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How do drivers use automation? Insights from a survey of partially automated vehicle owners in the United States

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ABSTRACT

In this study we investigate how partially automated vehicles (Tesla electric vehicles with "Autopilot") are used, including how often automation is used, on what roads, in what weather, and in what traffic conditions. We use a latent class model to identify heterogenous classes of autopilot users, then we use a multinomial logistic regression model to understand the relationship between each latent class and several independent variables, including socio-demographics and vehicle miles travelled (VMT). The latent class model revealed four latent classes: *very frequent users,* who use it most frequently; *frequent users,* who use automation frequently in clear weather and on freeways; *semi-frequent users* who use it for less than half their trips and only on freeways, in clear weather, when there is no traffic; and *infrequent users,* who use it the least often and only in clear weather, on freeways, when there is no traffic. The multinomial logistic regression model revealed significant differences in VMT between the clusters. *Very frequent* and *Frequent users* drive close to 15,000 miles per year, whereas *Semi frequent* and *Infrequent* users drive around 10,000 miles per year. The results suggest that consumers who purchase partially automated vehicles and use them frequently may travel more.

1. Introduction

Fully automated vehicles are not yet available for consumers to purchase, except for vehicle trials in closed environments or on open roads with a trained driver behind the wheel. However, partially automated vehicles are already available for consumers to purchase and use. Table 1 shows an overview of the society of automotive engineers (SAE) 5 levels of vehicle automation and includes examples of each where applicable. Several original equipment manufacturers (OEMs) have vehicles with level 2 of automation already for sale, including Mercedes-Benz, BMW, Nissan, Kia, Audi, and Tesla. In this study we focus on partially automated Tesla battery electric vehicles (BEVs) (Tesla Model S, X, and 3 with Autopilot) (Tesla, 2018). Based on sales data taken from Securities and Exchange Commission (SEC) filings at the end of Q4 2018 more than 350,000 of these Level 2 automated vehicles have been sold globally. Research on partial automation has so far focused on issues such as trust in the technology, perceptions of safety and comfort (Lee et al., 2018; Abraham et al., 2017a), how drivers learn about the technology (Abraham et al., 2018), impact on number of vehicle collisions, and other issues (Chan, 2017). The use of the vehicles by drivers in different weather, traffic, and road conditions, the frequency the systems are used, and the impact on travel appears to have been overlooked. The aim of this study is to understand how level 2 partially automated vehicles are used. Specifically we seek to answer the following research questions: on what roads, in what weather, and in what traffic conditions is automation likely to be used; how frequently is automation used; and

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Table 1
The SAE 5 levels of vehicle automation (SAE, 2014).

SAE level	SAE name	Description	Existing example
0	No Automation	The human driver controls all aspects of driving always. The vehicle may have warning systems.	Lane Departure Warning
1	Driver Assistance	The vehicle may be able to control steering or acceleration/deceleration using information from the external environment. The human driver performs all driving tasks.	Adaptive Cruise Control or Lane Keep Assist
2	Partial Automation	The vehicle may be able to control both steering and acceleration/deceleration using information from the external environment. The human driver is considered to be performing all driving tasks.	Adaptive Cruise Control and Lane Keep Assist, Autopilot
3	Conditional Automation	The vehicle can control all driving tasks (steering, acceleration/deceleration) under certain conditions and will not operate unless all conditions are met, the vehicle monitors the environment. A human driver may need to respond to a request to take over the vehicle and acts as the back-up system.	n/a
4	High Automation	The vehicle can control all driving tasks (steering, acceleration/deceleration) under certain conditions and will not operate unless all conditions are met, the vehicle monitors the environment. The vehicle may request a human to intervene though intervention is not necessary.	n/a
5	Full Automation	The vehicle can control all driving tasks (steering, acceleration/deceleration) and monitors the environment. The human could choose the manage the vehicle if they desire. The vehicle may have no human controls.	n/a

are socio-demographics, travel patterns (including commute distance and vehicle miles travelled), or attitudes correlated with how consumers use automation? Understanding how partially automated vehicles are being used, and the relationship between use of automation and travel, may reveal their positive or negative impacts.

In this study, we use results from a questionnaire survey of 424 owners of Tesla BEVs of which 386 have autopilot hardware which is software enabled. The sample is not representative of car buyers or drivers in the USA and was chosen as they are a group of early adopters of partially automated vehicles. This makes them a unique group who have experience with this new technology. It is hoped that insights from these users will lead to a greater understanding of how consumers use partially automated vehicles, these insights may be able to inform efforts to understand how fully automated vehicles may impact transportation systems and travel behavior, including their impact on vehicle miles travelled (VMT). To characterize the different types of autopilot users we use a latent class model which uses input variables on the use of automation by road type, weather conditions, traffic conditions, and use on a trip basis and on commute trips. We then use a multinomial logistic regression model to understand any relationships between socio-demographic, travel, and attitudinal variables and the different classes of autopilot user.

