that have been used widely in past studies to evaluate preferences of future buyers of CVs (Abraham *et al*., 2017; Bansal *et al*., 2016; Daziano *et al*., 2017). Also,

some studies used the contingent valuation method to determine the amount people are willing to pay for CV attributes (Kyriakidis *et al.*, 2015; Liu *et al.*, 2019a, Liu *et al.*, 2019b, Schoettle and Sivak, 2014). Obviously, Logit models were used the most in past stated preference studies on this topic; however, new approaches of the Logit model should be implemented to identify homogenous and heterogeneous variables in the dataset which is not possible with standard types of the Logit model. Therefore, this study uses an Alternative-Specific Mixed Logit Regression approach to incorporate heterogeneity considerations.

3. Methodology

The current study undertakes the stated preferences choice modeling methodology. An Alternative-Specific Mixed Logit Regression Model or Mixed Logit Model (MXL) has been utilized due to its more flexible heterogeneous capability to provide more realistic choice patterns regarding the factors that influence respondents' final decisions (Jaffry and Apostolakis, 2011).

3.1. Survey

The data collection process has been performed based on an online survey. The survey had two main components: sociodemographic data and attributes of purchasing an autonomous vehicle. The researchers designed the survey using Sawtooth software (Sawtooth Software, 2009) which is, by consensus, the leading provider of conjoint analysis software. The survey links were promoted nationwide in the U.S. through advertising websites (such as craigslist) and social media networks. The survey was administered from September 2013 through April 2014; and 529 usable responses were received.

The data has been archived and preserved electronically. All participants first received explanations about the goal of the survey and confidential issues in the survey's first screen. The survey was divided into three sections: first, the most important socioeconomic characteristics (e.g., gender, age, and the number of adults and children under 18 in the household), last vehicle purchase/lease experience, and current spatial pattern of commuting trips. The survey also asked participants about the minimum and maximum amount of money that they will pay for a new vehicle. Drivers were then asked the level of knowledge about the autonomous vehicles. The next section focused on drivers' stated preferences for purchasing CVs. Participants were first provided with a description of the different levels of CVs according to the definitions of the National Highway Traffic Safety Administration (NHTSA) for CVs (National Highway Traffic Safety Administration, 2018).

3.2. Survey

After the data collection process, 529 valid responses were implemented for analysis. A summary of selected socioeconomic variables is presented in Table 1. Gender was balanced, with 51.2% male and 48.8% female respondents, which is not much different from the national average (0.97 male/female) (United States Census Bureau, 2017). The age distribution also reflected the national statistics.

As to race/ethnicity, Whites were somewhat similar to the national average, about 65.6%. With respect to education, 29.5% had graduate-level academic degrees. This is a little higher than the national average of 28.1% (United States Census Bureau, 2017). The overrepresentation of these

highly educated participants might be due in part to the recruitment method, as many participants were from the Morgan State University and research centers in various academic institutions. While the median household income was $61,372 in 2017 (United States Census Bureau, 2017), the number of respondents in each income group was balanced. Other socioeconomic variables were also compared to the national statistics. The distributions of demographic characteristics were generally similar to the national statistics, making our sample relatively representative.

