UNFOLDING THE STATE OF THE ADOPTION OF CONNECTED AUTONOMOUS TRUCKS BY THE COMMERCIAL FLEET OWNER INDUSTRY

Abstract

This paper attempts to address two particular questions about the adoption of connected autonomous trucks (CATs) by trucking companies: (i) what are the factors affecting the decisions to adopt different levels of autonomous trucks? and (ii) how many with what sizes are the groups of CAT adopters? We employ choice modeling and latent-class cluster analysis (LCCA) to address the two questions. US companies working in the freight industry are contacted and 400 full responses are collected. The data is analyzed descriptively and detailed results of modeling efforts are presented and discussed. Focusing on the first question, companies view automation Level 2 not significantly different than Regular trucks. We observe that small-sized companies are more likely to adopt the higher levels of automation, and large companies may be willing to adopt only when the technology become more affordable. Cargo type is found to have some impact on the adoption: for example, companies carrying foodstuff are more likely to adopt higher levels of automation. Having promoters of new technologies in the company increases the likelihood of adoption and the impact is more visible for the higher levels of automation. Turning to the second question, our results indicate that there could be five categories of CAT adopters which is consistent with what the Theory of diffusion of Innovations (DOI) suggests. However, the sizes of the *Innovators* and *Early Majority* classes would respectively be four and two times of DOI's general suggestion. Overall, it is speculated that the CAT adopter distribution may not be a bell-shaped curve but more of a right-skewed figure. This can be contributed to explicit financial benefits of CATs which could incentivize companies to adopt earlier.

Keywords

Autonomous deriving; adoption; diffusion of innovations; latent class cluster analysis; discrete choice; trucks.

1. Introduction

There is a saying in the United States (US) that states "If it got there, a truck brought it" (LeMay et al., 2013). The saying is proven to be true when trucking industry statistics are scrutinized. According to the American Trucking Association, trucks carried about 70% of the total freight tonnage in 2017 (Costello, 2017). Also, reports submitted to the US Congress indicate that trucks carry about 75% of the total cargo moved in the US, measured in tonnage or value (Frittelli, 2017; Frittelli, 2020). This market share is contributed to the 209,000-mile national truck network providing high-level accessibility to every freight generator across the country. In terms of freight ton-mile, trucks move about 40% of the freight within the US, which is due to the higher efficiency of rail transportation on long routes. Trucks continue to act as the backbone of the US freight transportation system as the demand for the trucking industry's services is forecasted to increase at an annual rate of 1.4% through 2045 (Bhattarai et al., 2021; BTS, 2015).

Trucks also play an indisputable role in the highway transportation system in the US. There were more than 273 million on-road vehicles in the US in 2018, of which 2.9 million were combination trucks (i.e., a 1.06% share) and 10.3 million were single-unit trucks (i.e., a 3.77% share). The left-hand-side panel of Figure 1 shows how the number of trucks has changed over the 1970-2018 period. The number of combination trucks has increased by 182% while the share of combination trucks has been relatively stable over this period. We observe a similar rate of increase for the number of single-unit (SU) trucks while no specific trend can be identified for the share of SU trucks. In terms of generated annual VMT, however, we observe a different trend. Combination trucks traveled about 184 billion miles in 2018, up 243% from 1970. The share of combination trucks in total VMT also increases steadily (but not monotonically). We observe a less sharp rate of increase in the VMT generated by SU trucks with no noticeable trend. Overall, it can be concluded that although the share of combination trucks in total on-road vehicles has remained relatively constant over time, the annual VMT that a truck generates follows an increasing trend indicating that combination trucks continue to make a more significant impact on the highway transportation system.

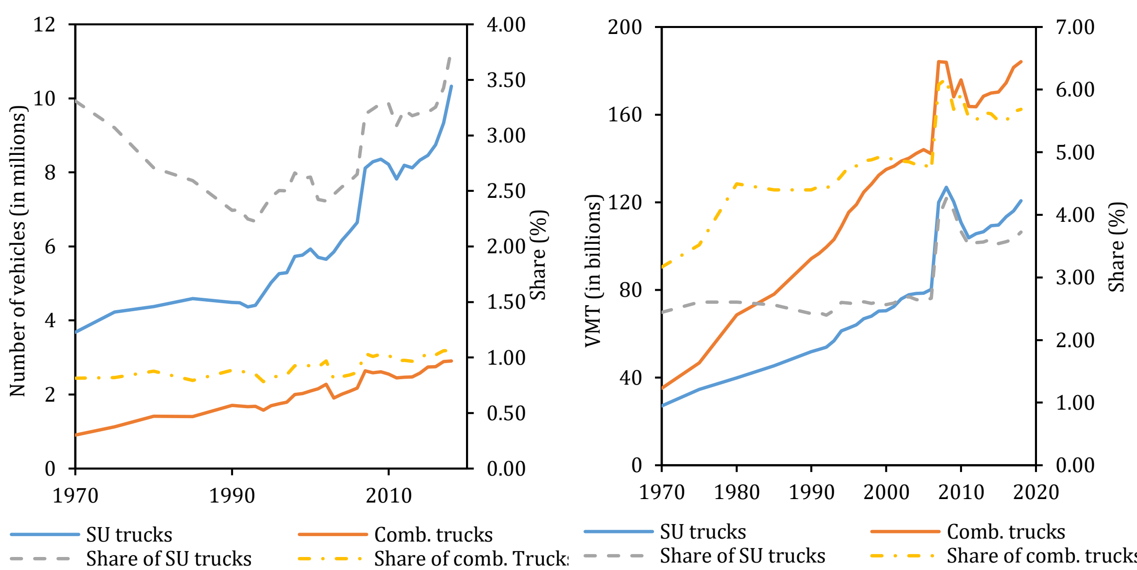

Figure 1: Number and annual VMT of single-unit (SU) and combination trucks (source: BTS (2020a; 2020b))

The automated driving technology, as an advancement revolutionizing safety, comfort, travel behavior, environmental impacts of transportation, and economy, has arrived faster than initial expectations. For example, the 2021 Mercedes Benz S-Class seems to be more than a Level 2 automated system offering a variety of features including enhanced night vision, auto park, active lane-keeping, and blind-spot assist, active distance assist, collision prevention, as well as Drive Pilot system working at speeds up to 37 mph (Mercedes Benz R&D, 2020).

One major user of the automated driving technology would be the trucking industry. The automated driving technology can impact the trucking industry and freight transportation system in a more revolutionary manner, compared to passenger car users. First, automated trucks of Level 5 may not need a driver at all. A major rule currently restricting trucking companies is the Hours-of-Service regulation of the US Department of Transportation (US DOT) which does not permit a driver to drive for more than 11 hours per day (FMCSA, 2020). Without a driver, trucks can operate outside the time window of HOS. When that happens, the growing share of trucks in the overall VMT of highway transportation system may increase drastically, which in turn exacerbates negative impacts of transportation such as noise pollution and emissions. Note that automated trucks of Level 2-4 could have the same impact but probably to a lower extent as drivers have less task in driving highly automated trucks. Second, 43% of operational costs of a trucking company is driver compensation, according to Costello (2017). This portion of the cost can be eliminated entirely or partially with the implementation of automated trucks of Levels 4 and 5. In addition, platooning, synchronization with the traffic signaling system, and application of real-time traffic data could improve fuel efficiency thereby cutting operational costs. As a result, trucking companies may choose to charge less to improve their competitive presence in the freight transportation market. This could lead to induced demand for the trucking industry and a further increase in VMT and emissions. It becomes important for the US DOT, state DOTs, and transportation planning agencies to explore how connected autonomous trucks (CATs) are perceived by commercial trucking companies so that appropriate infrastructure planning can be made in the future.

Due to (i) the large number of trucks in the overall highway vehicle fleet, (ii) the significant share of combination trucks in the total annual VMT generated by highway vehicles, and (iii) potential fundamental impacts of CATs on the trucking industry, there is a need to explore different aspects of adoption of CATs by the trucking industry. To the best of our knowledge, however, the literature is primarily focused on the adoption of autonomous vehicles by individuals and several important questions regarding firm-level adoption are yet to be answered. This paper, in particular, addresses two crucial questions: *what are the factors affecting the decisions to adopt different levels of autonomous trucks* and *how many with what sizes are the groups of CAT adopters?*

The remainder of this paper is organized as follows. In the subsequent section, we review the literature on autonomous vehicles and discuss how firm adoption is different from individual adoption. Building upon the synthesis of the literature, we elaborate on research gaps and explicitly present our contributions. Section 3 details the procedure of data collection and discuss descriptive statistics of the collected data, ensued by a brief presentation of the methodological background of the approaches used in the study in Section 4. In Section 5, we put forward our results and discuss them in detail. The paper is concluded in Section 6 with a summary of major findings and directions for future research.

2. Literature Review and Paper Contributions

Autonomous driving has been of the focus of numerous studies in the past decade. Researchers have explored issues such as safety (Alonso et al., 2011; Gurney, 2013; Fagnant and Kockelman, 2015;

Kalra and Paddock, 2016; Liu and Khattak, 2016; Deb et al., 2020; Yang and Fisher, 2021; Rahman et al., 2021; van Wees, 2021), congestion and traffic operations (Le Vine and Polak, 2016; Le Vine et al., 2017; Vincent AC and Verhoef, 2016; Maciejewski and Bischoff, 2017; van den Berg, Le Vine et al. 2019; Guo et al., 2020; Martin-Gasulla and Elefteriadou, 2021), travel behavior (Harper et al., 2016; Hohenberger et al., 2016; Truong et al., 2017; Bansal and Kockelman, 2018; Acheampong et al., 2021; Nair and Bhat, 2021; Moody et al., 2020; Wang et al., 2020; Penmetsa et al., 2019), environmental impacts (Tsugawa et al., 2011; Brown et al., 2014; Wadud et al., 2016), infrastructure design and assessment (Chen et al., 2017; Talebian et al., 2019), and forecasting market penetration (Chen et al., 2016; Lavasani et al., 2016; Bansal and Kockelman, 2017; Noruzoliaee et al., 2018; Shabanpour et al., 2018; Talebian and Mishra, 2018).

One important question in the field of automated driving research revolves around the factors impacting the adoption of the technology. From the methodological perspective, discrete choice modeling is the predominant approach used to understand how the demand for the technology will develop. From the perspective of research outcome, the literature offers mixed insights. Among all, Haboucha et al. (2017) find large overall hesitations toward the adoption of autonomous vehicles (AVs) among Israelis and Americans. Using data collected in Puget Sound, Washington, Lavieri et al. (2017) find that educated, technologically savvy, younger urban residents are likely to adopt the AVs technology sooner than others. Pettigrew et al. (2019) observe that individuals with higher education, and shorter driving history are found to be more likely to adopt first. Menon et al. (2016) suggest that demographics may have little impact on AV adoption when familiarity about benefits and concerns of AVs is included in the model specification. Liu et al. (2017) witness that longer-distance travelers in Austin, Texas prefer shared AVs over human-driven vehicles mainly due to lower travel burdens. Bansal et al. (2016) suggest that safety and equipment failure are the most important perceived benefit and concern of AVs, from the perspective of 347 Austinites who participated in the research survey. A survey of Americans by Bonnefon et al. (2016) shows that younger male respondents are more enthusiastic about using autonomous vehicles. The study by Gurumurthy and Kockelman (2020) alludes to privacy as an unimportant concern for AV travelers. Wang et al. (2020) observe that supporters of stricter traffic regulations have a positive attitude about AVs implying that they see AVs as a safer transportation mode, compared to human-driven cars. Sharma and Mishra (2020) investigate the impact on automation Level 4 adoption of social values and find that AV adoption positively impacts social values of an individual in his/her peer network.