The outline of this paper is as follows: first we review literature that investigates travel behavior and automated vehicles, then we outline the methods used, we then present the results of this study, and conclude the study with a discussion, implications for policymakers, and future research needs.

1.1. Introduction to Tesla automated vehicles

Table 1 shows an overview of SAE's levels of automation (SAE, 2014). The levels go from 0 to 5 with Level 0 being non automated vehicles and Level 5 fully automated. The vehicles in this study are Tesla BEVs with autopilot hardware and software installed. At the time of conducting this study the system is a SAE Level 2 partial automation system. According to Tesla the system can "*match speed to traffic conditions, keep within a lane, automatically change lanes without requiring driver input, transition from one freeway to another, exit the freeway when your destination is near, self-park when near a parking spot and be summoned to and from your garage*". The system is designed to assist drivers, with Tesla stating *"Every driver is responsible for remaining alert and active when using Autopilot, and must be prepared to take action at any time"* (Tesla, 2018). The Tesla owner manual has 26 pages describing how the system works and its limitations (Tesla, 2019), the document describes the different features of Autopilot which are: traffic-aware cruise control, autosteer, autopark, lane assist, collision avoidance assist, and speed assist.

2. Literature review

Research on fully automated vehicles is expanding with studies investigating who the buyers of the technology will be (Hardman et al., 2018; Abraham et al., 2017b; Zmud et al., 2019), consumer preferences and perceptions (Abraham et al., 2017a; Kyriakidis et al., 2015; Berliner et al., 2018; Merat et al., 2017), and how the vehicles may be used. The latter being the most relevant to this study. Research into automated vehicle use has used several different methods to understand how the vehicles may be used. Much of this research has focused on the impact of fully automated vehicles on travel, particularly with a focus on changes to VMT. One method is using stated preference methods to ask survey takers how they might use automated vehicles and how the vehicles could change their travel patterns. A second method to understand travel behavior and automated vehicles is the use of modeling techniques which use assumptions on how people might use the vehicles. The final method is to allow consumers to trial the vehicles, though at present trials are limited to simulated automated vehicles or vehicles in closed environments.

Most surveys on automated vehicles have focused on consumer acceptance or purchase intentions (Abraham et al., 2017b; Kyriakidis et al., 2015; Becker and Axhausen, 2017; Gurumurthy and Kockelman, 2017; Hardman et al., 2018), some studies also investigate whether consumers believe their travel patterns will change as a result of full automation, often using stated preference methods. A survey by Zmud et al. (2016) investigated consumer acceptance and travel behavior impacts of automated vehicles in Texas. The study found no potential increases in VMT. This was due to most respondents believing their routines, routes, activities, or home location would not change. Half of the respondents did think their inter-city travel would increase due to reduced stress and fatigue of longer distance driving. A survey of 2588 consumers in the USA found that consumers anticipate using automated vehicles for more longer distance travel compared to non-automated vehicles (Gurumurthy et al., 2017).

Modelling studies have focused on changes to travel, often specifically focusing on VMT. Perrine et al. (2018) used a travel demand model to understand changes to long distance travel because of driverless vehicles. They found that long distance travel could increase by around 12% due to mode shift from airlines. Schoettle and Sivak (2015) modelled the impact of automated vehicles on travel behavior using NHTS data. They calculated the hypothetical minimum number of vehicles needed per household to complete all existing travel, with 1.2 emerging as the minimum. They found that per vehicle VMT would increase by 75%, with no increase in fleet VMT. Childress et al. (2015) used an activity model to explore potential impacts of automated vehicles in Washington State, USA. Their modeling of four different scenarios found that VMT changes could be anywhere between a reduction of 35% or increase of 19.6%. Increases in VMT were most likely in a scenario where automated vehicles were privately owned and not shared. Wadud et al. (2016) used a framework to model the potential impacts of automated vehicles on emissions, travel demand, and carbon emissions. They highlight considerable uncertainty in what the impacts of the vehicles will be due to the introduction of complementary technologies and other changes in travel behavior. They suggest that the vehicles could have a positive or negative impact on VMT and emissions depending on how they are used. This is also highlighted by Sperling (2018) who state that the vehicles could reduce VMT if they are shared, however single occupant vehicles would likely lead to increases in travel. Finally Brown et al. (2014) calculate possible emissions increases, they consider the impacts of eco-driving, platooning, efficient routing, and other potential methods to increase efficiency. They consider faster travel speeds and providing mobility to currently underserved populations as ways in which fuel consumption could increase.

A final study gave car owning households 60 hours of free chauffeur service to simulate owning a fully automated driverless vehicle (Harb et al., 2018). The experiment mimics owning a driverless vehicle as the driving task is removed for the participants. In their sample of 13 participants VMT increased between 4 and 341%. The results are not statistically significant, the sample size is small and could be impacted by the novelty of having a chauffeur, and the vehicles are not a true driverless or automated vehicle. Though the study does show how VMT could increase, mainly due to respondents making more trips and sending their vehicles on errands without them in the vehicle.

