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# Understanding use patterns of partially automated electric vehicles

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## Summary

Previous research on automated vehicles has focused on fully automated or driverless vehicles, which are yet to be introduced to the market. Partially automated vehicles, which are already available for consumers to purchase and use, have been largely overlooked. In this study we investigate how partially automated vehicles (Tesla electric vehicles with "Autopilot") are used, including how often automation is used, and on what road, weather, and traffic conditions it is used. Using a latent class model we identify four heterogeneous groups of autopilot users. The clusters range from; frequent any road users, who use it most frequently and on a variety of roads; to frequent clear weather freeway users, who use automation frequently but only in clear weather and on freeways; to 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 to infrequent users, who use it the least often and only in clear weather, on freeways, when there is no traffic. A multinomial logistic regression model was used to understand the characteristics of each automated vehicle user clusters. The model found that two frequent user classes have higher VMT, and better perceptions of technology compared to the other classes. Infrequent users were found to have shorter commute distances and worse perceptions of new technologies. The research suggests that automated vehicle use may be correlated with higher vehicle miles travelled and the vehicles will be used by consumers with positive perceptions of new technologies.

*Keywords: Automated vehicles; survey; vehicle miles travelled; Tesla;*

# 1 Introduction

Fully automated vehicles are not yet available for consumers to purchase, except for some small vehicle trials in closed environments or on open roads with a trained driver behind the wheel. However, partially automated vehicles (SAE Level 2) are already available for consumers to purchase and use. Several original equipment manufacturers (OEMs) also have vehicles with level 2 of automation already for sale, including those sold by Mercedes-Benz, BMW, and Tesla. In this study we focus on partially automated Tesla BEVs (Tesla Model S, X, and 3 with autopilot)[1]. Based on sales data taken from SEC filings at the end of Q3 2018 more 250,000 of these Level 2 automated vehicles had been sold globally. There is no research currently published on how these vehicles are being used by drivers, including how often they use it, on what roads, in which traffic conditions, etc. Understanding how these partially automated vehicles are being used, and the relationship between use of automated and travel behavior, may reveal their positive and negative impacts, which policymakers could use to avoid any unwanted consequences from the vehicles.

In this study, we use results from a questionnaire survey of 424 owners of Tesla BEVs of which 347 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 making them a unique group of consumers who have experience with partial automated vehicle technology. The aim of this study is to understand how level 2 partially automated vehicles are used by this group of consumers. It is hoped that these insights will lead to a greater understanding of how consumers will use partially and fully automated vehicles, these insights may be able to inform efforts to understand how automated vehicles may impact the transportation systems and travel behavior. 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 conductions, and use on a trip basis and on commute trips. We then use a multinomial logistic regression model to understand any relationships between sociodemographic and attitudinal variables and the different classes of autopilot use.

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.

# 2 Literature Review

Research into automated vehicles has used several different methods to understand the potential impacts of the vehicles. One method to understand travel behavior and automated vehicles is the use of modeling techniques which use assumptions on how people might use the vehicles, often with a focus on changes to vehicle miles travelled (VMT). Another method is to survey consumers and ask them how they might use automated vehicles and how the vehicles could change their travel patterns. The final method is to allow consumers to trail the vehicles, though at present trials are limited to simulated automated vehicles or vehicles in closed environments. There are no studies currently published that model the impact of partially automated vehicles or present empirical evidence on how partially automated vehicles are used. Fagnant & Kockelman [2] suggest that automated vehicles could lead to reductions in per mile emissions and but may increase travel demand as the vehicles could increase road capacity and increase the mobility of currently underserved groups. None of the studies identified by the authors of this study consider the use of semi-automated vehicles.

Modelling studies have focused on changes to travel demand, often specifically changes to VMT. Perrine et al. [3] used a travel demand model to understand any 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 to driverless vehicles. Schoettle and Sivak [4] 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%. They assume no increase in fleet VMT in this scenario. Childress et al. [5] used an activity model to explore potential impacts of automated vehicles in Washington State, USA. They modeling of four different scenarios and found that VMT impacts 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. A final modelling study found that depending on rates of adoption automated vehicles could cause increases in VMT of between 5% and 35%.