There exist a few studies looking at CAT adoption at the firm-level. Simpson et al. (2019) estimate the adoption of CATs by freight transportation companies using a modified Bass model which accounts for heterogeneity in internal and external influences among companies. The authors find a CAT market penetration of 20-95%, depending on the improvement rate of the technology, how public opinion on AVs evolves, and external factors (i.e., marketing and price). Simpson and Mishra (2020) attempt to incorporate peer effects into a discrete choice model that predicts CAT adoption. Their analysis suggests that smaller companies are more likely to change their decisions following larger companies' decisions. Both studies discussed so far are based on parameters related to other innovations as well as a set of ad-hoc assumptions. Anderhofstadt and Spinler (2020) use a choice-based conjoint analysis to study how 69 employees from freight companies in Germany evaluate major features of autonomous alternative fuel trucks. Maximum driving range and refueling/recharging time are found to be the most important attributes while the least important feature is tank-to-wheel emissions. The survey also suggests that the market penetration of the new technology cannot be elevated unless truck manufacturers, trucking firms, infrastructure providers, and policymakers closely coordinate. In a qualitative study, Kishore Bhoopalam et al. (2021) report the range of perspectives existing among

Dutch truck drivers. The study suggests that the drivers think platooning will ultimately become widespread in the industry but at the cost of lower work quality and job satisfaction for truck drivers.

While the technology of automated driving for automobiles shares many similarities with that for trucks, drivers of adoption, as well as the adoption process itself, differ fundamentally. Some believe that companies can adopt an innovation faster and easier than individuals as there exists less heterogeneity among users of the innovation within the company. For example, employees who are supposed to use a new communication technology mostly have similar education. Furthermore, companies can conveniently educate their employees thereby making the adoption process faster and smoother. On the other hand, partial adoption of an innovation within a company can result in inconsistency in operations lowering the overall efficiency. Let us consider the communication technology example again. If some employees stick to the old technology, inconsistencies between the old and new technologies may lead to incomplete or imperfect communications. Therefore, companies are better off adopting an innovation to a full extent. Doing so, however, is sometimes time- and/or budget-intensive, and this is particularly true about the adoption of automated trucks by large trucking firms. Third, the organizational theory suggests that firm size plays a key role in the adoption of firms. The decision-making process in a small organization is typically centralized and major decisions are made by the owner-manager (Dyer Jr and Handler, 1994). It is believed that the smaller the firm, the closer innovative behavior of the firm to that of the owner. In light of this, it is important to account for the characteristics of the owner (manager) when modeling the decision to adopt (Donckels and Fröhlich, 1991; Hausman, 2005). Major characteristics impacting a firm's behavior are gender (Liedholm and Mead, 1993; McPherson, 1996; Millward and Freeman, 2002), age (Khan and Manopichetwattana, 1989), education level (Hausman, 2005; Khan and Manopichetwattana, 1989; Robson et al., 2009), and experience level (Hausman, 2005). Also, it is important to consider firm-level attributes such as firm age (Coad et al., 2016; Huergo and Jaumandreu, 2004) and organizational resources (Rogers, 2010). Decision making in large firms is not concentrated in the hands of one person and thus collective behavior of the firm's managers will impact adoption. Therefore, organizational attributes such as age (Huergo and Jaumandreu, 2004) and organizational resources play a role. In light of these, there is a need for research explicitly addressing the adoption of CATs by trucking companies considering that the literature on adoption of this technology by individuals may not be of much help and relevance.

In summary, we note that there has been far less research on how the freight sector will react to this innovative technology, despite the significant impact of trucks on the transportation system. Indeed, previous studies are mostly focused on (i) platooning potentials and impacts (Kunze et al., 2011; Tsugawa et al., 2011; Sugimachi et al., 2013; Tsugawa, 2013; Castritius et al., 2020; Hassan, 2020; Zhang et al., 2020), (ii) business impacts of autonomous trucks (Fritschy and Spinler, 2019; Lingmont and Alexiou, 2020; Slowik and Sharpe, 2018), and (iii) adoption of the technology. Within the adoption domain, the literature is focused on overall perceptions about the technology (Engholm et al., 2020; Pudasaini and Shahandashti, 2020) as well as modeling adoption using simplified approaches based on the adoption of previous studies (Simpson et al., 2019; Simpson and Mishra, 2020).

We identify three important gaps in the domain of adoption of the automated driving technology by trucking firms:

1. The literature on the overall perceptions about the technology is still immature and requires further research. We conduct a survey and collect data that help us better understand the overall perceptions about CATs. Due to the difficulty in reaching out to freight companies and asking for their opinions about the automated driving technology, such insights are a valuable

and important addition to the literature.

2. While a wide set of choice models are employed to understand preferences for passenger automated vehicles, an application that uses real-world data to elicit the preferences of trucking firms is absent from the literature. We develop choice models to identify drivers of CAT adoption and shed light on the extent to which these drivers impact firms' decisions regarding CAT adoption. We attempt to explore if and how adoption drivers change with the technology cost.
3. The theory of Diffusion of Innovations (DOI), a widely used theory for explaining the adoption of new technologies, suggests that the percentage of the population that adopts over time typically follows a bell-curve curve and adopters are broadly categorized into the five groups of *Innovators*, *Early Adopters*, *Early Majority*, *Late Majority*, and *Laggards.* However, there has been no research attempting to understand if CAT adoption will involve the same number of categories and if the sizes of CAT adopter categories will be the same as those suggested in DOI. We perform latent class cluster analysis (LCCA) to conjecture about the number of categories of CAT adopters as well as the sizes of the clusters. This piece of information could be of help to policymakers to better prepare for the future by prioritizing infrastructure investments taken into consideration the overall process of adoption.

In conclusion, it should be highlighted that data availability and quality are the main constraints preventing us from applying more advanced methodologies. This said, this paper is the first of its kind to analytically explore the decision to use the automated driving technologies at the firm-level and offer original insights into the overall process of CAT adoption.

3. Survey Design and Results

3.1. Descriptive Statistics

There are roughly 900,000 for-hire carriers in the United States, according to the American Trucking Association (2020). Of those companies, 91.3% operate six or fewer trucks, and 97.4% operate fewer than 20 trucks. 7.8 million individuals are employed in jobs that involve trucking activities, and 3.5 million people are employed as truck operators. While it would be ideal to survey the entire population to obtain the most accurate dataset, it is rarely a feasible option. The dataset used in this research is obtained through a national stated-preference survey sent to over 2,500 trucking companies in the US. We hired a market research company to collect the responses. Initially, we received 416 responses. Incomplete survey responses and quick response time are considered as two criteria in the data hygiene process. A total of 16 observations were eliminated in the data cleaning process leaving 400 observations for the modeling process.

The survey includes five blocks. The first block includes a short description of the survey. Figure 2 (left-hand panel) shows a snapshot of the welcome page of the survey on a smartphone. The second block includes questions about participants' socioeconomic characteristics like age, educational attainment, and employment duration with the existing trucking firm. The third block includes questions that relate to the participant's trucking company. Participants are asked about the number of employees, number of power units, business region, market coverage, type of cargo transported, annual mileage of trucks, and their perceptions toward their respective company's policies. The fourth block introduces autonomous trucks to the participants, followed by a set of questions attempting to elicit companies' perceptions toward different anticipated characteristics of CATs including the associated risks, cost-effectiveness, and performance comparison with the conventional trucks. Finally, in the fifth block, the participants are shown an infographic about the five different levels of automation (SAE On-Road Automated Vehicle Standards Committee, 2018). The participants are then presented with four stated preference scenarios to capture their companies' willingness to adopt different fleets with varying costs of automated technologies.[1] Scenario 1 is the most expensive, and Scenario 4 is the least expensive. In Scenario 1, the price of automation Level 2 is $10,000, and the price increases by $10,000 for each higher level. The additional price of the highest level of automation would then be $40,000, which is consistent with the literature (Bansal and Kockelman, 2017; Talebian and Mishra, 2018; Loeb and Kockelman, 2019; Rashidi et al., 2020). Similarly, for Scenario 2, the price of automation Level 2 is $7,500, and the price increases by $7,500 for each higher level of autonomous fleet. In Scenarios 3 and 4, the price of automation Level 2 are $5,000 and $2,500, and the prices of higher levels of autonomous fleet are determined the same as in Scenarios 1 and 2. In all four scenarios, the base scenario pertains to regular vehicles which encompasses both SAE Levels 0 and 1 considering the fact that almost all brand-new trucks are now equipped with major advanced driver-assistance systems. Figure 2 (right-hand panel) shows Scenario 4 of the choice experiment's snapshot delineating different fleets' capabilities and price.

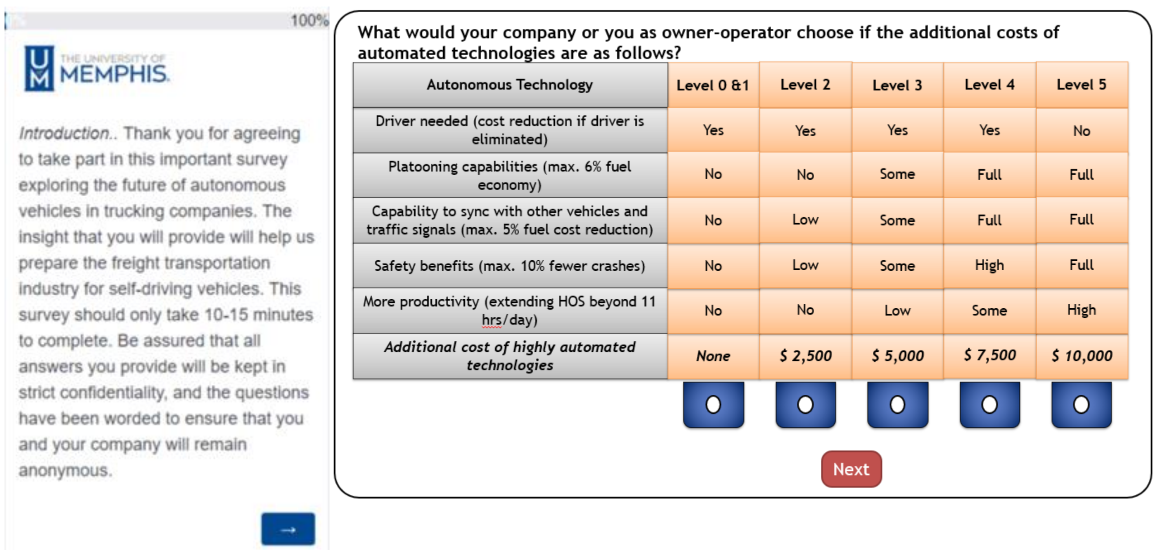

Figure 2: A snapshot of the survey welcome page on a smartphone (left-hand panel) and choice experiment page (right-hand panel)

3.2. Descriptive Statistics

Descriptive statistics of the categorical variables, covering the companies' socioeconomic and operational characteristics, are presented in Table 1. An effort is made to ensure that the responses are not skewed toward large or small companies, thereby company-size responses are relatively symmetric. Approximately 36% of responses are from small-sized companies, whereas mid-sized and large companies contributed to an almost equal proportion of responses (32%). The majority of company representatives are aged between 35 and 55 years (57%). Approximately 34% of the representative had at least a bachelor's degree. About 32% of representatives are working with their respective companies for the past 6 to 15 years. About 36% of the companies had less than 50 trucks or power-driven units, 41% had a nationwide presence, 35% of companies' trucks' average trip length is less than 200 miles, and about 36% of trucks have an annual mileage between 100,000 to 200,000 miles. Most companies are involved in machinery/electronics, construction material, and foodstuffs, whereas only 5% are involved in transporting live animals. Approximately 60% of companies do their

[1] While having multiple increments on the base price provides more price variability, we consider four levels to limit the time required to complete the survey and avoid compromising data quality.

business in the Midwest US, while about 4% conduct business outside the US. The majority of the companies (76%) own truck fleet, whereas 30% contract trucks from other companies. About 31% of companies have members advocating for autonomous vehicles.