The literature review shows that there are no studies currently published that investigate potential impacts of partially automated vehicles or that present empirical evidence on partially automated vehicle use. Most studies focus on fully automated or driverless vehicles. This research gap, the use and potential impacts of partially automated vehicles, is the subject of our study.

3. Method

The results of this study come from a questionnaire survey of 3002 consumers in 36 states throughout the United States. This sample was gathered in March and April 2018. Of these 3002 consumers only 424 are included in this study, these are those who own a Tesla BEV. We do not have information on whether the remainder of survey takers have partial automation or not, therefore they are not included in the study. Survey respondents were sent a letter by mail that outlined survey topics and provided a link to access the survey in addition to a personal token they could use to access it. The survey focused on several topics related to electric vehicles, automated vehicles, and shared vehicles. The sections relevant to this study include:

1. Vehicle Purchase Information
2. Use patterns of autopilot
3. Household information
4. Attitudes towards travel, sustainability, & climate change

VMT was calculated based on respondents self-reported odometer readings and the period they have owned their vehicle. The measure of VMT in this study is on a vehicle by vehicle basis, it is the total number of miles driven by respondents main vehicle per year. Odometer readings that exceed 50,000 miles per year were excluded from the analysis.

3.1. Autopilot use questions

Tesla BEV owners were asked if they have autopilot hardware installed in their vehicle and if the software that allows the use of autopilot is enabled. Those who indicated they have autopilot hardware and software enabled were asked additional questions. First they were asked “How frequently do you use autopilot?”, they could answer this question on a continuous slider bar from “Never” to “Every Trip”. Next respondents were shown a map on which they had previously entered their commute, they were asked “You previously indicated that this was your commute, which is a distance of *n* miles [map shown]. “How much of this trip do you estimate is done using autopilot?” Respondents could answer this on an ordinal scale with the following options:

- "I don't use autopilot on this trip"
- "0–20% of the trip"
- "21–40% of the trip"
- "41–60% of the trip"
- "61–80% of the trip"
- "81%-100% of the trip"

Next survey takers were asked questions on autopilot use for different road types (freeways, urban roads, rural roads, parking lots), weather conditions (clear weather, night, rain, snow, fog), and traffic conditions (no traffic, fast moving traffic, slow moving traffic, stop and go traffic). Respondents were asked how likely they were to use autopilot for each scenario on a Likert scale from "Very unlikely", "Unlikely", "Neutral", "Likely", to "Very Likely".

3.2. Statistical analysis

3.2.1. Latent class analysis

Latent class cluster analysis was used to classify autopilot users based on their responses to the questions outlined above. Latent class analysis is frequently used in the transportation literature as a way to cluster consumers (Lee et al., 2017; Shen, 2009; Lee et al., 2016; Vermunt and Magidson, 2002; Goulias, 1999). In total, 15 ordinal variables are included in the analysis. Eq. (1) illustrates a latent class analysis model without covariates (Axsen et al., 2015; Shen, 2009; Lee et al., 2016; Vermunt and Magidson, 2002): x is a single nominal latent variable, y_{it} denotes the response variable, and T is the number of individuals. In this paper, the class membership is a function of individuals' use of autopilot. Therefore, y_{it} is individuals' autopilot usage, x is the class membership of the autopilot usage patterns. $f(y_{it}|x)$ the is conditional probability density for response variable i of individual t given condition of the membership x.

$$f(y_i) = \sum_{k=1}^{K} P(x) \prod_{t=1}^{T} (y_{it}|x) \tag{1}$$

To estimate the model, we employ the Expectation–Maximization (EM) algorithm along with Newton–Raphson Maximum Likelihood Estimation (Vermunt and Magidson, 2002). We note that although the estimation results from the two algorithms are quite stable, this model is very sensitive to local maxima of the likelihood function. Testing multiple models with different sets of parameter start values help to resolve this issue (Goulias, 1999). Another operational issue for estimation is that the degrees of freedom are rapidly exhausted as the number of parameters is increased (usually by increasing the number of classes). In this regard, model identification (ability to estimate parameters) and convergence (subsequent estimation step parameters are not close enough) can be difficult to achieve. Therefore, we employ the following hierarchical approach to address this issue:

(a) A model with only one class assumption is estimated.
(b) Increasing the number of latent classes until the model is impossible to identify and the resulting classes become too small.
(c) Selecting a suitable number of classes is selected based on multiple goodness of fit criteria, including Bayesian Information Criterion (BIC), Akaike Information Criterion (AIC) and the Consistent Akaike Information Criterion (CAIC). Although AIC, BIC, CAIC do not measure the goodness of fit directly, they can be used to compare models to determine whether the model uses more or less parameters, indicating they can be used as relative model fit indices for latent class analysis (McCutcheon, 2002; Nylund et al., 2007).