Wadud et al. [6] used a framework to model the potential impacts of AVs 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 found 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 [7] who state that the vehicles could reduce VMT if the vehicles are shared, however single occupant automated would likely lead to increases in travel.

Finally Brown et al. [8] 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.

Most surveys on AVs have focused on consumer acceptance or purchase intentions of the vehicles [9–13]; however studies also investigate whether consumers believe their travel patterns will change as a result of vehicle automation, often using stated preference methods. A survey by Zmud investigated [14] 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 their respondent though did think their inter-city travel would increase due to reduced stress and fatigue of driving there. A survey of 2588 consumers in the USA found that consumer anticipate using AVs for longer distance travel compared to using non-automated vehicles [15].

A final study gave car owning households 60 hours of free chauffeur service to simulate what travel would be like owning a fully automated driverless vehicle [16]. The experiment mimics owning a driverless vehicle as the driving task is removed from the participants. This study found that driverless vehicles could lead to increased VMT, in their sample of 13 participants VMT increased between 4-341%. 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 vehicles, the results do show how VMT could increase though. The increase in VMT was due to respondents making more trips and sending their vehicles on errands without them in the vehicle.

# 3 Methods

The PH&EV Research Center at the University of California, Davis administered a questionnaire survey to 30,000 consumers in 36 states throughout the United States in March and April 2018. The sample contained 20,000 consumers who were PEV owners and 10,000 ICEV owners who were included as a point of comparison. These survey respondents were sent a letter by mail that outlined the survey topics and provided a link to access the survey in addition to a personal token they could use to access the survey. The survey focused on several topics related to electric vehicles, automated vehicles, and shared vehicles.

Respondents are asked several questions about whether they have autopilot, how frequently they use it, and in what conditions they are likely to use it. First respondents were asked if they have autopilot hardware installed in their vehicle, and if they have the software that allows the use of autopilot enabled. Those who indicated they have autopilot hardware and software enabled were asked subsequent questions about autopilot use.

Latent class cluster analysis was used to classify autopilot users based on t heir responses to the above questions. In total, 15 ordinal variables are included in the analysis. 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 & Magidson, 2014). 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 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 generate a smaller number of variables making the data more manageable in additional analysis 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.

# 4 Results

Latent class analysis revealed four heterogeneous clusters of Tesla owners based on their frequency of autopilot use for all trips, and on their commute; and on what roads, weather, and traffic conditions they are likely to use autopilot. Figure 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. Figure 2 shows how often respondents indicate they use autopilot on a trip basis (from never to every trip) and what proportion of their commute is completed using autopilot (from 0% of the trip to 100% of the trip). Finally, Figure 3 shows how likely drivers of partially automated vehicles are to use the automated driving systems in different weather conditions, traffic conditions, and road types. We name each latent class based on their defining characteristics, which we describe in detail below:

- Frequent clear weather freeway users (n=152): These respondents indicate they use autopilot on average for 75% of their trips, and use it for 33.2% of their commute. They are most likely to use autopilot on 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, or in rain, fog, or snow.
- Semi-frequent users (n=140): These users indicate they use autopilot on average for 41.1% of their trips, 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 traffic, on rural or urban roads, and at night, in rain, fog, or snow.
- Frequent any road users (n=57): These respondents are the most frequent users of autopilot. They use the automated driving for 92% of their trips and use it 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): These autopilot users are the least frequent users of the automated driving, indicating they only use it for 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. Next we use a multinomial logistic regression model to understand the relationship between the four clusters (and the non-automated Tesla group) and socio-demographic and attitudinal variables.