Table 1: Descriptive statistics of the survey results: categorical variables (N= 400)

Variable	Percentage	Variable	Percentage
Age		Types of cargo transported	
Under 25 years	5.0	Live Animals	5
26-30 years	9.5	Foodstuffs	46
31-35 years	10.3	Construction Material	49
36-40 years	16.8	Fuels	15
41-45 years	13.8	Chemicals	27
46-50 years	13.5	Textiles	33
46-50 years	11.8	Machinery/Electronics	49
56-60 years	9.8	Motorized Vehicles	27
More than 61 years	9.8	Waste/Scrap Metals	22
Education		Other	18
Ed. cat. 1- High school or below	22.0	Market coverage	
Ed. cat. 2- Some college	20.5	Local	16
Ed. cat. 3- Associate's degree	14.0	Regional	28
Ed. cat. 4- Bachelor's degree	25.5	National	41
Ed. cat. 5- Graduate degree (Masters' or Doctorate)	7.8	International or Global	15
Ed. cat. 6- Trade, technical, or vocational training	10.3	Region of business*	
Employment duration		Northwest	37.5
Less than one year	8.3	Northeast	47.5
1 to 2 years	17.8	Midwest	55.5
3 to 5 years	23.3	South	59.8
6 to 10 years	19.3	Southwest	44.5
11 to 20 years	12.8	Individuals promoting/advocating for autonomous trucks in the near future	
Over 21 years	18.8	Yes	31.8
Company's size: number of employees/drivers		No	68.2
1-10	14.3	Number of power units	
11-50	21.5	1-10	17.8
51-100	16.0	11-50	22.8
101-250	7.5	51-100	16.8
251-500	9.0	101-250	9.5
501-1000	10.0	251-500	6.8
1001-2500	6.3	501-1000	7.8
Over 2500	15.5	1001-2500	5.8
Truck ownership status		Over 2500	13.0
Own	75.8	Annual mileage of Trucks	
Rent	23.5	Less than 50,000 miles	7.5
Contract	29.3	50,000-99,999 miles	24.5
Average trip length of Trucks		100,000-149,999 miles	19.8
0-50 miles	7.8	150,000-199,999 miles	16.3
51-200 miles	27.8	200,000-299,999 miles	12.3
201-500 miles	33.8	300,000-399,999 miles	7.8
Over 500 miles	30.8	Over 400,000 miles	12.0

Notes: * US states are grouped into five regions according to their geographic position in the Contiguous US. The Northwest region includes Washington, Oregon, Montana, Idaho, and Wyoming. The Southwest region includes California, Nevada, Utah, Arizona, Colorado, and New Mexico. The South region includes Texas, Oklahoma, Arkansas, Louisiana, Mississippi, Alabama, Tennessee, Kentucky, Georgia, Florida, North Carolina, South Carolina, Virginia, West Virginia, Maryland, and Delaware. The Midwest region includes North Dakota, South Dakota, Nebraska, Kansas, Minnesota, Iowa, Missouri, Wisconsin, Illinois, Indiana, Michigan, and Ohio. The Northeast region includes Pennsylvania, New Jersey, New York, Connecticut, Massachusetts, Rhode Island, Vermont, New Hampshire, and Maine.

Nationwide estimates for some variables in Table 1 are adopted from the 2002 Vehicle Inventory and Use Survey (VIUS) (US Census Bureau, 2004) and Census Current Population Survey (US Census Bureau, 2021) and presented in Table 2. While we use the latest version of the VIUS survey, the current statistics could be different. It should be noted that as all measures are expressed in terms of percentage, it would be reasonable to expect minor differences given that the industry has not fundamentally. We also note that person-level statistics are associated with all occupations in the transportation and material moving industry.

Table 2: Nationwide statistics for selected variables

Variable	Percentage	Variable	Percentage
Market coverage		Average trip length of Trucks	
High school or below	60.51	50 miles or less	53.3
Some college	20.71	51 to 100 miles	12.4
Associate's degree	5.34	101 to 200 miles	4.4
Bachelor's degree	9.81	201 to 500 miles	4.2
Graduate degree (Masters' or Doctorate)	3.45	501 miles or more	5.3
Trade, technical, or vocational training	0.17	Off-the-road, not reported, NA	20.4
Age		Types of cargo transported	
Under 25 years	13.29	For hire transportation or warehousing	18.5
26-30 years	12.64	Vehicle leasing or rental	5.6
31-35 years	11.02	Agriculture, forestry, fishing, or hunting	14.4
36-40 years	10.48	Mining	1.6
41-45 years	10.47	Utilities	3.4
46-50 years	9.84	Construction	18.6
46-50 years	11.09	Manufacturing	4.1
56-60 years	10.15	Wholesale trade	5.2
More than 61 years	11.01	Retail trade	6.5
Primary Operator Classification		Waste management	5.3
Own	71.4	Services (Arts, entertainment, etc.)	5.5
Rent	17.7	Others, not reported, NA	11.4
Other, NA	10.9	Medium/Heavy Truck Registrations*	
Market coverage		Midwest	30.26
Operated within the home base state (i.e., local)	76.0	Northeast	12.81
		Northwest	6.08
Other, not reported, NA	24.0	South	37.57
		Southwest	13.28

Notes: *This variable is presented as a proxy for the region of business. NA: Not Applicable.

Table 3 describes the attitude questions asked in the survey and Table 4 delineates descriptive statistics for these questions. Companies are asked to respond to questions on a 7-point Likert scale (1 being strongly agree and 7 strongly disagree). The last two columns in Table 4 delineate the mean and standard deviation of the responses. Overall, most companies have specialized skill sets, directed by small groups of leaders and value established practices over innovations. Companies favor testing first-generation CATs over partial and full adoption when available in the market. Most companies believe that CATs will be more complicated, unaccountable (in terms of liability), riskier (financially and physically), and expensive than conventional trucks. The companies have mixed opinions toward governmental regulations toward their decision to adopt CATs. While automotive companies and various public sector agencies have been making significant advancements to the development of CAV technologies for commercial vehicles, the United States Congress has not yet passed comprehensive legislation governing AV operation for either passenger or commercial vehicles, various State Departments of Transportation (DOTs) have developed guidelines in registration, operation and legislation. This could contribute to the mixed opinions toward governmental regulations. DOTs play a crucial role in operation, and maintenance of various aspects of the transportation infrastructure, the regulatory environment at the state level may in fact be the most important element in facilitating the adoption of CAV technologies for commercial vehicles. While the literature governmental regulation of passenger CAV is somewhat studied (Bartolini et al., 2017; Brodsky, 2016; Claybrook and Kildare, 2018; Geistfeld, 2017; Ilková and Ilka, 2017; Smith and Svensson, 2015) the commercial vehicle CAVs are scarce. The majority of companies are not completely familiar with the CATs and would not be prepared to implement them into their existing fleet. Most companies believe that their competitors will adopt first, and such competitors will not influence the companies' decision to adopt or reject CATs.

Table 3: Definition of attitude variables

Category	Variable	Definition
Managerial attributes	Opin1	Most of the employees in my company tend to have very specialized skill-sets that enable them to perform specific tasks
	Opin2	My company is primarily directed by a small group of leaders with a well-established chain of command
	Opin3	My company values the stability of established practices or technologies more than it values innovation
Implementation and testing	Opin4	My company would be likely to purchase or contract with at least one autonomous truck for experimentation
	Opin5	My company would be likely to begin replacing trucks at the end of their lifespan with autonomous trucks instead of conventional models
	Opin6	My company would be likely to begin converting its working fleet to autonomous trucks
	Opin14	My company is prepared to implement autonomous trucks into its fleet once they are made commercially available
Attitudes toward the automated driving technology	Opin7	My company would consider autonomous trucks to be better than conventional truck models
	Opin8	My company would consider autonomous trucks to be more complex to operate or maintain than conventional truck models
	Opin9	My company would believe that autonomous trucks are more likely to cause collisions or injuries than conventional truck models
	Opin10	My company would consider investing in autonomous trucks to be a greater financial risk than conventional truck models
	Opin11	My company would be less likely to adopt autonomous trucks because of concerns about liability in case of collisions
	Opin12	My company would consider autonomous trucks to be more cost-effective than conventional truck models
	Opin13	Members of my company are very familiar with autonomous vehicle technology
	Opin15	Current governmental regulations would encourage my company to adopt autonomous trucks

Table 4: Descriptive statistics of the survey results: Opinion-related Likert scale variables (N =400)

Variable	Likert Scale levels: Strongly agree (1) to Strongly disagree (7)							Mean	SD.
	1	2	3	4	5	6	7		
Opin1	25%	39%	22%	10%	3%	1%	1%	2.33	1.17
Opin2	28%	36%	20%	8%	5%	2%	1%	2.35	1.28
Opin3	18%	27%	19%	23%	9%	3%	1%	2.92	1.43
Opin4	13%	22%	17%	17%	11%	8%	12%	3.64	1.91
Opin5	8%	14%	17%	23%	14%	10%	15%	4.08	1.82
Opin6	8%	12%	15%	23%	16%	13%	15%	4.21	1.81
Opin7	44%	16%	10%	30%	0%	0%	0%	2.25	1.29
Opin8	14%	19%	27%	24%	10%	4%	4%	3.24	1.51
Opin9	12%	15%	19%	35%	13%	4%	3%	3.44	1.45
Opin10	14%	18%	20%	31%	8%	6%	5%	3.37	1.57
Opin11	20%	22%	24%	20%	9%	4%	2%	2.97	1.50

Variable	Likert Scale levels: Strongly agree (1) to Strongly disagree (7)							Mean	SD.
	1	2	3	4	5	6	7		
Opin12	8%	14%	21%	29%	15%	6%	8%	3.75	1.59
Opin13	5%	13%	14%	28%	14%	14%	12%	4.24	1.69
Opin14	8%	11%	15%	35%	10%	12%	10%	4.01	1.66
Opin15	8%	11%	12%	26%	12%	14%	18%	4.37	1.83

4. Methodological Background

In this study, we use multinomial logit choice modeling and latent class cluster analysis to characterize CAT adoption. [2] In the next few paragraphs, we briefly discuss the methodology underlying each technique.

Focusing on discrete choice modeling, the basic principle is that each firm is faced with a set of options (i.e., different levels of automation), from which it selects only one. Each firm realizes a utility when selecting a certain alternative. Firms are rational and prefer the alternative yielding the highest utility. Suppose that firm i chooses alternative (i.e., automated truck level) k, the firm receives $U_{ik} = V_{ik} + \varepsilon_{ik}$ in utility, where V_{ik} is the observable (or deterministic) utility associated with the alternative's features as well as firm's characteristics, and ε_{ik} random utility accounting for the unobserved characteristics. The deterministic part is given by $V_{ik} = \mathrm{x}_{ik}\beta^T$, where x_{ik} is the vector entailing the attributes of firm i and automated truck level k and β the vector of unknown parameters. Firm i prefers automated truck level k to l if $U_{ik} > U_{il}$. Assuming independent and identically distributed error terms each following Gumbel distribution, the probability of choosing automated truck level k by firm i (i.e., p_{ik}) is given by $P_{ik} = \frac{e^{V_{ik}}}{\sum_{j \in A_i} e^{V_{jk}}}$, where A_i is the set of alternatives available to firm i. In our application, all firms have the same set of alternatives which means that all levels of automation are available to all firms. Our job is to estimate the vector of parameters, i.e., β, based on stated or revealed preferences data. This is typically done using the Maximum Likelihood Estimation (MLE) method.

Turning to LCCA, the technique's main assumption is that there exist C segments in the population of firms. The latent classes are exhaustive and mutually exclusive. LCCA probabilistically assigns firms to clusters; thus, measurement error is accounted for. This is in contrast to the conventional cluster analysis which deterministically assigns observations to a single cluster thereby ignoring the potential of misassignment to a wrong cluster. Furthermore, LCCA does not rely on the distance between each pair of observations, unlike traditional clustering methods such as K-means (Mohamed et al., 2013; Behnood et al., 2014). Another advantage of LCCA is that different variable types including counts, continuous, categorical, and nominal variables can be utilized in the analysis without any standardization (De Oña et al., 2013; Depaire et al., 2008). Compared to hierarchical clustering techniques, LCCA is not memory-intensive enabling us to develop models from large datasets (Brijs, 2002). The overall procedure of model estimation in LCCA is as follows. A class membership function

[2] An alternative approach is to use latent class choice modeling (LCCM) to answer research questions. Our modeling efforts, however, show that LCCM approach does not offer meaningful results. We speculate that the sample size is the primary reason for this. Application of LCCM to better understand CAT adoption is left for future research. That would definitely hinge upon availability of high-quality rich datasets. We also note that we have examined two nest structures in our modeling effort. In the first structure, regular truck is in nest A and automated driving technology Levels 2-5 are in nest B. In the second structure, regular truck is in nest A, Levels 2 and 3 are in nest B, and automated driving technology Levels 4 and 5 are in nest C. Scrutinizing the results of each structure in each scenario, we found no statistically-significant nesting.

is inferred from a set of observed variables. LCCA computes the probability of each individual observation belonging to each cluster and ultimately labels each observation with the cluster number having the highest probability (Sasidharan et al., 2015).