3.2.2. Multinomial logistic regression

One of the major benefits of using latent class cluster analysis is that the results of the model can be used to investigate the relationship between latent class clusters and external variables (Vermunt and Magidson, 2015). The latent class cluster model estimation provides probabilistic cluster membership for each respondent. These cluster memberships are used as the dependent variable in the Step-three model (multinomial logistic regression model) along with those that do not have autopilot. The step-three model was used to understand the relationship between autopilot users groups and individuals socio-demographic characteristics and their attitudes (in this case attitudinal factor loading described in Section 3.2.3), using Latent Gold 5.1 (Vermunt and Magidson, 2015). We use effect coding for the class membership, so that we can estimate parameters in terms of differences from the average and not from a reference category. With effect coding, the probability that a household belongs to category m is given as:

$$\eta_{m|z_i} = log\left(\frac{P(y = m|z_i}{[\prod_{m'=1}^{M} P(y = m'|z_i]^{1/M}}\right) = \beta_{m0} + \sum_{p=1}^{P} \beta_{mp} * z_{ip} \tag{1}$$

where m denotes an autopilot users groups, M denotes the total number of groups such that $1 \le m \le M$, z_i are covariates and y is the outcome variable observed in the data. Note, $\sum_{m=1}^{M} \beta_{m'p} = 0$ for $0 \le p \le P$, implying the sum of estimated parameters for each independent variable will be zero. As the denominator of the log function in Eq. (1) shows, with effect coding, the probability of belonging to category m is now compared with the average (geometric mean) of the probabilities of all M categories and not to a reference category. In this way, it is possible to identify the driving factors for all the autopilot usage groups. The following independent variables are tested in the model: age, gender, household size, highest level of education achieved, household income, commute distance, annual VMT, house type, and the attitudinal factors frustrated commuter, technophobe, and driving enthusiast.

3.2.3. Factor analysis

The questionnaire survey contained 23 attitudinal statements with which respondents could “Strongly Agree”, “Agree”, “Neither Agree nor Disagree”, “Disagree”, or “Strongly Disagree” with. The statements covered topics related to the environment, climate change, travel, driving, and technology. Factor analysis was used to reduce the number of variables while maintaining the variability of the data. To do this we conducted a factor analysis using principal axis factoring with an oblique rotation to extract factors from the 23 statements. The optimal number of factors in the model was determined using a scree plot of the Eigen values, we chose the number of factors based on when increasing the number of factors does not increase the explanatory power of the model.

A factor loading table for this analysis can be seen in a prior study (Hardman et al., 2018). These loadings can be used to understand each respondent’s attitudes towards various issues associated with the environment, climate change, travel, driving, and technology. The analysis resulted in 7 factors which explain about 60% of the variance in the data and have the following attributes based on responses to the 23 statements:

- Technological Environmentalist- pro technology attitudes, believing in climate change, and positive attitudes to reduce the effects of climate change.
- Frustrated Commuter-believing traffic congestion is a problem, finding commuting stressful, and dissatisfaction with commuting.
- Status seeking car owner- belief that owning a car is a symbol of success and finding enjoyment in driving.
- Reluctant car owner- being okay not owning a car.
- Technophobe- negative attitudes towards new technologies.
- Environmentalist- pro environmental, but not pro technology attitudes.
- Driving Enthusiast- finding enjoyment in driving.

In the multinomial logistic regression model only the frustrated commuter, technophobe, and driving enthusiast factors are used. We omitted the other 4 factors for several reasons. First there is less of a tangible link with these and use of partially-automated vehicles, the other factors are related more to environmental attitudes and attitudes to owning a vehicle in general. Second factor scores for these factors were highly skewed (with either high or low scores), this is perhaps due to the sample being adopters of similar vehicles, meaning they share some attitudinal traits. The factor scores for the frustrated commuter, technophobe, and driving enthusiast cluster were closer to a normal distribution, suggesting greater heterogeneity for these attitudes among the sample.

4. Results

First, we present the socio-demographic profile of Tesla BEV owning households. Then, we explore the latent classes of partially automated vehicle users. Finally, we explore the results of the multinomial regression model (Step-three model) that investigates the latent classes in more detail.

4.1. Socio-demographic profile of respondents

Table 2 shows respondents socio-demographic information. Mean number of household vehicles is 2.6, which is similar to other samples of PEV owners. Mean number of people in the household is 2.7. Average age of the sample is 57 years old, with the largest group of respondents being aged 60–69. 80% of the sample is male. This age distribution and gender split is similar to previous samples of PEV adopters. 96.7% of respondents own their home, and 90.1% live in a detached house. This sample of partially automated BEV adopters are highly educated, 91.3% have graduated college, with 56.8% of the sample completing postgraduate education. Household income is higher than previous studies at $285,000 per year. This is perhaps related to this sample all being adopters of Tesla Model S, Model X, and Model 3 BEVs, the purchase price of which ranges from $51,000 to $140,000. In this sample, self-reported vehicle MSRP is a mean of $104,000 and median of $98,000.