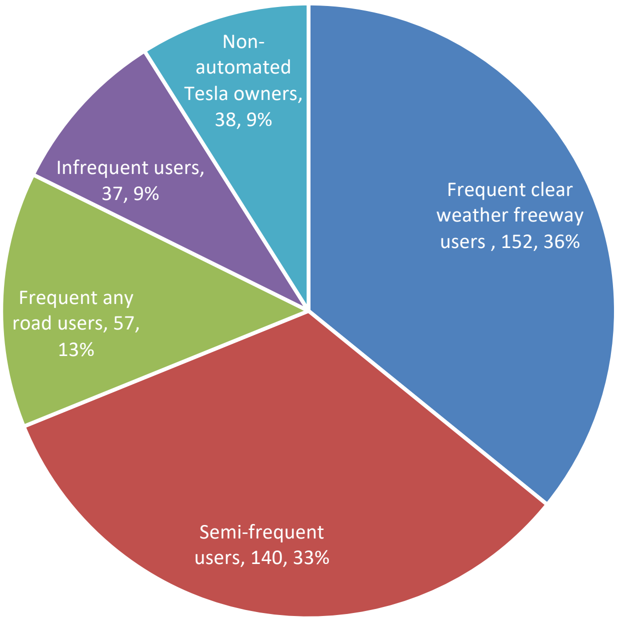


Figure 1: Proportion of the 4 latent classes of autopilot users and owners of non-automated Tesla BEVs in the sample (n=424).

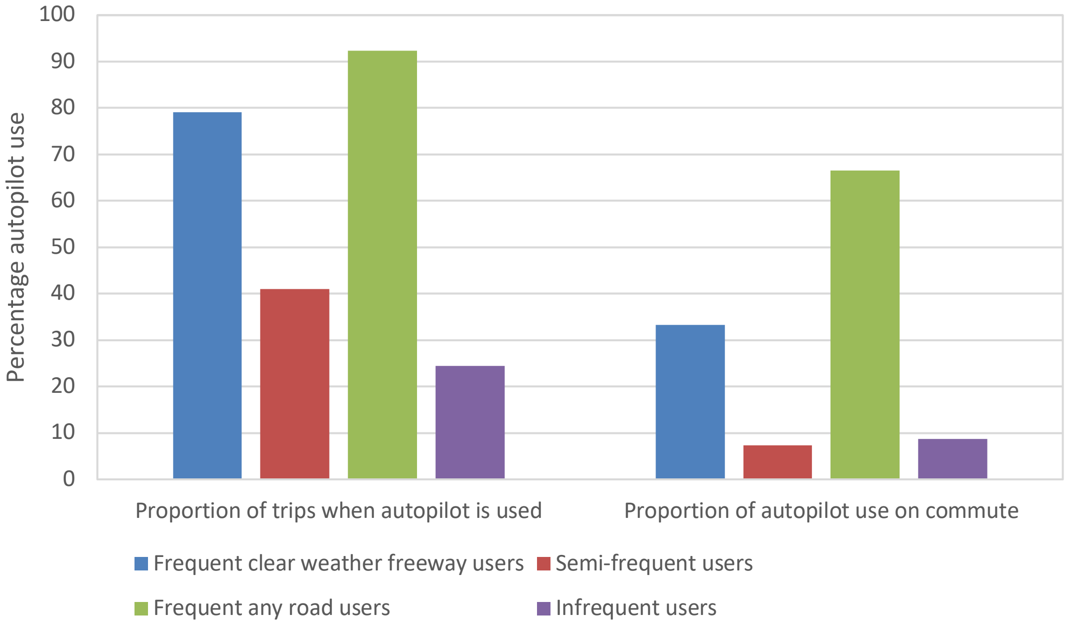


Figure 2: Self-reported autopilot use (from never (0%) to every trip (100%)) and the percentage of drivers commute that is driven using autopilot (from 0% to 100% of the trip) for the four latent classes.