Latent class cluster model in its basic version has the form of $f(\mathbf{y}_i|\boldsymbol{\theta}) = \sum_{c=1}^{C} \pi_c\, f_k(\mathbf{y}_i|\theta_c)$, where C is the number of clusters, θ the model parameters, $\mathbf{y}_i$ a firm's scores on the set of observed variables (also called indicators, outcome variables, or endogenous variables), and π_c the prior probability of firm i belonging to latent cluster c. The latter would essentially be the size of cluster c. Given θ, the distribution of $\mathbf{y}_i$, i.e., $f(\mathbf{y}_i|\theta)$, is a mixture of class-specific densities denoted by $f_c(\mathbf{y}_i|\theta_c)$. Here, a common assumption is that indicators are continuous variables normally distributed within latent classes. The basic model can be extended by allowing nominal, ordinal, or count variables to serve as indicators. In that case, the generalized form of latent class cluster model mixing $\mathbf{y}$s is $f(\mathbf{y}_i|\theta) = \sum_{c=1}^{C} \pi_c \prod_{j=1}^{J} f_c(y_{ij}|\theta_{jc})$, where J is the total number of indicators, and j a particular indicator. Note that this model does assume local independence. Here, instead of using a single multivariate distribution, an appropriate univariate distribution function for each y_{ij} is specified. Normal Gaussian distribution, multinomial distribution, adjacent-category ordinal logistic regression, and Poisson distribution are typically used for continuous, nominal, ordinal, and count variables, respectively. Ultimately, the set of parameters (i.e., θ) is estimated using an expectation maximization method (Depaire et al., 2008; Lanza and Rhoades, 2013; Vermunt and Magidson, 2002).

We face a couple of challenges when conducting LCCA. The first is that *a priori* we are unaware of the right number of unobserved classes. To address this, it is recommended to develop multiple models with different numbers of classes and choose the one yielding the lowest Bayesian Information Criterion (BIC). Overall, the classes should be interpretable and meaningful. For example, an *n*-class model may be preferred to an (*n*+1)-class model if the (*n*+1)-class model involves a cluster that is too small, i.e., contains a very small number of firms (Bae et al., 2017; Lee et al., 2019). The second challenge revolves around the selection of appropriate variables for the class membership function. Swait (1994) suggests including attitude-related variables as well as socioeconomic attributes of respondents in the membership model.

5. Results and discussions

5.1. Multinomial Choice Modeling

This section presents our modeling results aiming to shed light on determinants of autonomous technology adoption by freight firms. Examining various specifications of choice models, we find that models with generic variables are mostly uninterpretable with insignificant coefficients and very low goodness-of-fit measures. Table 5 presents the most meaningful alternative-specific MNL model for the Highly Expensive scenario (Scenario 1). We also run this model for the other levels of the additional price of automated trucks, i.e., Scenarios 2, 3, and 4, to investigate if the variables contributing to the likelihood of adoption remain statistically meaningful. Variables included in the model intent to capture (i) respondent-related, (ii) company-related, and (iii) alternative-varying attributes. The additional cost of autonomous technology is the only variable that is found to offer a better fit if considered as a generic variable. Focusing on the Highly Expensive technology scenario, several important observations are made:

i. The respondent's age has negative coefficients for Levels 3, 4, and 5 that are significant at 99%, 99%, and 85% levels. This makes sense as age is broadly known to negatively correlate with an individual's innovativeness (Khan and Manopichetwattana, 1989; Lambert-Pandraud and Laurent, 2010). The coefficient for Regular trucks is positive and significant at 85% level. This positive sign is also intuitive as older individuals tend to stick to the established routines and day-to-day existence. The coefficient for automation Level 2 is also positive but insignificant. This may suggest that the individuals see the Level 2 of automation more of regular truck. We observe positive coefficients for all three less expensive technology cost scenarios augmenting our inference.[3]

ii. The results suggest that individuals' education plays a role in describing the decision to adopt; however, different levels of education appear in the utility functions of different alternatives. Interestingly, possession of a graduate degree, including MSc and PhD, has no statistically meaningful impact on adoption. Having an Associate's degree, professional degree, trade, technical, or vocational training, on the other hand, positively impacts the likelihood of adoption.

iii. As expected, the additional cost of the technology has a negative coefficient significant at 90% level suggesting that the more expensive the technology, the lower the propensity of firm adoption.

iv. The variables pertaining to owning and contracting trucks have negative coefficients but are significant only for Regular trucks. This is consistent with our intuition. Overall, whether an alternative could elevate economic productivity is among the top factors informing decision-making at the firm-level. CATs have certain potentials allowing trucking firms to improve profitability. Thus, companies already having regular trucks are expected to seek more cost-effective alternatives and are less likely to purchase the existing technology again. Likewise, companies contracting truckers are less likely to go with Regular trucks.

v. Some variables associated with the region of operation are significant predictors of technology adoption. Operating in the US South region is only significant for Regular trucks which can be related to the traditionally conservative practices in the Southern states. On the other hand, companies operating in Midwestern and Northwestern states are more likely to adopt the highest level of autonomous technology.

vi. Not surprisingly, "having promoters of new technologies in the company" is a variable that is significant for all levels of automation and in different scenarios of the technology additional cost. Also, the coefficient increases, but not monotonically, with the technology level suggesting that the impact of having such promoters on the propensity of adoption is greater for higher levels of automation.

vii. Overall, we find a minor impact of cargo type on adoption likelihood considering that transporting foodstuffs appears in the utility function of automation Level, 3 and waste materials is only significant for level 2. The positive coefficient for foodstuffs can be interpreted fairly reasonably. In general, food is a perishable good; thus, the 11-hour driving limit poses a major restriction to the food transportation industry, and the technology helping relax this constraint is favored.

viii. The number of power units is the only significant variable elucidating the adoption impact of firm size. Recall from our previous observations that Level 2 is viewed not significantly different than Regular trucks. The negative sign of the variable "Number of trucks below 100" in the utility function of automation Level 2 indicates that small- and medium-sized companies are less likely to adopt this level of technology. Indeed, a full transformation of the fleet to high levels of autonomous technology would be extremely costly; thus, it is expectable that large companies retain their existing fleet (at least at the early stages of introduction of the technology). On the

[3] While age is a continuous variable in the real-world, we were not able to ask a respondent's age in our survey, mainly due to privacy concerns that individuals have. Considering that we have relatively short age categories, we assign each individual with a random age to ease the modeling procedure. This is done by drawing a random number from the uniform distribution defined on the interval to which the individual belongs.

other hand, the positive sign of the variable “Number of drivers below 50, in the utility function of Level 5 refers to the higher likelihood of adoption of this alternative by small-sized companies.

As Table 5 indicates, the model that is fitted to the Highly Expensive scenario is not suitable for the other three scenarios as they offer much lower goodness-of-fit measures as well as several insignificant and counter-intuitive coefficients. This implies that the set of variables describing the adoption decision hinges upon the technology price level. To further investigate this, we develop a set of models that best-fit Expensive, Slightly Expensive, and Least Expensive cost levels, i.e., Scenarios 2, 3, and 4, respectively. Table 6 presents our modeling results. We observe the following points:

i. Age has positive signs for the Regular truck alternative across all three scenarios but the coefficient in the Least Expensive scenario is insignificant. We observe similar signs for this variable with the Level 2 alternative. These are in-line with our previously-made observations indicating that the Level 2 is viewed as an innovation not significantly different from the existing technology. The variable is significant in Expensive and Slightly Expensive scenarios for both alternatives. In each of the latter two scenarios, as well as in the Highly Expensive Scenario, the coefficient for Level 2 is smaller than that for Regular trucks which shows the lower positive impact of age on the adoption of Level 2 trucks, compared to Regular trucks. Age’s sign follows our expectation in all three scenarios for Levels 3-5 of the technology, except in the Slightly Expensive scenario with Level 3 where we see a positive coefficient significant at 90% level.

ii. The respondents’ education levels still play a role. In particular, the Associate’s degree has the highest frequency of appearance in the utility functions of different alternatives. Still, a graduate degree seems to have no major impact on individuals’ stated preferences.

iii. The impact of employment history is the same as what we observed previously. Those hired recently express that their companies are less likely to go with the higher levels of automation.

iv. Firm size plays a different role if the technology price level reduces, i.e., we move from the Highly Expensive scenario to other scenarios. Particularly, there exists an indication that large firms may also show an interest in the highest level of automation. This is not counter-intuitive. With the technology becoming less expensive, even large firms could manage to change their fleet to autonomous.

v. The additional cost of automation has a positive sign in two scenarios but both are insignificant.

vi. The variable indicating presence of promoters of innovative technologies remains highly significant across all scenarios. Also, the coefficient value increases with the technology level, and this happens in all three scenarios.

vii. The variable referring to owing vehicles remains significant for Regular trucks in all three scenarios reinforcing the conclusion that firms owning a fleet are less likely to adopt Regular trucks. The impact of the variable Contract is the same as what we observed previously. The impact on the adoption of regular trucks of the variable Contract is always smaller than that of the variable Own.

viii. The negative signs of average truck daily mileage below 200 and annual mileage below 200k could mean that in general, mileage positively influences the adoption propensity of alternatives: the lower(higher) the mileage, the lower(higher) the likelihood of adoption.

ix. We observe that different geographical variables appear in the utility functions of different alternatives in the four cost scenarios. Southwest and Northeast are the most frequent variables. It can be inferred that companies working in the Northeast region are more likely to adopt higher levels of the automated technology.

x. Cargo type also plays a role. In particular, it seems that companies transporting live animals are less likely to adopt the higher levels of the technology. As in the Highly Expensive scenario, transporting foodstuffs positively impacts the propensity of adoption of the technology.

Table 5: Coefficient estimates with multinomial logit choice model in the four scenarios of price