4.2. Latent classes of autopilot users

Of the 424 Tesla BEV households in this sample 386 have a vehicle with autopilot hardware and software installed. Latent class analysis revealed four heterogeneous clusters of Tesla autopilot users. Fig. 1 shows the proportion of each cluster, the figure also shows the group of Tesla owners that do not have a partially automated Tesla BEV. Fig. 2 shows how often respondents indicate they use autopilot on a trip basis and what proportion of their commute is completed using autopilot. Finally, Fig. 3 shows how likely drivers are to use the automated driving systems in different weather conditions, traffic conditions, and road types. We name each latent class based on their frequency of using autopilot, though they have other distinguishing features, which we describe in detail below:

- *Frequent users* (n = 152): These respondents indicate they use autopilot on 75% of their trips on average and use it for 33.2% of their commute. They are most likely to use autopilot on a freeway, in clear weather or at night, and are likely to use the automated driving in a variety of traffic conditions. They are less likely to use autopilot on rural or urban roads, in rain, fog, or snow.

Table 2
Sociodemographic profile of all BEV (Tesla Model S, X &, 3) owners in this sample (n = 424).

		N	%
Number of Household Cars	1	54	12.7%
	2	179	42.2%
	3	113	26.7%
	4	48	11.3%
	5	30	7.1%
Number of People in the Household	1	51	12.0%
	2	192	45.3%
	3	71	16.7%
	4	81	19.1%
	5	23	5.4%
	6	5	1.2%
	7	1	0.2%
Age	15–18	1	0.2%
	19–29	4	1.0%
	30–39	49	11.6%
	40–49	75	17.8%
	50–59	97	23.0%
	60–69	118	28.0%
	70–79	67	15.9%
	80 or older	10	2.4%
Gender	Female	86	20.3%
	Male	338	79.7%
Home Ownership	Other	1	0.2%
	Own	410	96.7%
	Rent	13	3.1%
House Type	Apartment Building	15	3.5%
	Attached house (townhouse, duplex, triplex)	27	6.4%
	Detached house (single family home)	382	90.1%
Highest Level of Education	High School Graduate or GED	2	0.5%
	Some College	31	7.3%
	College Graduate	106	25.0%
	Some Graduate School	40	9.4%
	Masters, Doctorate, or Professional Degree	241	56.8%
	I prefer not to answer	4	0.9%
Household Income	Less than $50,000	3	0.7%
	$50,000 to $99,999	26	6.1%
	$100,000 to $149,999	52	12.3%
	$150,000 to $199,999	51	12.0%
	$200,000 to $249,999	44	10.4%
	$250,000 to $299,999	36	8.5%
	$300,000 to $349,999	24	5.7%
	$350,000 to $399,999	21	5.0%
	$400,000 to $449,999	15	3.5%
	$450,000 to $499,999	13	3.1%
	$500,000 or more	66	15.6%
	I prefer not to answer	73	17.2%

- *Semi-frequent users* (n = 140): These users indicate they use autopilot on 41.1% of their trips on average and use it for only 7.3% of their commute. They are most likely to use autopilot on freeways, in clear weather, and when the roads are free from traffic. They are less likely to use autopilot in any traffic, on rural or urban roads, at night, in rain, fog, or snow.
- *Very frequent users* (n = 57): These respondents are the most frequent users of autopilot. They use automation on 92% of their trips and for 66.5% of their commute. They indicate they are likely to use autopilot on any road type (apart from parking lots), in any traffic conditions, and in clear weather, at night, during rain and fog, but not during snow.
- *Infrequent users* (n = 37): This user class uses automated driving the least, indicating they only use it on 24.5% of trips and use it for 8.7% of their commute. They are less likely to use autopilot on any road type, and are only slightly likely to use it on freeways, in clear weather, and on empty roads. They are unlikely to use it on non-freeway roads, in any inclement weather, and when any traffic is present on the roads.

Interestingly the only variables where the likelihood of using autopilot converges across all groups is for use in snow and use in parking lots. All groups indicate they are unlikely to use the vehicles automated driving capabilities in these conditions. The latent class model demonstrates the different classes of partially-automated vehicle users.

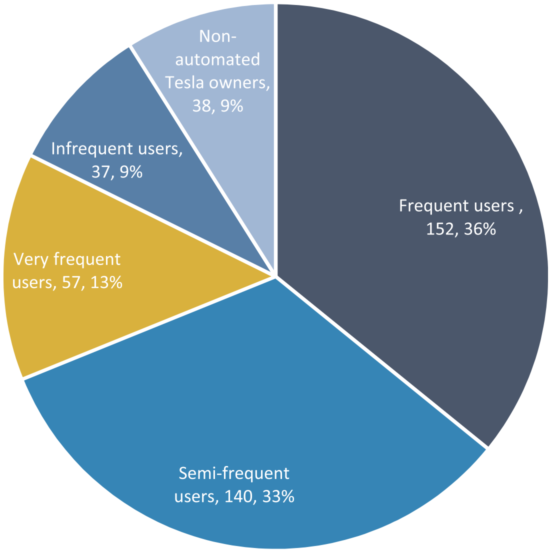

Fig. 1. Proportion of the 4 latent classes of autopilot users and owners of non-automated Tesla BEVs in the sample.