Table 1

Summary of Participants' Characteristics

Demographics	Characteristics	Study (%)[3]	U.S. (%)[3]
Gender [1]	Male	51.2	49.2
	Female	48.8	50.8
Age [1]	Less than 30	21.4	21.8
	30 - 39	21.6	16.9
	40 - 49	22.9	17.7
	50 - 59	21.4	17.9
	60 and more	12.9	16
Race/ethnicity [1]	White (Non-Hispanic)	65.6	67.9
	Hispanic	5.1	14.4
	Black/African-American	17.3	11.8
	Asian	5.9	4.9
	Other	32	1
Education [1]	Associate degree and lower	38.5	25.7
	Bachelor's degree	31.9	20.5
	Master's degree	19.5	23.0
	Doctoral or postdoctoral degree	10.1	30.9
Household annual income [1]	Less than $50,000	36.1	46.5
	$50,000 – $99,999	32.4	29.9
	$100,000 and more	31.5	23.6
Household size [1]	1	5.3	27.6
	2	30.2	33.7
	3 and more	64.5	38.7
Type of current vehicle [2]	Sedan or coupe	44.4	49.0
	SUV	21.1	10.6
	Van	5.4	3.5
	Truck SUV	7.1	23.6
	Other	28.6	13.3
Total driving time during a day	Less than 0.5 hour	0.11	-
	0.5 to 1 hour	0.29	-
	1 to 1.5 hours	0.28	-
	1.5 to 2 hours	0.22	-
	More than 2 hours	0.10	-

[1] *2011-2015 American Community Survey 5 Year Estimates for the U.S. values*

[2] *National Transportation Statistics 2018; The U.S. Department of Transportation's Bureau of Transportation Statistics*

[3] *Percentages may not total 100 due to rounding*

3.3. Explanation of Attributes

After comprehensive studies and examinations of past studies on the issues of willingness to pay for emerging and advanced transportation, especially successful incentives for promoting using battery electric vehicles (as advanced vehicles) in the U.S, five main attributes have been selected – collision warning, driver assistance, enhanced safety, roadway information, and travel assistance – as the main attributes that may influence the decision of drivers in purchasing a connected autonomous vehicle. The questions and attributes were verified by researching current purchasing incentives and rebates of the main automobile manufacturers in the U.S., interviewing related experts, and investigating related published studies (Shin *et al.*, 2016). Although researchers designed attributes of the survey based on the results of expert consultations and pretests, participants were able to comment about their experiment and provide feedback. The design of questions is based on answering this question: What type of CV do respondents want to buy as their next vehicle when the CV is an available personal vehicle in the market? Of course, the CV is not currently available in the market and incentive policies for selling CVs might differ from current incentive policies for internal combustion engine vehicles (ICEVs); however, perceptible attributes and levels in the survey would help respondents engage more with the survey and also provide policy makers and market economists with more understandable outcomes. This study also found that the minimum and maximum value to spend on the next vehicle is $16,377 to $27,605 (Shin *et al.*, 2015).

3.3.1. Collision Package

The survey asked respondents what type of collision warning and prevention features they want to have in their next vehicle. The survey considered four levels for this attribute according to the current engine type of vehicles on the market: front collision warning, side collision warning, front and side collision warning, all-around collision warning. There is interest in the automotive market for purchasing collision warning systems, but some factors including price are still the main barriers to using these advance features (Razaob *et al.*, 2019). This study adds $0 for selecting "nothing," $350 for selecting "front collision warning" (level 2), $600 for selecting "side collision warning" (level 3), $900 for selecting "front and side collision warning" (level 4) and $1,100 for selecting "all-around collision warning" (level 5).

3.3.2. Driver Assistance

Surveying this attribute illustrated to what degree respondents were willing to pay for automation and driving assistance. As Bansal and Kockelman (2017) explored, there is no intention in the U.S. to pay big extra money for any of the advanced automation technology; therefore, the extra money for automation of the vehicle should be at a reasonable price that makes the survey realistic for the respondent. According to the reviewed studies and the current automotive market, the study considered $0 for selecting "nothing," $600 for an extra for "lane departure system" (level 2), $750 for "intersection and left turn assist system" (level 3) and $1,000 for "pedestrian and cyclist alert and do not pass warning" (level 4).

3.3.3. Enhanced Safety Package

This attribute focused on pedestrian and cyclist detection and a collision avoidance feature that is an important safety factor when purchasing the next CV. This study, after reviewing designed automated safety features of main car manufacturers in the U.S., categorized enhanced safety packages into three categories. Therefore, the participants pay an extra $300 for selecting "do not pass warning" (level 2), $750 for selecting "pedestrian and cyclist alert" (level 3), $750 for selecting "pedestrian and cyclist alert and do not pass warning system" (level 4).