Level	Variable	Highly Expensive		Expensive		Slightly Expensive		Least Expensive	
		Coefficient	t-test	Coefficient	t-test	Coefficient	t-test	Coefficient	t-test
Regular	Age	0.0147	1.61	0.0641	7.63	0.0184	2.31	0.0023	0.283
	Own	-0.98	-3.31	-0.652	-2.2	-0.665	-2.26	-0.733	-2.33
	Contract	-0.581	-1.95	-0.465	-1.57	-0.47	-1.62	-0.47	-1.53
	South	0.553	2.14	0.304	1.19	0.0857	0.332	0.0544	0.201
Level 2	Constant	-0.749	-1.17	-0.471	-0.73	-0.651	-0.928	-1.62	-2.12
	Age	8.25E-3	0.847	0.0495	5.1	0.00456	0.41	1.52E-4	0.0134
	Employed- 2 years	0.679	2.37	-0.0215	-0.0701	-0.0166	-0.0514	-0.0153	-0.0433
	Some college credit	0.708	2.41	0.0284	0.0892	-0.458	-1.21	0.0852	0.236
	PUs below 100	-0.656	-2.4	-0.119	-0.416	-0.0237	-0.0778	-0.265	-0.796
	Ann. mil. below 100k	0.49	1.7	0.146	0.507	0.453	1.52	0.594	1.8
	Promoters	1.87	4.11	1.59	3.15	1.18	2.32	2.85	4.67
	Waste	0.547	1.82	0.356	1.08	0.226	0.628	-0.213	-0.482
Level 3	Constant	1.1	1.99	0.268	0.545	-0.462	-0.907	0.565	1.03
	Age	-0.0375	-3.74	0.0262	2.87	-0.00762	-0.815	-0.0322	-3.24
	Associate's degree	0.863	2.57	0.636	1.94	0.83	2.52	0.38	1.12
	Promoters	2.19	4.95	2.61	5.66	2.17	4.84	2.69	4.57
	Foodstuffs	0.524	2.03	0.219	0.885	0.549	2.21	-0.252	-0.96
	Southwest	0.596	2.27	0.303	1.22	0.31	1.24	-0.387	-1.43
Level 4	Constant	1.97	3.61	0.475	0.889	0.615	1.55	0.325	0.802
	Age	-0.051	-4.73	0.0164	1.47	-0.0206	-2.35	-0.0277	-3.12
	Promoters	3.07	6.69	2.58	5.3	2.15	4.82	2.37	4.08
Level 5	Constant	-1.75	-3.15	-0.135	-0.267	-0.0674	-0.177	0.0119	0.0296
	Age	-0.0201	-1.44	0.00242	0.2	-0.0253	-2.59	-0.0309	-3.4
	Employed-10 years	1.3	2.49	0.616	1.43	0.259	0.794	0.0491	0.174
	Education cat. 6	1.28	2.78	0.377	0.725	-0.271	-0.465	0.146	0.35
	Drivers below 50	0.963	2.31	-0.164	-0.418	-0.237	-0.674	0.0572	0.209
	Promoters	2.81	5.04	2.66	5.07	2.51	5.24	3	5.17
	Midwest	0.864	2.01	-0.0249	-0.0676	0.281	0.816	0.204	0.706
	Northwest	0.962	2.33	0.916	2.56	0.292	0.855	0.453	1.6
Generic	Add'l cost	-4.07E-05	-1.78	2.61E-06	0.0928	-6.12E-06	-0.163	-1.40E-05	-0.182
		Final LL: -527.69		Final LL:-566.17		Final LL:-586.29		Final LL:-592.32	
		ρ^2: 0.18	$\bar{\rho}^2$: 0.134	ρ^2: 0.121	$\bar{\rho}^2$: 0.0739	ρ^2: 0.0893	$\bar{\rho}^2$: 0.0427	ρ^2: 0.0799	$\bar{\rho}^2$: 0.0333
		AIC: 1115.39	BIC: 1235.13	AIC:1192.35	BIC:1312.09	AIC:1232.59	BIC:1352.33	AIC:1244.64	BIC:1364.38

Notes: Education category 6 includes professional degree, trade, technical, or vocational training. PU: Power Unit. Employed-X years: Employed in the past X years

Table 6: Coefficient estimates for multinomial logit choice models that best fit Scenarios 2, 3 and 4

Level	Expensive			Slightly Expensive			Least Expensive		
	Variable	Coefficient	t-test	Variable	Coefficient	t-test	Variable	Coefficient	t-test
Regular	Age	0.0567	6.77	Age	0.0331	4.09	Age	0.00977	1.14
	Own	-0.672	-2.24	Own	-0.684	-2.26	Some high school	0.713	2.37
	Contract	-0.412	-1.4	Contract	-0.469	-1.56	Daily mi. below 200	-0.499	-1.84
	Northwest	-0.559	-2.13	Daily mi. below 200	-0.722	-2.63	Own	-0.53	-1.78
							Transport	0.421	1.33
Level 2	Constant	-0.702	-1.22	Constant	-1.02	-1.58	Constant	-0.831	-1.17
	Age	0.0413	4.48	Age	0.0178	1.69	Age	0.00849	0.769
	Promoters	1.78	3.55	Some high school	0.473	1.4	Associate's degree	-1.6	-2.08
	National	-0.608	-2.16	Education cat. 6	0.802	1.95	Promoters	2.95	4.91
				Promoters	1.31	2.6	Machinery	-0.46	-1.47
							Northeast	-0.464	-1.41
Level 3	Constant	-0.0692	-0.145	Constant	-0.353	-0.686	Constant	0.633	1.24
	Age	0.0169	1.83	Age	0.00859	0.909	Age	-0.0243	-2.47
	Associate's degree	0.628	1.91	Associate's degree	0.624	1.86	Bachelor's degree	-0.489	-1.5
	Promoters	2.74	6.01	Daily mi. below 200	-0.636	-2.12	Promoters	2.89	4.91
	Animals	-1.38	-1.97	Promoters	2.15	4.81			
	Fuels	0.492	1.54	Foodstuffs	0.579	2.29			
Level 4	Constant	0.0104	0.0201	Constant	0.419	1.03	Constant	0.0195	0.0479
	Age	0.00865	0.772	Age	-0.00535	-0.602	Age	-0.0206	-2.25
	Promoters	2.66	5.48	Some high school	-0.868	-2.23	Contract	-0.499	-1.63
	Northeast	-0.532	-1.8	Promoters	2.39	5.2	Promoters	2.69	4.57
				Animals	-1.61	-1.84	Southwest	1.12	4.04
				Midwest	-0.75	-2.69			
				Southwest	1.13	4.13			
Level 5	Constant	0.382	0.807	Constant	0.118	0.311	Constant	-0.0532	-0.144
	Age	-0.00344	-0.289	Age	-0.0181	-1.69	Age	-0.0202	-2.31
	Employed-10 years	0.736	1.84	Employed-2 years	-1	-2.3	Graduate degree	0.808	2.01
	PUs below 100	-0.915	-2.7	Bachelor's degree	0.587	1.87	Promoters	3.02	5.24
	Ann. mi. below 200k	-0.701	-2.1	Promoters	2.5	5.31	Chemicals	0.494	1.84
	Promoters	2.51	4.84	Northeast	0.8	2.65	Regional	-0.541	-1.62
	Waste	-1.03	-2.35				Southwest	0.717	2.59
Generic	Add'l cost	1.65E-05	0.629	Add'l cost	-1.63E-05	-0.439	Add'l cost	1.33E-05	0.183
	Final LL: -555.59	ρ^2: 0.137	$\bar{\rho}^2$: 0.0966	Final LL: -562.84	ρ^2: 0.126	$\bar{\rho}^2$: 0.0807	Final LL: -570.4	ρ^2: 0.114	$\bar{\rho}^2$: 0.0705
	AIC: 1163.18	BIC: 1266.96		AIC: 1183.68	BIC: 1299.43		AIC: 1196.82	BIC: 1308.58	

It is also interesting to take a look at elasticity values as they are unitless and can be interpreted in a straightforward manner. To be able to compare elasticities of different levels of automation, we only explore the three variables of age, cost, and Promoters which refers to having promoters of new technologies in the company (Table 7). Elasticities are examined for the Highly Expensive scenario (Scenario 1) because the three variables are all statistically significant only in this scenario. Focusing on the elasticity with respect to the additional cost of automation, we observe that the probability becomes more elastic with the technology level which is intuitive. The higher levels of automation are already more budget-intensive than the lower levels and it would not surprising to see a higher amount of reduction in the adoption probability in response to an increase in the cost of automation. The absolute values of the elasticity measures are also in a reasonable range. Turning to the elasticity with respect to the age variable, the positive elasticity for Level 2 is consistent with our previous findings suggesting that trucking firms view this technology level more of regular trucks. We expect to see an increase in the absolute value of elasticity because a positive attitude about the higher levels of automation requires a more tech-savvy attitude which is commonly seen to negatively correlate with age. The elasticity measure for Level 5, however, does not follow our expectation but it should be also recalled that the corresponding coefficient is statistically-significant only at 85.1% level. A similar trend is anticipated for the Promoters variable but the sign of the measure for Level 3 as well as the value of elasticity for Level 5 seem to be counter-intuitive.

Table 7: Elasticity of choice probabilities with respect to selected variables in Scenario 1

Model elasticity	Autonomous driving technology level			
	Level 2	Level 3	Level 4	Level 5
Elasticity of the probability with respect to cost	-0.2914	-0.5918	-0.8885	-1.331
Elasticity of the probability with respect to age	0.7397	-0.9457	-1.234	-0.2627
Elasticity of the probability with respect to Promoters	-0.1349	-0.1166	0.4091	0.114

5.2. Latent Class Cluster Analysis

Next, we present our modeling efforts to explore if firms adopting the autonomous driving technology would be categorized into the five well-known groups, as suggested in the Theory of Diffusion of Innovations (Rogers, 2010). As noted above, the optimal number of latent classes is not *a priori*; thus, we first develop latent class clustering models with one to eight clusters and then determine the superior model. Goodness-of-fit measures for these models are presented in Table 8. To perform LCCA, we use a wide set of predisposing and attitude variables. The former includes socio-economic characteristics of respondents (i.e., Age and Education category variables) and company attributes (i.e., average daily mileage) while the latter includes variables explaining overall firm management practices (i.e., Opin2) as well as variables showing firm-level attitudes toward CATs (i.e., Opin8, Opin9, Opin10, Opin11, Opin12, and Opin13). It should also be noted that several other models are developed using other variables but other models are found to offer lower goodness-of-fit measures and very high bivariate residuals. The model with five latent classes has the lowest BIC and therefore is selected for further scrutiny. This number of latent classes is consistent with what the Theory of DOI suggests.

Table 8: Goodness-of-fit statistics for latent class models with one to eight clusters

Model	Npar	LL	L^2	BIC(LL)
1-Cluster	56	-6,574.12	8,360.61	13,483.75
2-Cluster	76	-6,478.51	8,169.40	13,412.38
3-Cluster	96	-6,378.58	7,969.53	13,332.34
4-Cluster	116	-6,316.02	7,844.42	13,327.06
5-Cluster	136	-6,250.63	7,713.62	13,316.09
6-Cluster	156	-6,215.23	7,642.84	13,365.13
7-Cluster	176	-6,199.32	7,611.02	13,453.14
8-Cluster	196	-6,169.72	7,551.81	13,513.77

Notes: Npar refers to the number of parameters estimated in the model

Clearly, by increasing the number of clusters and/or indicators, the number of parameters to be estimated dramatically increases. It is therefore essential to impose restrictions to class-specific variance–covariance matrices in order to achieve a greater level of parsimony and stability (Vermunt and Magidson, 2002). In Table 9, we present multiple pair-wise measures, i.e., bivariate residuals, helping examine the covariance among ten indicators used to find latent clusters. Bivariate residuals follow a Pearson Chi-square distribution divided by the degree of freedom number (Pani et al., 2020). Assuming a significance level of 0.05, bivariate residuals are compared to $\chi^2_{critical}$ = 3.84. All residuals presented in Table 9 are lower than 3.84 indicating that the 5-Cluster model may not fall short in reproducing the association between different pairs of variables.

Table 9: Bivariate residuals for the latent class model with 5 classes

Indicators	Opin2	Opin8	Opin9	Opin10	Opin11	Opin12	Opin13	Age	Ed. cat.	Avg. mil.
Opin2	.									
Opin8	0.019	.								
Opin9	0.041	0.928	.							
Opin10	0.166	0.000	3.080	.						
Opin11	0.638	2.345	1.0E-04	3.351	.					
Opin12	0.049	0.009	0.441	0.011	1.274	.				
Opin13	0.482	0.000	1.031	0.287	2.518	2.110	.			
Age	0.610	0.104	0.368	0.108	0.748	1.199	2.107	.		
Ed. cat.	0.172	1.612	0.222	0.202	0.395	1.133	1.472	1.661	.	
Avg. mil.	1.377	0.792	0.523	0.511	0.776	0.184	0.733	1.127	0.860	.

It is common in LCCA to label the classes. To do so, we take a look at class response percentages within selected attitude variables presented in Table 10. The rationale behind the selection of these variables (i.e., Opin4, 5, 6, and 14) is that they explicitly ask about the likelihood of testing and implementation of the autonomous technology; thus, they can show the general attitude about adoption. To be able to compare luster sizes with the general group categories that DOI suggests, we use the same terminology as in DOI. The clusters' labels are as follows:

- *Cluster-2*: with the lowest mean across all variables, this cluster includes "*Laggards*".
- *Cluster-5*: this cluster has the second-lowest mean across all four variables and is therefore labeled "*Late Majority*".
- *Cluster-1*: we label this cluster "Early Majority" as it has the third-lowest mean across the four attitude variables.
- *Cluster-4*: this cluster consistently scores the second-highest mean; thus, it is identified as "*Early Adopters*".
- *Cluster-3*: we tag this cluster "*Innovators*" considering that we observe the highest means for this cluster across all variables.