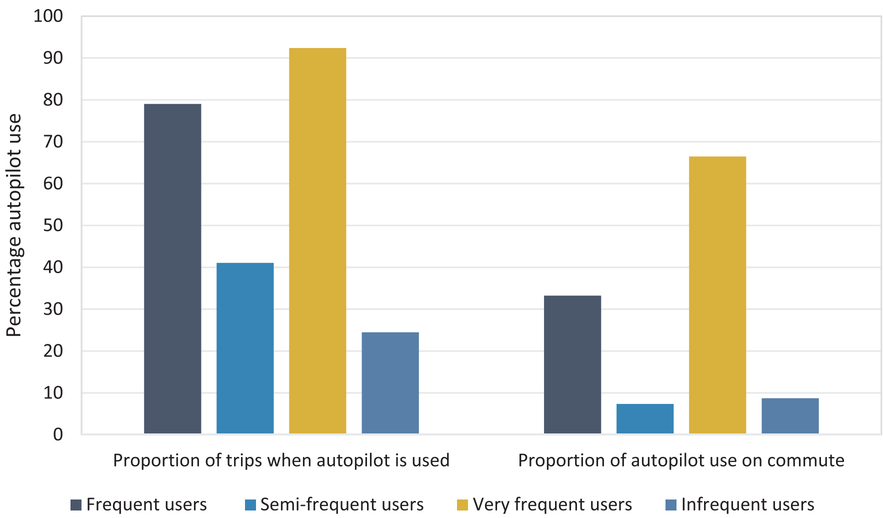

Fig. 2. Self-reported autopilot use (from never (0%) to every trip (100%)) and the percentage of drivers commute that is driven using autopilot (from 0% to 100% of the trip) for the four latent classes.

4.3. Understanding autopilot users

Table 3 shows the results of the step-3 model, the model includes each of the 4 partially-automated vehicles user clusters and the group of respondents who have a Tesla without automation. The model shows that *Frequent users* consist of younger consumers, who are more likely to be male, with fewer people in the household, who are less likely to have a post graduate degree, they have higher annual VMT, and have less technophobic attitudes. *Semi-frequent users* are those that have shorter commute distances, have more technophobic and driving enthusiast attitudes, perhaps explaining why they use automated driving less often. The only significant variables for *Very frequent users* are VMT, which was positive, and the technophobe factor, which was negative. *Infrequent users* have lower VMT and seem to have technophobic attitudes. Finally, the group of Tesla owners who do not have autopilot are more likely to be female, likely to have larger household sizes, likely to have a postgraduate degree, have lower household income, and lower VMT than the other clusters.

The Wald statistic for the model is highest for VMT and the technophobe factor. This indicates that VMT and attitudes to technology are influential factors in explaining the probability of latent class membership. The model shows that both groups of frequent autopilot users (*Frequent users* and *Very frequent users*) have higher VMT and more positive attitudes to technology compared to the other clusters. This indicates that the best predictors of being a frequent user of vehicle automation are higher VMT and positive attitudes to technology. This is supported by *Infrequent users* and having lower VMT and being technophobic. The non-