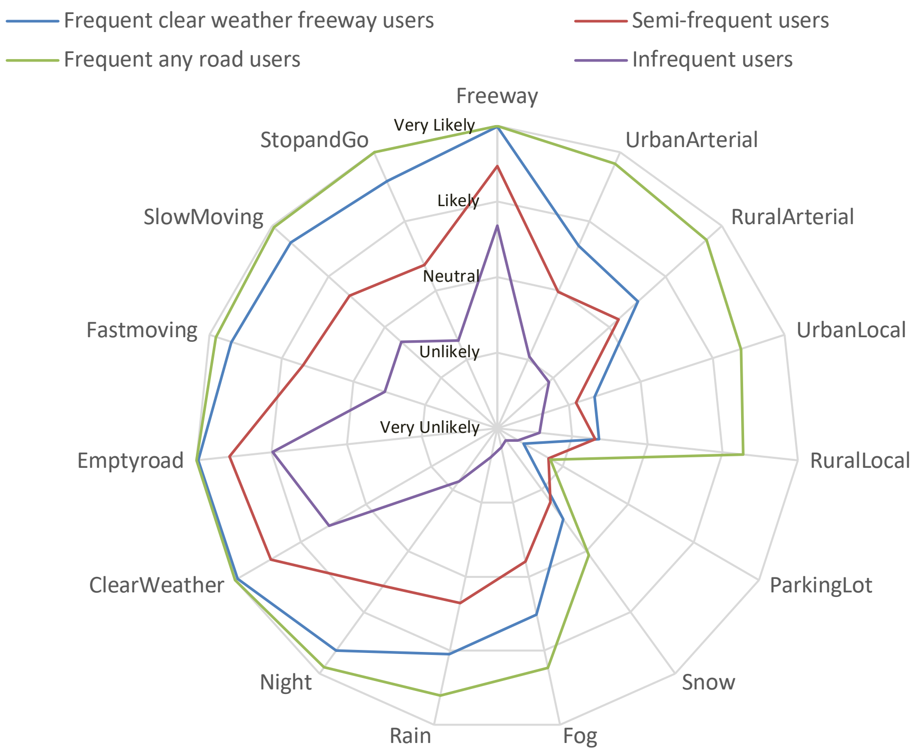


Figure 3: Self-reported likelihood of using autopilot on various road types, weather conditions, and traffic conditions for the 4 latent classes of partially automated vehicle.

Step-3 regression is used to understand the heterogenous clusters of autopilot users. The model is used to understand the characteristics of each cluster based on their socio-demographic information and their attitudes using the attitudinal factors generated using factor analysis. Table 3 shows the results of this model, the model includes each of the 4 partially-automated vehicles user clusters and the group of respondents who do not have a partially automated vehicle. The models shows that the Frequent clear weather freeway 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 do not have technophobic attitudes. Semi-frequent users are those that have shorter commute distances, and are more technophobic and likely to be driving enthusiasts, perhaps explaining why they use the automated driving less often. The only significant variables for Frequent any road users only are VMT, which was positive, and the technophobe cluster, which was negative. This suggests they have significantly longer VMT and they perceive technology better than the other clusters. 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 model shows that both groups of frequent autopilot users (Frequent clear weather freeway users and Frequent any road users) have higher VMT and have positive attitudes to technology compared to the other clusters. This perhaps indicates that the best predictors of being a frequent user of autopilot are higher VMT and positive attitudes to technology. This is perhaps supported by infrequent users and having lower VMT and being technophobic. The non-automated Tesla owners also have lower VMT and lower household incomes which may point to them being self-selecting group who opt to not to purchase a vehicle with autopilot because they drive less and have a lower household income.