Table 10: Class response percentage within selected attitude variables in the model with 5 classes

Variable	Class	Likert Scale levels: Strongly agree (1) to Strongly disagree (7)							Mean	STD
		1	2	3	4	5	6	7		
Opin4: purchase or contract with at least one autonomous truck for experimentation	Class-1	4.09	7.81	12.27	23.05	22.68	22.68	7.43	4.50	1.54
	Class-2	59.57	17.02	12.77	2.13	2.13	6.38	0.00	1.89	1.43
	Class-3	5.41	0.00	0.00	0.00	2.70	43.24	48.65	6.19	1.37
	Class-4	6.06	0.00	0.00	12.12	12.12	24.24	45.45	5.79	1.62
	Class-5	35.71	21.43	21.43	0.00	0.00	7.14	14.29	2.86	2.21
Opin5: begin replacing trucks at the end of their lifespan with autonomous trucks instead of conventional models	Class-1	5.58	10.41	17.47	31.97	19.33	11.15	4.09	3.99	1.45
	Class-2	68.09	12.77	10.64	6.38	2.13	0.00	0.00	1.62	1.05
	Class-3	5.41	2.70	0.00	2.70	13.51	45.95	29.73	5.73	1.52
	Class-4	6.06	0.00	3.03	6.06	24.24	27.27	33.33	5.58	1.58
	Class-5	42.86	28.57	0.00	7.14	7.14	7.14	7.14	2.57	2.06
Opin6: begin converting its working fleet to autonomous trucks	Class-1	6.69	11.90	20.82	31.60	18.22	9.29	1.49	3.77	1.39
	Class-2	61.70	21.28	8.51	4.26	4.26	0.00	0.00	1.68	1.09
	Class-3	5.41	2.70	2.70	0.00	2.70	43.24	43.24	5.95	1.60
	Class-4	6.06	3.03	6.06	3.03	33.33	15.15	33.33	5.33	1.73
	Class-5	42.86	28.57	0.00	14.29	7.14	0.00	7.14	2.43	1.87
Opin14: implement autonomous trucks into its fleet once they are made commercially available	Class-1	8.92	15.99	15.99	34.57	15.61	6.69	2.23	3.61	1.44
	Class-2	74.47	10.64	4.26	6.38	0.00	2.13	2.13	1.62	1.34
	Class-3	0.00	2.70	5.41	5.41	5.41	43.24	37.84	5.95	1.27
	Class-4	9.09	3.03	3.03	12.12	18.18	21.21	33.33	5.24	1.89
	Class-5	35.71	42.86	7.14	14.29	0.00	0.00	0.00	2.00	1.04

In Table 11 below we take a look at class probabilities and how they are compared with adopter categorization suggested by the DOI Theory. LCCA suggests that some 10% of companies would be *Innovators* which is much greater than what the Theory of DOI suggests. DOI and LCCA suggest a relatively comparable size for the *Early Adopters* class. We observe that our estimate for the *Early Majority* is about two times of the amount suggested by the DOI Theory. LCCA, on the other hand, suggests that the *Late Majority* class is far smaller than the DOI's suggestion. It can be inferred that the size of the inflated *Early Majority* group is realized by attracting firms from the *Late Majority* class. Our estimate for the *Laggard* class is also comparable to what we see in the DOI Theory. Overall, we speculate that the CAT adopter distribution may not have a perfect bell-shaped curve but be more of right-skewed. This finding is understandable because CATs bring explicit economic benefits to the trucking industry (Next Big Future, 2019) incentivizing companies to adopt earlier. More specifically, platooning and computerized smoother driving combined can lower fuel consumption by at least 20%, cutting the total operating cost substantially (Andersson and Ivehammar, 2019). Also, driver compensation accounts for 43% of the operating cost of a trucking company (Costello, 2017), which can be partially– or even fully – saved by replacement of regular trucks by Level 5 autonomous trucks. In addition to lower costs, CATs have the potential to boost trucking productivity. For example, it is said that an autonomous truck can travel across the US in 2 days, three days less than regular trucks (Next Big Future, 2019). (i) Major investments of giant logistics firms (i.e., Amazon) on CATs (Data Driven Investor, (ii) significant competition among tech companies and startups (e.g., Waymo, Tesla, Volvo, Embark, TU Simple, Kodiak Robotics, and Starsky) to develop the technology earlier (ATBS, 2018; TTNews, 2021), and (iii) substantial pre-orders of autonomous trucks by sophisticated shippers and carriers (Forbes, 2021) are real-world evidences confirming the enthusiasm of the freight industry to implement the self-driving technology as soon as possible.

Table 11: Class sizes in the latent class model with 5 clusters

Cluster	3	4	1	5	2
Title	Innovators	Early Adopters	Early Majority	Late Majority	Laggards
Size	10.10%	8.20%	66.32%	3.43%	11.95%
Adopter categorization in DOI	2.5%	13.5%	34%	34%	16%

To further understand the characteristics of the latent classes, we inspect class response percentages within some socio-demographic and firm-level variables (Table 12). We notice a clear positive skew in the age of respondents in Cluster 3 (*Innovators*) which is consistent with our previous observation indicating younger individuals are more likely to state that their companies will adopt CATs earlier. Indeed, more than 70% of individuals in Cluster-3 are less than 40 years old. On the other hand, this percentage is only 21.28% for Cluster-2 (i.e., *Laggards*) which is in-line with the nature of the class. Switching to education, we see that the majority of *Innovators* have a graduate degree showing an overall positive impact on the innovativeness of advanced academic studies. On the opposite, *High School Diploma or below* is the most frequent education category among *Laggards* which is not surprising. We also take a look at firm-specific variables. We see that about two-thirds of *Laggards* serve the US South region while only 38% of *Innovators* do so. Also, about 60% of *Innovators* transport foodstuffs, up 25% from *Laggards*. These observations reinforce our previous inference.

Table 12: Class response percentage within socio-demographic and firm-level variables in the model with 5 classes

Variable	Category	Cluster-1	Cluster-2	Cluster-3	Cluster-4	Cluster-5
Age category	Under 25 years	5.58	4.26	5.41	3.03	0
	26-30 years	10.41	2.13	21.62	3.03	0
	31-35 years	9.29	6.38	24.32	12.12	0
	36-40 years	16.73	8.51	18.92	24.24	21.43
	41-45 years	13.01	19.15	18.92	12.12	0
	46-50 years	14.5	19.15	2.7	12.12	7.14
	46-50 years	9.67	23.4	5.41	6.06	42.86
	56-60 years	10.41	6.38	2.7	12.12	21.43
	Over 61 years	10.41	10.64	0	15.15	7.14
Education category	Ed. Cat. 1	23.05	25.53	16.22	15.15	21.43
	Ed. Cat. 2	21.93	21.28	8.11	24.24	14.29
	Ed. Cat. 3	13.38	14.89	13.51	15.15	21.43
	Ed. Cat. 4	27.14	21.28	24.32	24.24	14.29
	Ed. Cat. 5	4.83	2.13	32.43	15.15	0
	Ed. Cat. 6	9.67	14.89	5.41	6.06	28.57
Employment time	Less than 1 year	9.67	10.64	2.7	3.03	0
	1-2 years	18.22	21.28	16.22	12.12	14.29
	3-5 years	23.05	17.02	24.32	36.36	14.29
	6-10 years	18.22	12.77	37.84	12.12	28.57
	11-15 years	11.15	19.15	10.81	15.15	21.43
	16-20 years	9.29	10.64	2.7	12.12	14.29
	21-25 years	4.46	2.13	5.41	3.03	0
	Over 25 years	5.95	6.38	0	6.06	7.14
Ownership	Own	72.49	78.72	86.49	81.82	85.71
	Rent	23.79	8.51	35.14	24.24	35.71
	Contract	32.71	12.77	21.62	39.39	14.29

Variable	Category	Cluster-1	Cluster-2	Cluster-3	Cluster-4	Cluster-5
Avg. daily mileage	0-50 mil.	8.92	12.77	2.7	0	0
	51-200 mil.	29.74	27.66	21.62	21.21	21.43
	201-500 mil.	35.32	21.28	43.24	33.33	21.43
	Over 500 mil.	26.02	38.3	32.43	45.45	57.14
Number of power units	1-10	16.36	27.66	10.81	12.12	42.86
	11-50	23.42	29.79	13.51	24.24	7.14
	51-100	17.84	12.77	16.22	9.09	28.57
	101-250	7.81	6.38	27.03	12.12	0
	251-500	7.06	0	16.22	6.06	0
	501-1000	8.18	4.26	5.41	6.06	21.43
	1001-2500	7.06	4.26	2.7	3.03	0
	Over 2500	12.27	14.89	8.11	27.27	0
Region	Northwest	38.29	42.55	29.73	42.42	14.29
	Southwest	44.24	46.81	32.43	60.61	35.71
	South	62.45	61.7	37.84	69.7	35.71
	Midwest	57.99	48.94	40.54	63.64	50
	Northeast	49.07	51.06	27.03	57.58	35.71
	Outside	1.49	0	2.7	0	0
Cargo type	Animals	4.09	6.38	13.51	3.03	7.14
	Foodstuffs	44.61	34.04	59.46	69.7	28.57
	Construction	46.84	44.68	56.76	69.7	42.86
	Fuels	14.5	12.77	29.73	15.15	7.14
	Chemicals	24.91	25.53	32.43	36.36	21.43
	Textiles	32.34	23.4	40.54	51.52	7.14
	Machinery	47.96	40.43	48.65	66.67	50
	Transport	24.91	17.02	29.73	45.45	14.29
	Waste	21.56	17.02	21.62	27.27	7.14

6. Conclusion

The trucking industry acts as the backbone of the US freight transportation system by not only providing point-to-point services to shippers but also offering access to rail and air transportation systems. Also, VMT increase on highway transportation system has been rising at a rate that is greater than truck fleet size increase rate suggesting that the annual mileage that a truck travels has been increasing. This trend is expected to continue over the next decade, mainly due to economic and population growth and flourish of e-shopping. The emergence of automated driving technology may change the trucking industry to a great extent. It is anticipated that trucks run more miles as restrictions pertaining to Hours-of-Service will be lifted or eased. Removing drivers from cabs, which will only happen with the highest level of automation, can lower operation costs substantially allowing trucking companies to charge lower which in turn can induce demand. Yet the factors impacting the adoption of autonomous trucks are not well-understood. In addition, it is not clear if adopters of automated trucks could be categorized in the five well-known groups suggested in the Theory of Diffusion of Innovations (DOI). It is also unknown if the sizes of CAT adoption categories follow the general numbers offered by DOI.

This paper contributes to the literature by presenting choice models and latent class cluster analysis aiming to (i) elicit drivers of adoption of highly automated driving technologies by freight companies and (ii) estimate the number and sizes of categories of CAT adopters. Companies working in the freight industry are contacted and 400 full responses are collected. The data is analyzed descriptively and detailed results of modeling efforts are presented and discussed.

Our choice models suggest that independent of the technology cost, older individuals suggest that their company would be less likely to adopt the higher levels of adoption. Companies view the automation Level 2 not significantly different than Regular trucks. We observe that the location in which the company is providing transportation services plays a role in the propensity of adoption. Also, cargo type is found to have some impact on the adoption. Having promoters of new technologies in the company increases the likelihood of adoption and the impact is more visible for the higher levels of automation. Our latent-class cluster analysis suggests that there could be five categories of CAT adopters which is consistent with what DOI suggests. However, the size of the *Innovators* class would be about four times of DOI's general suggestion. Also, the Early Majority group would be about two times of what we see DOI and the size of the *Laggards* class is smaller than our observation from DOI. Overall, it can be conjectured that the CAT adopter distribution may not be a bell-shaped curve but more of a right-skewed figure. This can be contributed to explicit financial benefits of the automated driving technology which could incentivize companies to adopt earlier. We notice that a large portion of *Laggards* operate in the US south region. Most *Innovators* share the point that they transport foodstuffs.