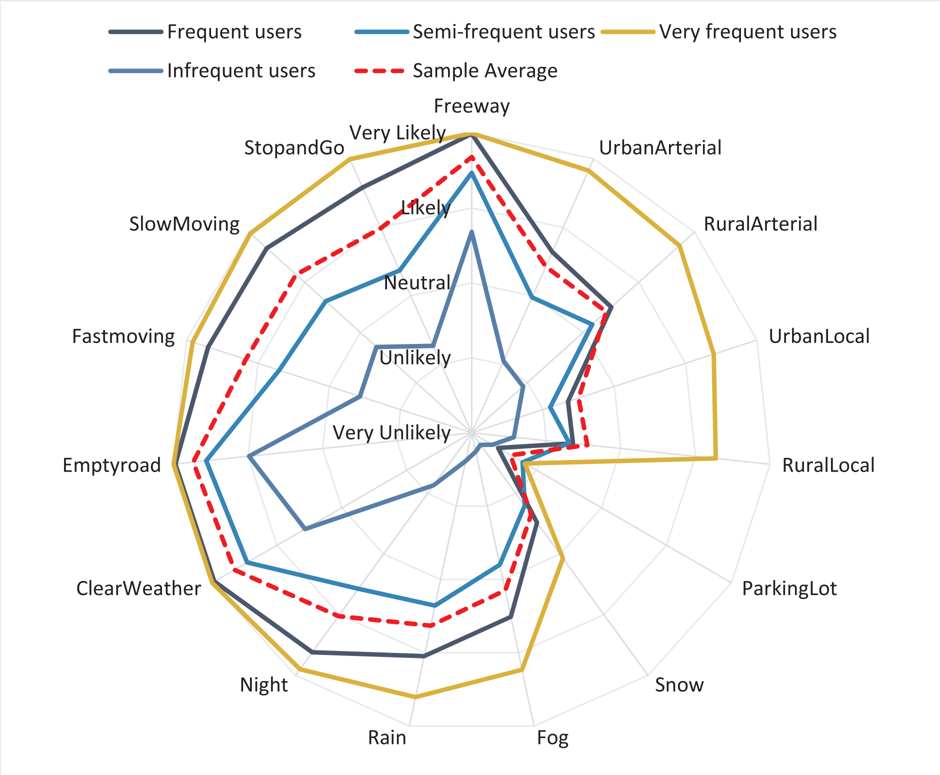

Fig. 3. Self-reported likelihood of using autopilot on various road types, weather conditions, and traffic conditions for the 4 latent classes of partially automated vehicle owners. The broken red line shows the sample mean response.

automated Tesla owners also have lower VMT which may point to them being self-selecting group who opt to not to purchase autopilot option because they drive less.

5. Conclusion and discussion

Our investigation into the use of partially automated vehicles (Tesla BEVs with Autopilot) revealed four heterogenous clusters of partially automated vehicle users. The clusters range from *Very frequent users*, who use automated driving the most, to *infrequent users,* who use it the least. The largest cluster in our sample are *Frequent users* who may be more pragmatic or cautions in their use of autopilot compared to *Very frequent users*. *Frequent users* indicate they mostly use it on freeways and in clear weather, which are conditions that the use of automation is recommended (Tesla, 2019).

Using a multinomial logistic regression model, we investigated the relationship between the latent classes and socio-demographics, attitudes, commute distance, and VMT. The model shows that *Very frequent users* and *Frequent users* travel more miles per year and have positive attitudes towards technology. They may use autopilot frequently because they have higher VMT meaning that they have more motivation to use it often. The positive attitudes to technology may also help explain why they use it frequently and use it in varying traffic conditions as they place more trust in the technology. *Semi-frequent users* have shorter commute distances and have technophobic and driving enthusiast attitudes. These users negative attitudes to technology, enjoyment they find in driving, and shorter commutes may explain why they use automated driving features on fewer trips, use it less on their commute, and only use it on freeways, empty roads, and in clear weather. *Infrequent users* have lower annual VMT and are technophobic. The fewer miles they travel and their poor attitudes to technology explain why they do not use autopilot frequently, and are unlikely to use it in any conditions other than empty freeways in clear weather. Finally, the non-automated Tesla owners lower household income may be one reason they did not select the US$5000 option of autopilot (at the time of purchasing their vehicle). The higher proportion of females could be explained by women sometimes being less likely to adopt new technologies compared to men, as has been the case with electric vehicles (Kurani et al., 2018). Finally, their lower VMT may point them being a self-selecting group who did not purchase autopilot because they travel less, and therefore did not perceive it to be substantially beneficial to them. As of April 2019, all Tesla vehicles sold come with standard autopilot, thus eliminating the possibility of future buyers not having use of automation.

An interesting finding of the model is the relationship between being a frequent user of autopilot and annual VMT. Both *Very frequent users* and *Frequent users* have significantly higher VMT than all other clusters. Mean VMT, from self-reported odometer readings, for these clusters is 14,809 (*Frequent users*) and 14,853 miles per year (*Very frequent users*). The VMT for the other groups is 9143 miles for *Infrequent users,* 10,590 miles for *Semi-Frequent users,* and 9795 miles for the group of non-automated Tesla owners. We

Table 3
Step-three (multinomial logistic regression) model results.

	Frequent users			Semi-frequent users			Very frequent users			Infrequent users			Non-automated Tesla owners				
Covariates	Estimate	z-value		Estimate	z-value		Estimate	z-value		Estimate	z-value		Estimate	z-value		Wald	p-value
Age	−0.020	−1.991	**	0.000	−0.003		0.022	1.521		−0.004	−0.245		0.002	0.167		5.224	0.270
Male_1	0.613	2.145	**	−0.032	−0.128		0.448	1.174		−0.505	−1.433		−0.524	−1.677	*	8.196	0.085
HHsize	−0.159	−1.651	*	0.002	0.017		−0.202	−1.331		0.134	0.746		0.226	1.675	*	6.447	0.170
Postgrad	−0.407	−2.025	**	−0.328	−1.608		−0.137	−0.489		0.169	0.528		0.704	2.226	**	8.573	0.073
Income	0.000	0.124		0.001	1.244		0.000	−0.179		0.002	1.484		−0.003	−2.310	**	6.897	0.140
CmtDist	0.006	0.993		−0.026	−1.732	*	0.008	1.061		0.010	0.875		0.002	0.176		3.310	0.510
VMT	0.000	3.716	***	0.000	−0.350		0.000	3.384	***	0.000	−1.985	**	0.000	−1.789	*	18.403	0.001
Detached_1	0.523	1.224		−0.429	−1.242		−0.234	−0.548		−0.268	−0.403		0.407	0.694		3.576	0.470
FrustCmters	−0.114	−1.237		0.027	0.280		0.111	0.806		−0.169	−1.030		0.145	1.098		4.077	0.400
TechnoPhobes	−0.187	−1.867	*	0.150	1.671	*	−0.392	−2.260	**	0.235	1.670	*	0.194	1.391		11.197	0.024
DrivEnthuiasts	−0.009	−0.127		0.131	1.771	*	0.153	1.434		−0.149	−1.475		−0.125	−1.085		7.032	0.130