*Table 1: Step-three (multinomial logistic regression) model results.*

| | Frequent clear weather freeway users | | | Semi-frequent users | | | Frequent any road users | | | Infrequent users | | | Non-automated Tesla owners | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Covariates | Estimate | z-value | | Estimate | z-value | | Estimate | z-value | | Estimate | z-value | | Estimate | z-value | | W |
| Age | -0.0197 | -1.9908 | ** | 0 | -0.0029 | | 0.0218 | 1.5208 | | -0.0039 | -0.2452 | | 0.0019 | 0.1668 | | |
| Male_1 | 0.6128 | 2.1453 | ** | -0.0318 | -0.1282 | | 0.4476 | 1.1742 | | -0.5051 | -1.4329 | | -0.5235 | -1.6771 | * | |
| Household Size | -0.1594 | -1.6511 | * | 0.0018 | 0.0172 | | -0.2019 | -1.3312 | | 0.1335 | 0.7458 | | 0.226 | 1.6752 | * | |
| Postgrad | -0.4069 | -2.0251 | ** | -0.3284 | -1.6083 | | -0.1369 | -0.4887 | | 0.1688 | 0.5279 | | 0.7035 | 2.2263 | ** | |
| Income | 0.0001 | 0.124 | | 0.001 | 1.2441 | | -0.0002 | -0.179 | | 0.002 | 1.4837 | | -0.0029 | -2.3098 | ** | |
| Commute Distance | 0.0064 | 0.9927 | | -0.0259 | -1.7322 | * | 0.0076 | 1.0606 | | 0.0103 | 0.8749 | | 0.0016 | 0.1756 | | |
| VMT | 0.0001 | 3.7164 | *** | 0 | -0.3496 | | 0.0001 | 3.3841 | *** | -0.0001 | -1.9853 | ** | -0.0001 | -1.7892 | * | |
| Detached_1 | 0.5232 | 1.2243 | | -0.4285 | -1.2419 | | -0.2341 | -0.5478 | | -0.2679 | -0.4026 | | 0.4073 | 0.6941 | | |
| Frustrated Commuter | -0.1135 | -1.2369 | | 0.0274 | 0.2797 | | 0.1107 | 0.8063 | | -0.1694 | -1.0298 | | 0.1448 | 1.098 | | |
| Technophobe | -0.187 | -1.8673 | * | 0.1502 | 1.6714 | * | -0.3915 | -2.2596 | ** | 0.2346 | 1.6697 | * | 0.1936 | 1.3912 | | |
| Driving Enthusiast | -0.0093 | -0.127 | | 0.1309 | 1.7706 | * | 0.1526 | 1.4342 | | -0.149 | -1.4751 | | -0.1252 | -1.0853 | | |

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

# 5 Conclusion and Discussion

Our investigation into the use of partially automated vehicles (Tesla BEVs with Autopilot) revealed different clusters of users based on their self-reported use of automated driving on a trip basis, on their commute, and on different roads, in different weather conditions, and in different traffic conditions. Using a latent class model four clusters were identified ranging from *Frequent any road users,* who use automated driving the most, to *infrequent users,* who use it the least. The largest cluster in our sample are *Frequent clear weather freeway users,* who may be more pragmatic or cautions in their use of autopilot, compared to *frequent any road user*, indicating they mostly use it on freeways and in clear weather.

Using a multinomial logistic regression model, we investigated the characteristics of each cluster of autopilot users. The model found that frequent users of autopilot (*Frequent clear weather freeway users* and *frequent any road users*) are those who travel more miles per year and have positive attitudes towards technology. They may use autopilot more frequently because they have higher VMT meaning they may be more fatigued motivating them to use it more 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 compared to technophobic consumers. *Semi-frequent users* have shorter commute distances, and have technophobic and driving enthusiast attitudes. These respondents negative attitudes to technology; enjoyment they find in driving; and shorter commutes, which may be less stressful, 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.

An interesting finding of the model is the relationship between being a frequent user of autopilot and annual VMT. Both clusters of frequent users (*Frequent clear weather freeway users* and *Frequent any road users*) have significantly higher VMT than all other clusters. Mean VMT, from self-reported odometer readings, for these clusters is 14,809 (*Frequent clear weather freeway users*) and 14,853 miles per year (*Frequent any road users*). *Infrequent users* and *semi-frequent user*s, and the group of non-automated Tesla owners all have substantially lower annual VMTs of around 10,000 per year. We cannot determine a causal relationship between the use 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. Conversely semi-automated driving systems may increase the comfort of driving, increase safety perceptions, reduce driver fatigue, and increase the potential for multi-tasking for drivers. These factors could reduce the negative utility driving and increase car owner's willingness to drive, thus increasing their VMT. This would support previous studies that suggest automated vehicles will increase VMT [3–5,17]. However, prior to concluding that partially automated vehicles have a causal relationship with VMT more research is needed, including more questionnaire survey work and qualitative interviews. 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 vehicles, 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.).

This study aimed to provide an early look on the use patterns of partially automated vehicles. It is hoped that this will encourage more research into understand these vehicles, which are on the roads today, and not just fully automated vehicles whose market introduction has not yet begun.

# Acknowledgements

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# Authors

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