This study can be extended in a few directions. While looking at drivers of adoption of different levels of automated driving is beneficial, trucking companies may choose a step-by-step transition, mainly due to uncertainty in technology cost. In that scenario, some features of automated driving will gradually be added to the existing vehicles. To better understand the characteristics of that adoption procedure, one could investigate how each piece of technology is perceived by trucking firms. In addition, exploring new datasets on perceptions about CATs could reinforce the findings of this paper. Also, the application of more advanced methodologies, conditional on data availability, could shed light on elements of CAT adoption that could not be discovered by this study. As noted previously, CATs could pose significant benefit in terms of reducing operational cost because of limited to no involvement of drivers. This benefit may not be realized easily as some labor unions are strongly against the legislation of self-driving commercial trucks. Industry experts believe that it may take a decade or more for fully-automated trucks to become fully operational on the roadway because of the complexity of interaction with other road users. Also, humans will be needed to handle the many non-driving tasks such as coupling tractors and trailers, fueling, inspections, paperwork, communicating with customers, loading and unloading, etc. Labor unions advocate for skilled and trained drivers such that the truck-driver workforce problem can be better addressed during the transition to the full automation era (Pacific Standard, 2018; The New York Times, 2017; UC Berkeley Labor Center, 2018). It would be interesting to see if the existence of the labor union would affect the company's adoption.

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References

Acheampong, R.A., Cugurullo, F., Gueriau, M., and Dusparic, I. (2021) Can autonomous vehicles enable sustainable mobility in future cities? Insights and policy challenges from user preferences over different urban transport options. *Cities*, 112, 103134

Alonso, J., Milanés, V., Pérez, J., Onieva, E., González, C., and De Pedro, T. (2011) Autonomous vehicle control systems for safe crossroads. *Transportation Research Part C: Emerging Technologies,* 19, 1095-1110.

American Transportation Research Institute. (2020) *Critical Issues in the Trucking Industry – 2020.* Presented to American Trucking Association, Arlington, VA.

Anderhofstadt, B. and Spinler, S. (2020) Preferences for autonomous and alternative fuel-powered heavy-duty trucks in Germany. *Transportation Research Part D: Transport and Environment,* 79, 102232.

Andersson, P. and Ivehammar, P. (2019) Benefits and costs of autonomous trucks and cars. *Journal of Transportation Technologies*, 9(2), 121-145.

ATBS (2018) Self-Driving Trucks: Are Truck Drivers Out of a Job? Available at https://www.atbs.com/post/self-driving-trucks-are-truck-drivers-out-of-a-jo, Accessed on July 28, 2021.

Bae, Y., Kim, J., and Chung, J. (2017) Psychological traits to eco-friendly transportation systems: latent class approach. *Transportation Research Procedia,* 25, 4270-4284.

Bartolini, C., Tettamanti, T., and Varga, I., 2017. Critical features of autonomous road transport from the perspective of technological regulation and law. *Transportation Research Procedia*, 27, 791–798.

Bansal, P. and Kockelman, K.M. (2018) Are we ready to embrace connected and self-driving vehicles? A case study of Texans. *Transportation,* 45, 641-675.

Bansal, P. and Kockelman, K.M. (2017) Forecasting Americans' long-term adoption of connected and autonomous vehicle technologies. *Transportation Research Part A: Policy and Practice,* 95, 49-63.0

Bansal, P., Kockelman, K.M., and Singh, A. (2016) Assessing public opinions of and interest in new vehicle technologies: An Austin perspective. *Transportation Research Part C: Emerging Technologies,* 67, 1-14.

Behnood, A., Roshandeh, A.M., and Mannering, F.L. (2014) Latent class analysis of the effects of age, gender, and alcohol consumption on driver-injury severities. *Analytic Methods in Accident Research,* 3, 56-91.

Bhattarai, S., Golias, M.M., Mishra, S., and Talebian, A. (2020) Multidimensional resource allocation for freight transportation project planning and decision making. *Transportation Research Part A: Policy* *and Practice*, *137*, 95-110.

Bonnefon, J.F., Shariff, A., and Rahwan, I. (2016) The social dilemma of autonomous vehicles. *Science (New York, N.Y.),* 352, 1573-1576.

Brijs, T. (2002) Retail market basket analysis: a quantitative modelling approach.

Brodsky, J.S., 2016. Autonomous vehicle regulation: How an uncertain legal landscape may hit the brakes on self-driving cars. *Berkeley Technology Law Journal*, 31, 851–878.

Brown, A., Gonder, J., and Repac, B. (2014) An analysis of possible energy impacts of automated vehicle. *Road Vehicle Automation*Anonymous , pp. 137-153. Springer.

BTS (2015) Freight facts and figures 2015. US Department of Transportation, Washington DC.

BTS (2020a) Number of U.S. Aircraft, Vehicles, Vessels, and Other Conveyances. Available at https://www.bts.gov/content/number-us-aircraft-vehicles-vessels-and-other-conveyances, Accessed on July 19, 2021.

BTS (2020b) U.S. Vehicle-Miles. Available at https://www.bts.gov/content/us-vehicle-miles, Accessed on July 19, 2021.

Castritius, S., Hecht, H., Möller, J., Dietz, C.J., Schubert, P., Bernhard, C., Morvilius, S., Haas, C.T., and Hammer, S. (2020) Acceptance of truck platooning by professional drivers on German highways. A mixed methods approach. *Applied Ergonomics,* 85, 103042.

Chen, Z., He, F., Yin, Y., and Du, Y. (2017) Optimal design of autonomous vehicle zones in transportation networks. *Transportation Research Part B: Methodological,* 99, 44-61.

Chen, Z., He, F., Zhang, L., and Yin, Y. (2016) Optimal deployment of autonomous vehicle lanes with endogenous market penetration. *Transportation Research Part C: Emerging Technologies,* 72, 143-156.

Claybrook, J. and Kildare, S., 2018. Autonomous vehicles: No driver… no regulation? *Science*, 361, 36–37.

Coad, A., Segarra, A., and Teruel, M. (2016) Innovation and firm growth: Does firm age play a role? *Research Policy,* 45, 387-400.

Costello, B. (2017) *Truck Driver Shortage Analysis.* American Trucking Associations.

Data Driven Investor (2021) 18 companies and startups that are leading the race for the autonomous trucks. Available at https://medium.datadriveninvestor.com/18-companies-and-startups-that-are-leading-the-race-for-the-autonomous-trucks-4ba5a50e6dee, Accessed on July 28, 2021.

De Oña, J., López, G., Mujalli, R., and Calvo, F.J. (2013) Analysis of traffic accidents on rural highways using Latent Class Clustering and Bayesian Networks. *Accident Analysis & Prevention,* 51, 1-10.

Deb, S., Carruth, D.W., and Hudson, C.R. (2020) How communicating features can help pedestrian safety in the presence of self-driving vehicles: virtual reality experiment. *IEEE Transactions on Human-Machine Systems,* 50(2), 176-186.

Depaire, B., Wets, G., and Vanhoof, K. (2008) Traffic accident segmentation by means of latent class clustering. *Accident Analysis & Prevention,* 40, 1257-1266.

Donckels, R. and Fröhlich, E. (1991) Are family businesses really different? European experiences from STRATOS. *Family Business Review,* 4, 149-160.

Dyer Jr, W.G. and Handler, W. (1994) Entrepreneurship and family business: Exploring the connections. *Entrepreneurship Theory and Practice,* 19, 71-83.

Engholm, A., Björkman, A., Joelsson, Y., Kristoffersson, I., and Pernestål, A. (2020) The emerging technological innovation system of driverless trucks. *Transportation Research Procedia,* 49, 145-159.

Fagnant, D.J. and Kockelman, K. (2015) Preparing a nation for autonomous vehicles: opportunities, barriers and policy recommendations. *Transportation Research Part A: Policy and Practice,* 77, 167-181.

FMCSA (2020) Summary of Hours of Service Regulations. Available at https://www.fmcsa.dot.gov/regulations/hours-service/summary-hours-service-regulations, Accessed on March 17,2021.

Forbes (2021) The Autonomous Truck Revolution Is Right Around The Corner. Available at https://www.forbes.com/sites/stevebanker/2021/05/11/the-autonomous-truck-revolution-is-right-around-the-corner/?sh=3896f0cc2c96, Accessed on July 28, 2021.

Fritschy, C. and Spinler, S. (2019) The impact of autonomous trucks on business models in the automotive and logistics industry–a Delphi-based scenario study. *Technological Forecasting and Social Change,* 148, 119736.

Frittelli, J. (2020) *Federal Freight Policy: In Brief.* Congressional Research Service.

Frittelli, J. (2017) *Autonomous and Semi-Autonomous Trucks.* Congressional Research Service.

Geistfeld, M.A., 2017. A roadmap for autonomous vehicles: State tort liability, automobile insurance, and federal safety regulation. *California Law Review*, 105, 1611.

Guo, J., Cheng, S., and Liu, Y. (2020) Merging and Diverging Impact on Mixed Traffic of Regular and Autonomous Vehicles. *IEEE Transactions on Intelligent Transportation System*s, 22(3), 1639-1649.

Gurney, J.K. (2013) Sue my car not me: Products liability and accidents involving autonomous vehicles. *University of Illinois Journal of Law, Technology & Policy,* 2013, 247-277.

Gurumurthy, K.M. and Kockelman, K.M. (2020) Modeling Americans' autonomous vehicle preferences: A focus on dynamic ride-sharing, privacy & long-distance mode choices. *Technological Forecasting and Social Change,* 150, 119792.

Haboucha, C.J., Ishaq, R., and Shiftan, Y. (2017) User preferences regarding autonomous vehicles. *Transportation Research Part C: Emerging Technologies,* 78, 37-49.

Harper, C.D., Hendrickson, C.T., Mangones, S., and Samaras, C. (2016) Estimating potential increases in travel with autonomous vehicles for the non-driving, elderly and people with travel-restrictive medical conditions. *Transportation Research Part C: Emerging Technologies,* 72, 1-9.

Hassan, L.A.H. (2020) *Less-than-Truckload Freight Planning Problem: Designing the Service Network for Fleet Automation,* .

Hausman, A. (2005) Innovativeness among small businesses: Theory and propositions for future research. *Industrial Marketing Management,* 34, 773-782.

Hohenberger, C., Spörrle, M., and Welpe, I.M. (2016) How and why do men and women differ in their willingness to use automated cars? The influence of emotions across different age groups. *Transportation Research Part A: Policy and Practice,* 94, 374-385.

Huergo, E. and Jaumandreu, J. (2004) How does probability of innovation change with firm age? *Small Business Economics,* 22, 193-207.

Ilková, V. and Ilka, A., 2017. Legal aspects of autonomous vehicles—An overview. *Proceedings of the 21st international conference on process control (PC)*, IEEE, 428–433.

Kalra, N. and Paddock, S.M. (2016) Driving to safety: How many miles of driving would it take to demonstrate autonomous vehicle reliability? *Transportation Research Part A: Policy and Practice,* 94, 182-193.

Kishore Bhoopalam, A., van den Berg, R., Agatz, N. and Chorus, C. (2021) The long road to automated trucking: Insights from driver focus groups. SSRN: https://ssrn.com/abstract=3779469 .

Khan, A.M. and Manopichetwattana, V. (1989) Innovative and noninnovative small firms: Types and characteristics. *Management Science,* 35, 597-606.

Kunze, R., Haberstroh, M., Ramakers, R., Henning, K., and Jeschke, S. (2011) Automated truck platoons on motorways–a contribution to the safety on roads. *Automation, Communication and Cybernetics in Science and Engineering 2009/2010*, 415-426. Springer.

Kunze, R., Ramakers, R., Henning, K., and Jeschke, S. (2009) Organization and operation of electronically coupled truck platoons on German Motorways. In *Automation, Communication and Cybernetics in Science and Engineering 2009/2010,* 427-439, Springer, Berlin, Heidelberg.

Lambert-Pandraud, R., and Laurent, G. (2010) Why do older consumers buy older brands? The role of attachment and declining innovativeness. *Journal of Marketing*, 74(5), 104-121.

Lanza, S.T. and Rhoades, B.L. (2013) Latent class analysis: an alternative perspective on subgroup analysis in prevention and treatment. *Prevention Science,* 14, 157-168.