* < 0.10, ** < 0.05, *** < 0.01.

cannot determine a causal relationship between the use of a partially automated BEV and VMT. Self-selection causality could mean those who drive more opted to purchase a BEV with partial automation with plans to use it frequently. However semi-automated driving systems may reduce the negative utility of driving by increasing comfort, increasing safety perceptions, reducing driver fatigue, and increasing the potential for multi-tasking for drivers. These factors may increase drivers willingness to travel by vehicle, thus increasing their VMT. These findings support previous studies that suggest fully automated vehicles will increase VMT (Bierstedt et al., 2014; Perrine et al., 2018; Schoettle and Sivak, 2015; Childress et al., 2015).

5.1. Policy implications

Fully automated vehicles could cause substantial changes to transportation systems (Sperling, 2018), however these vehicles are several years from commercial market introduction (Shladover, 2018), which may provide good time horizons to plan for their implementation. Partially automated vehicles are on the roads today, the Tesla vehicles explored in this study and vehicles from other automakers may already be impacting travel behavior. The potential for partially automated vehicles to increase VMT has implications for the US goal of reducing VMT (US Department of Transportation, 2014) & California's goal of reducing greenhouse gas emissions through reducing VMT (California Office of Planning and Research, 2013). The fact that the automated vehicles in this study are electric presents further difficulties. There are currently no use-based fees for electric vehicles, upcoming fees for electric vehicles are annual fees that do not differ based on the amount of driving a vehicle owner does. This means there is no existing mechanism that could be used to curb VMT increases, which may mean new policy approaches are needed, for example a road users charge (Jenn, 2018).

Some of the functionality of partial automation is intended to be used on freeways and highways in clear weather (Tesla, 2019). Results from this study suggest that drivers use partial automation in situations other than these. SAE Level 2 Partial Automation represents an interesting area of automation. The human driver is considered to be driving the vehicle at all times, though the systems do not always have a way of informing them to take over in environments when the system isn't supposed to be used (e.g on rural roads). Level 3 Conditional Automation can be used in limited conditions and will not operate unless certain conditions are met. These systems would disengage and inform the driver to take control of the vehicle in environments where it is not intended to be used. Policymakers may wish to consider how to manage the use of automated vehicles in environments where they are not intended to be used, as this may have safety implications.

5.2. Future research and limitations

More research is needed to determine a whether there is a causal relationship between owning or using a partially automated vehicle and VMT. Such research should focus on how partial automation has impacted travel behavior, and should look to isolate the impact of partial automation from other factors such as free charging (that is available for many Tesla owners), the smoother driving of an electric vehicle, the potentially reduced cost of driving a BEV compared to a conventional vehicle, and any recent lifestyle changes that may impact partially automated vehicle owners travel behavior (e.g increasing household size, moving home location, moving work location, etc.). The sample size used in this study is small and limited to one automaker, future research should aim to gather larger sample sizes, which may be possible as the market introduction of partially-automated vehicles continues. This data collection effort should also aim to gather insights into vehicles other than Tesla BEVs with partial automation. Several automakers including Audi, Toyota, Nissan, Honda, Kia, BMW, Mercedes, General Motors and others have vehicles with partial automation on the market. In addition to questionnaire surveys, qualitative interviews with the users of these vehicles could reveal more information about how partially automated vehicles are used and could explore any causal relationships between autopilot use and VMT.

Despite being from the users of automated vehicles the data in this study is still self-reported. It is therefore impacted by the issues of any self-reported data including the difficulty of consumers to accurately estimate their own behavior. The latent classes in our study could also exist due to differences we are unable to observe. This may include differences in actual travel patterns of drivers. For example, differences between the classes could be impacted by the roads drivers frequently use, with some using freeways more or less than others. To address this studies should gather data that is not self-reported by vehicle owners. This could include installing data loggers in partially automated vehicles or working with automakers to analyze their data from the vehicles. Other studies have also highlighted the need to gather valid behavioral data on automated vehicles to help inform modelling efforts, policymakers, and transportation service providers (Zmud et al., 2019).

All of this research can help shed more light into how partially automated vehicles are used. The hope will be that any unintended negative consequences could be avoided, and that the introduction of partially automated vehicles will lead to positive societal outcomes. We hope that that this study will encourage more research into understanding these vehicles.

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