3.3.4. Roadway Information Package

Basically, roadway information features will improve drivers' travel behavior by providing real-time data. Questions about this attribute aimed to assess how much providing roadway information automatically may affect preferences of customers in purchasing the CV. Sayer *et al*. (2007) stated that providing roadway information systems may affect the drivers' travel pattern. Therefore, this attribute included four levels: $0 for selecting "nothing," $300 for selecting "slow/stop/wrong-way vehicle advisor" (level 2), $300 for selecting "road condition notification" (level 3), and $500 for selecting "road condition notification and slow/stop/wrong-way vehicle advisor" (level 4).

3.3.5. Travel Assistance Package

Questions about this attribute concentrated on determining which group of participants is more interested in using travel assist systems. The travel assistance features help drivers to

drive more smoothly. After reviewing current promotions in the automotive market, four different levels have been designed for this attribute: $0 for selecting "nothing," $250 for selecting "real time travel planning & route optimization" (level 2), $500 for selecting "parking spot locator" (level 3), and $700 for selecting "real time travel planning & route optimization and parking spot locator" (level 4).

3.4. Alternative-Specific Mixed Logit Model

In this section the structure of the utilized MXL model will be discussed. The index d (d = 1, 2, …, D) has been considered for participants, f for the features (f = 1, 2, …, F) and c for the choice occasion. Therefore, the utility of the individual d associates with the features f on choice occasion c can be written as equation (1):

$$U_{dfc} = (\gamma + \lambda_d) Z_{dfc} + \zeta_{dfc} \qquad (1)$$

Where Z_{dfc} is a vector of feature attributes and the interactions of attributes among themselves and with respondent's characteristics, affecting the utility of individual d for feature f at the cth choice occasion. γ is a corresponding vector of the mean effects of the coefficients of Z_{dfc} on feature choice and λ_d is a vector with its mth element representing unobserved factors specific to individual d. ζ_{dfc} represents a choice-occasion specific idiosyncratic random error term assumed to be identically and independently standard Gumbel distributed (Sener *et al*., 2009).

Therefore, in this study, the features that have been selected by participants were

considered as the dependent variable. The feature value in each attribute was considered as the independent variable and the features were considered as the alternative variable. Obviously, the sociodemographic characteristics and travel behavior attributes of respondents were selected as the case-specific variables. As a result, researchers conducted five separate MXL models.

4. Results

The probabilities were estimated as a function of participants' socioeconomic characteristics. All statistical analyses were conducted using STATA 15. Statistical significance was evaluated at 0.1, 0.05, and 0.01 probability levels. The feature of "nothing" (level 1) was selected as the reference category in all models.

The first MXL model is related to features of the collision attribute. Two variables of driving hours and education attainment were statistically significant in the model. As shown in Table 2, higher educational attainment and more driving hours in a day are related to choosing "front and side collision warning systems".

Table 2
Summarized the MXL Model Results for Attribute 1

Attribute[1]	Feature	Coef.[2]	Std.Err[3]	z	P>|z|	[95% Conf. Interval]	
Level 2	Driving hours	0.24	0.14	1.68	0.092	-0.04	0.53
	Education	0.22	0.13	1.7	0.09	-0.03	0.47
	Constant	-2.09	0.72	-2.89	0.004	-3.51	-0.67
Level 3	Driving hours	0.45	0.23	1.96	0.05	0.00	0.89
	Education	0.37	0.21	1.76	0.078	-0.04	0.79
	Constant	-4.61	1.26	-3.67	0	-7.07	-2.14
Level 4	Driving hours	-0.02	0.17	-0.11	0.914	-0.35	0.31
	Education	0.42	0.15	2.72	0.006	0.12	0.72
	Constant	-2.61	0.86	-3.02	0.003	-4.30	-0.92
Level 5	Driving hours	0.33	0.12	2.8	0.005	0.10	0.55
	Education	0.13	0.10	1.32	0.187	-0.06	0.33
	Constant	-1.10	0.56	-1.96	0.05	-2.21	0.00

[1] *log likelihood = -490.67, Prob> Chi2= 0.0079,* [2]*Coefficient,* [3]*Standard Error*

The second MXL model is related to features of the driver assistance attribute. Three variables of age, driving hours and education attainment were statistically significant in the model. As shown in Table 3, older people and drivers with more driving hours in a day are related to choosing "Lane Departure System and Intersection & Left Turn Assist".