Lavasani, M., Jin, X., and Du, Y. (2016) Market penetration model for autonomous vehicles based on previous technology adoption experiences. *Transportation Research Board 95th Annual Meeting, Washington D.C*.

Lavieri, P.S., Garikapati, V.M., Bhat, C.R., Pendyala, R.M., Astroza, S., and Dias, F.F. (2017) Modeling Individual Preferences for Ownership and Sharing of Autonomous Vehicle Technologies. *96th Annual Meeting of the Transportation Research Board, Washington D.C*.

Le Vine, S., Kong, Y., Liu, X., and Polak, J. (2017) Vehicle Automation, Legal Standards of Care, and Freeway Capacity. Available at SSRN 2794628 .

Le Vine, S., Kong, Y., Liu, X., and Polak, J. (2019) Vehicle automation and freeway 'pipeline' capacity in the context of legal standards of care. *Transportation,* 46(4), 1215-1244.

Le Vine, S. and Polak, J. (2016) A novel peer-to-peer congestion pricing marketplace enabled by vehicle-automation. *Transportation Research Part A: Policy and Practice,* 94, 483-494.

Lee, Y., Circella, G., Mokhtarian, P.L., and Guhathakurta, S. (2019) Heterogeneous residential preferences among millennials and members of generation X in California: A latent-class approach. *Transportation Research Part D: Transport and Environment,* 76, 289-304.

LeMay, S.A., Johnson, L., Williams, Z., and Garver, M. (2013) The causes of truck driver intent-to-quit: a best-fit regression model. *International Journal of Commerce and Management,* .

Liedholm, C. and Mead, D.C. (1993) *The Structure and Growth of Microenterprises in Southern and Eastern Africa: Evidence from Recent Surveys.* GEMINI.

Lingmont, D.N. and Alexiou, A. (2020) The contingent effect of job automating technology awareness on perceived job insecurity: Exploring the moderating role of organizational culture. *Technological Forecasting and Social Change,* 161, 120302.

Liu, J. and Khattak, A.J. (2016) Delivering improved alerts, warnings, and control assistance using basic safety messages transmitted between connected vehicles. *Transportation Research Part C: Emerging Technologies,* 68, 83-100.

Liu, J., Kockelman, K.M., Boesch, P.M., and Ciari, F. (2017) Tracking a system of shared autonomous vehicles across the Austin, Texas network using agent-based simulation. *Transportation,* , 1-18.

Loeb, B. and Kockelman, K.M. (2019) Fleet performance and cost evaluation of a shared autonomous electric vehicle (SAEV) fleet: A case study for Austin, Texas. *Transportation Research Part A: Policy and Practice*, 121, 374-385.

Maciejewski, M. and Bischoff, J. (2017) Congestion effects of autonomous taxi fleets. *Transport,* 33(4), 971-980.

Martin-Gasulla, M., and Elefteriadou, L. (2021) Traffic management with autonomous and connected vehicles at single-lane roundabouts. *Transportation Research Part C: Emerging Technologies,* 125, 102964.

McPherson, M.A. (1996) Growth of micro and small enterprises in southern Africa. *Journal of Development Economics,* 48, 253-277.

Menon, N., Pinjari, A.R., Zhang, Y., and Zou, L. (2016) Consumer Perception and Intended Adoption of Autonomous-Vehicle Technology: Findings from a University Population Survey. *Transportation Research Board 95th Annual Meeting, Washington D.C*.

Mercedes Benz R&D. (2020) Autonomous Driving - MBRDNA. 2020.

Millward, L.J. and Freeman, H. (2002) Role expectations as constraints to innovation: The case of female managers. *Communication Research Journal,* 14, 93-109.

Mohamed, M.G., Saunier, N., Miranda-Moreno, L.F., and Ukkusuri, S.V. (2013) A clustering regression approach: A comprehensive injury severity analysis of pedestrian–vehicle crashes in New York, US and Montreal, Canada. *Safety Science,* 54, 27-37.

Moody, J., Bailey, N., and Zhao, J. (2020) Public perceptions of autonomous vehicle safety: An international comparison. *Safety Science*, 121, 634-650.

Nair, G.S. and Bhat, C.R. (2021) Sharing the road with autonomous vehicles: Perceived safety and regulatory preferences. *Transportation Research Part C: Emerging Technologies*, 122, 102885.

Next Big Future (2019) Economic Impact of Self-driving Trucks. Available at https://www.nextbigfuture.com/2019/04/economic-impact-of-self-driving-trucks.html, Accessed on July 28, 2021.

Noruzoliaee, M., Zou, B., and Liu, Y. (2018) Roads in transition: Integrated modeling of a manufacturer-traveler-infrastructure system in a mixed autonomous/human driving environment. *Transportation Research Part C: Emerging Technologies,* 90, 307-333.

Pacific Standard (2018) Are the Teamsters Trying to Kill Driverless Tech, or Save the Truck Drivers? Available at https://psmag.com/economics/trucking-teamsters-driverless-tech, Accessed on July 19, 2021.

Pani, A., Mishra, S., Golias, M., and Figliozzi, M. (2020) Evaluating public acceptance of autonomous delivery robots during COVID-19 pandemic. *Transportation Research Part D: Transport and Environment,* 89, 102600.

Penmetsa, P., Adanu, E.K., Wood, D., Wang, T., and Jones, S.L. (2019) Perceptions and expectations of autonomous vehicles–A snapshot of vulnerable road user opinion. *Technological Forecasting and Social Change*, 143, 9-13.

Pettigrew, S., Dana, L.M., and Norman, R. (2019) Clusters of potential autonomous vehicles users according to propensity to use individual versus shared vehicles. *Transport Policy,* 76, 13-20.

Pudasaini, B. and Shahandashti, S. (2020) Impacts of Automated Trucking Technologies on the Critical Issues of Trucking Industry. *International Conference on Transportation and Development 2020,* , 37-47.

Rahman, M.H., Abdel-Aty, M. and Wu, Y. (2021) A multi-vehicle communication system to assess the safety and mobility of connected and automated vehicles. *Transportation Research Part C: Emerging Technologies*, 124, 102887.

Ramakers, R., Henning, K., Gies, S., Abel, D., and Max, H.M. (2009) Electronically coupled truck platoons on German highways. *Systems, Man and Cybernetics, 2009. SMC 2009. IEEE International Conference On,* , 2409-2414.

Rashidi, T.H., Najmi, A., Haider, A., Wang, C. and Hosseinzadeh, F. (2020) What we know and do not know about connected and autonomous vehicles. *Transportmetrica A: Transport Science*, 16(3), 987-1029.

Robson, P.J., Haugh, H.M., and Obeng, B.A. (2009) Entrepreneurship and innovation in Ghana: enterprising Africa. *Small Business Economics,* 32, 331-350.

Rogers, E.M. (2010) *Diffusion of Innovations.* Simon and Schuster.

Sasidharan, L., Wu, K., and Menendez, M. (2015) Exploring the application of latent class cluster analysis for investigating pedestrian crash injury severities in Switzerland. *Accident Analysis & Prevention,* 85, 219-228.

Shabanpour, R., Shamshiripour, A., and Mohammadian, A.K. (2018) Modeling Adoption Timing of Autonomous Vehicles: Innovation Diffusion Approach. *Transportation Research Board 97th Annual Meeting Location, Washington D.C*.

Sharma, I. and Mishra, S. (2020) Modeling consumers' likelihood to adopt autonomous vehicles based on their peer network. *Transportation Research Part D: Transport and Environment,* 87, 102509.

Simpson, J.R. and Mishra, S. (2020) Developing a methodology to predict the adoption rate of Connected Autonomous Trucks in transportation organizations using peer effects. *Research in Transportation Economics,* , 100866.

Simpson, J.R., Mishra, S., Talebian, A., and Golias, M.M. (2019) An estimation of the future adoption rate of autonomous trucks by freight organizations. *Research in Transportation Economics,* 76, 100737.

Slowik, P. and Sharpe, B. (2018) Automation in the long haul: Challenges and opportunities of autonomous heavy-duty trucking in the United States. *The International Council on Clean Transportation*.

Smith, B.W. and Svensson, J. (2015) Automated and autonomous driving: regulation under uncertainty. International Transport Forum, OECD.

Sugimachi, T., Fukao, T., Suzuki, Y., and Kawashima, H. (2013) Development of autonomous platooning system for heavy-duty trucks. *IFAC Proceedings Volumes,* 46, 52-57.

Swait, J. (1994) A structural equation model of latent segmentation and product choice for cross-sectional revealed preference choice data. *Journal of Retailing and Consumer Services,* 1, 77-89.

Talebian, A. and Mishra, S. (2018) Predicting the adoption of connected autonomous vehicles: A new approach based on the theory of diffusion of innovations. *Transportation Research Part C: Emerging Technologies,* 95, 363-380.

Talebian, A., Mishra, S., Golias, M., Khan, J.A., Santo, C.A., Wang, L., Jacobs, E.L., Astorne-Figari, C., and Simpson, J. (2019) A holistic index for readiness to accommodate connected autonomous vehicles. *Transportation Research Board 98th Annual Meeting, Washington D.C*.

The New York Times (2017) Teamsters Union Tries to Slow Self-Driving Truck Push. Available at https://www.nytimes.com/2017/08/11/business/dealbook/teamsters-union-tries-to-slow-self-driving-truck-push.html, Accessed on July 19, 2021.

Truong, L.T., De Gruyter, C., Currie, G., and Delbosc, A. (2017) Estimating the Trip Generation Impacts of Autonomous Vehicles on Car Travel in Victoria, Australia. *Transportation Research Board 96th Annual Meeting, Washington, D.C*.

TTNews (2021) When Will Trucks Drive Themselves? Available at https://www.ttnews.com/articles/when-will-trucks-drive-themselves, Accessed on July 28, 2021.

Tsugawa, S. (2013) An overview on an automated truck platoon within the energy ITS project. *IFAC Proceedings Volumes,* 46, 41-46.

Tsugawa, S., Kato, S., and Aoki, K. (2011) An automated truck platoon for energy saving. *Intelligent Robots and Systems (IROS), 2011 IEEE/RSJ International Conference On,* 4109-4114.

UC Berkeley Labor Center (2018) Driverless? Autonomous Trucks and the Future of the American Trucker. Available at https://laborcenter.berkeley.edu/driverless/, Accessed on July 19, 2021.

US Census Bureau (2004) 2002 Vehicle Inventory and Use Survey. US Department of Commerce, Washington, DC.

US Census Bureau (2021) Current Population Survey Data. Available at https://www.census.gov/programs-surveys/cps/data.html, Accessed on November 10, 2021.

van den Berg, Vincent AC and Verhoef, E.T. (2016) Autonomous cars and dynamic bottleneck congestion: The effects on capacity, value of time and preference heterogeneity. *Transportation Research Part B: Methodological,* 94, 43-60.

van Wees, K.A. (2021) Technology in the Driver's Seat: Legal Obstacles and Regulatory Gaps in Road Traffic Law. In Autonomous Vehicles, Springer, Singapore, 21-37.

Vermunt, J.K. and Magidson, J. (2002) Latent class cluster analysis. *Applied Latent Class Analysis,* 11, 60.

Wadud, Z., MacKenzie, D., and Leiby, P. (2016) Help or hindrance? The travel, energy and carbon impacts of highly automated vehicles. *Transportation Research Part A: Policy and Practice,* 86, 1-18.

Wang, S., Jiang, Z., Noland, R.B., and Mondschein, A.S. (2020) Attitudes towards privately-owned and shared autonomous vehicles. *Transportation Research Part F: Traffic Psychology and Behaviour,* 72, 297-306.

Yang, C.D. and Fisher, D.L. (2021) Safety impacts and benefits of connected and automated vehicles: How real are they? *Journal of Intelligent Transportation Systems*, 25(2), 135-138

Zhang, L., Chen, F., Ma, X., and Pan, X. (2020) Fuel Economy in Truck Platooning: A Literature Overview and Directions for Future Research. *Journal of Advanced Transportation,* 2020, Article ID 2604012.