Table 3

Summarized the MXL Model Results for Attribute 2

Attribute[1]	Feature	Coef.	Std.Err	z	P>|z|	[95% Conf. Interval]	
Level 2	Age	0.18	0.09	1.97	0.048	0.00	0.36
	Driving hours	0.22	0.12	1.9	0.057	-0.01	0.45
	Constant	-1.54	0.85	-1.82	0.069	-3.20	0.12
Level 3	Age	0.31	0.16	1.96	0.05	0.00	0.62
	Driving hours	0.45	0.19	2.32	0.021	0.07	0.83
	Constant	-3.85	1.47	-2.62	0.009	-6.72	-0.97
Level 4	Age	0.22	0.10	2.28	0.023	0.03	0.41
	Driving hours	0.26	0.12	2.07	0.038	0.01	0.50
	Constant	-1.60	0.90	-1.78	0.076	-3.37	0.17

[1] *log likelihood = -413.61, Prob> Chi2= 0.0091*

The third MXL model is related to features of the enhanced safety attribute. Two variables of age and education attainment were statistically significant in the model. As shown in Table 4, older people and drivers with more driving hours in a day are related to choosing "Pedestrian & Cyclist Alert and Do Not Pass Warning".

Table 4

Summarized the MXL Model Results for Attribute 3

Attribute[1]	Feature	Coef.	Std.Err	z	P>|z|	[95% Conf. Interval]	
Level 2	Age	-0.01	0.10	-0.11	0.914	-0.22	0.19
	Education	-0.05	0.12	-0.41	0.681	-0.29	0.19
	Constant	-0.93	0.64	-1.46	0.143	-2.18	0.32
Level 3	Age	0.21	0.10	2.1	0.036	0.01	0.41
	Education	0.22	0.12	1.81	0.07	-0.02	0.45
	Constant	-2.92	0.68	-4.27	0	-4.26	-1.58
Level 4	Age	0.09	0.09	1.03	0.305	-0.08	0.26
	Education	-0.13	0.10	-1.3	0.192	-0.33	0.07
	Constant	-0.60	0.54	-1.11	0.269	-1.66	0.46

[1] *log likelihood = -461.51, Prob> Chi2= 0.0372*

The fourth MXL model is related to features of the roadway information attribute. Two variables of household size ("Household Size) and maximum value for next vehicle (Max Paying) were statistically significant in the model. As shown in Table 5, people with bigger household size and drivers with higher maximum value for purchasing their next vehicle are related to choosing "Road Condition Notification and Slow/Stop/Wrong-Way Vehicle Advisor".

Table 5
Summarized the MXL Model Results for Attribute 4

Attribute[1]	Feature	Coef.	Std.Err	z	P>|z|	[95% Conf. Interval]	
Level 2	Household Size	-0.02	0.10	-0.17	0.865	-0.20	0.17
	Driving hours	0.16	0.12	1.42	0.154	-0.06	0.39
	Max Paying	0.08	0.05	1.74	0.082	-0.01	0.18
	Constant	-1.56	0.50	-3.11	0.002	-2.55	-0.58
Level 3	Household Size	-0.43	0.24	-1.82	0.07	-0.89	0.03
	Driving hours	0.01	0.22	0.06	0.954	-0.42	0.45
	Max Paying	0.19	0.07	2.72	0.006	0.05	0.33
	Constant	-2.36	0.90	-2.62	0.009	-4.12	-0.60
Level 4	Household Size	0.07	0.09	0.82	0.411	-0.10	0.25
	Driving hours	0.22	0.11	1.94	0.053	0.00	0.44
	Max Paying	0.12	0.04	2.62	0.009	0.03	0.21
	Constant	-2.10	0.50	-4.21	0	-3.08	-1.12

[1] *log likelihood = -416.72, Prob> Chi2= 0.0234*

The last MXL model is related to features of the travel assistance attribute. Two variables of age and driving hours were statistically significant in the model. As shown in Table 6, younger people are more likely to select the "real time travel planning & route optimization and parking spot locator" feature than older ones; however, those who drive shorter hours are more likely to select the feature of "parking spot locator".

Table 6
Summarized the MXL Model Results for Attribute 5

Attribute[1]	Feature	Coef.	Std.Err	z	P>|z|	[95% Conf. Interval]	
Level 2	Age	-0.10	0.09	-1.15	0.251	-0.28	0.07
	Driving hours	0.06	0.14	0.42	0.677	-0.22	0.34
	Constant	-0.78	0.59	-1.33	0.184	-1.93	0.37
Level 3	Age	-0.51	0.15	-3.35	0.001	-0.81	-0.21
	Driving hours	0.42	0.21	1.97	0.049	0.00	0.84
	Constant	0.76	0.86	0.89	0.376	-0.93	2.45
Level 4	Age	-0.25	0.09	-2.78	0.005	-0.42	-0.07
	Driving hours	0.17	0.14	1.22	0.223	-0.10	0.44
	Constant	0.21	0.56	0.38	0.707	-0.89	1.31

[1] *log likelihood = -432.63, Prob> Chi2= 0.0011*

5. Discussion and Conclusion

This study aimed to analyze driver preferences and WTP for CV features. Such knowledge is necessary for economists, policy makers, and decision makers in the automotive market to establish preferences of costumers, recognize the market's needs, and merit investment. Researchers crafted the conjoint survey – based on the literature review and successful incentives for advanced vehicles in the U.S. and offered insights into the key willingness-to-pay, adoption and attributes of CVs. As discussed in the literature review, CVs provide higher safety levels and more driving assistance abilities; therefore, the questions in the conducted conjoint survey were based on these two privileges. The results indicate that driving hours plays a privileged role among sociodemographic characteristics and driving behavior attributes of respondents. People who drive longer hours are more likely to purchase CV features. This pattern is similar to the one observed by Daziano *et al.* (2017) in which they found that people with longer driving ranges have a greater tendency toward using automated and emerging features in the vehicle.

The factor of age was shown to be a noticeable effect as the results showed that older people are more likely to purchase CV features. This result is in line with a previous study Fernandes *et al.* (2017) that mentioned older people may find automated and advanced features of a vehicle helpful in comfortably maintaining mobility, especially for older drivers with physical disabilities. An unexpected finding of this study was that there was no significant sign to prove people with higher income levels are more likely to purchase CVs' features. One explanation for this result can be low levels of knowledge and awareness about the effectiveness and performance of these emerging features (Zhang *et al.*, 2019). However, the results of this study proved those who are willing to pay more money for their next vehicle are more likely to use roadway information features.

Education was the other characteristic attribute that showed a significant relationship in which people with higher education levels were more likely to purchase enhanced safety features in their next vehicle. Similarly, some studies revealed that people with higher levels of education are more eager to use automated and advanced feature in the vehicle (Daziano *et al.*, 2017; Haboucha *et al.*, 2017). Finally, the factor of gender was not significant in purchasing and using CVs' features. Although it was expected that men might enjoy using CVs' features more, WTP and WTU for these features did not differ by gender. This finding dovetails with the results of some previous studies (Shin *et al.*, 2016; Zhang *et al.*, 2019). Future studies should consider more sociodemographic characteristics and driving behavior attributes as well as more CV features.

Acknowledgments

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