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Will Communication of Job Creation Facilitate Diffusion of Innovations in the Automobile Industry?

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Abstract: The electrification and automation of vehicles are two upcoming trends in the automobile industry. However, these two new technologies also raise public concerns related to road safety, range, and, most crucially, job creation in the automotive and transportation industries. This study investigates if job creation facilitates the diffusion of innovation. Analysis of 32,006 tweets from 33 global automobile manufacturers and their international job creation records revealed that communication of job creation can improve stakeholders' adverse social media engagement on vehicle electrification and automation, the latest innovations in transportation and logistics. Car manufacturers should continually communicate their job creation achievements to gain public acceptance when introducing innovations, which may improve the diffusion of innovations.

Keywords: diffusion of innovation; communication of job creation; electric vehicle; automated vehicle; social media analytics

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1. Introduction

The electrification and automation of vehicles are two major future trends in the automotive industry [1,2]. Because the global demand for transportation continues to increase, transportation is a major contributor to greenhouse gas emissions [1]. Electric vehicles (EVs) reduce the impact of automobiles on the environment (e.g., greenhouse gas emissions) [1]. Because of advanced planning capability, automated vehicles (AVs) can reduce road accidents, increase effective road capacity, and decrease fuel costs [3,4]. Some automobile manufacturers are advancing both of the aforementioned technologies simultaneously in their product innovation, whereas some are innovating their products with advancements in either technology depending on the firms' existing research and development capability, customer base, and customer acceptance. Previous studies observed the attitude–action gap among people for the purchase of EVs.

EVs and AVs, as innovations, have promoted substantial progress in the automobile industry. However, Lebeau et al. (2016) found that low public charging infrastructure discourages freight transporters to purchase EVs. Moreover, innovations might cause public anxiety regarding employment concerns (i.e., income inequality and job loss), the moral issue of new technologies, and the bottleneck of technology development [5]. The adoption of EV alternatives might negatively affect employment. The shift to EVs potentially reduces the demand for jobs because EVs have fewer moving parts than do internal combustion vehicles [6]. This relationship is common knowledge to the public, and it is these concerns that make people hesitant to the EV and AV. The anxiety caused by employment issues has resulted in employee protests and radical actions in the event of advanced technology adoption in operations in many sectors. For example, Bank of America tellers in New York staged a protest against the installation of new ATMs that can connect customers with tellers at a U.S.-based call center, which poses a threat to these tellers' livelihood (https://www.upi.com/Science_News/Technology/2013/11/23/Activists-protest-Bank-of-America-ATM-robot-tellers/52001385245394/, access date: 3 June 2020). Casino workers in Las Vegas staged a strike over the use of robots [7], and Walmart workers staged a strike over the retailer's push for automation in Chile in 2019 (https://www.japantimes.co.jp/news/2019/07/11/business/walmart-workers-strike-retailers-robot-push-chile/#.X0T_HsgzbLY, access date: 3 June 2020).

With EV and AV development, similar tension between innovations and employment has been occurring in the automobile industry. Onat, et al. [8] reported that 10% market penetration in Qatar for battery EVs caused 8% employment loss in Qatar. EVs have a simple structure, namely an electric motor with a large battery, which can be easily imported from regions with lower labor costs [6]. Therefore, the production of EVs may cause automobile manufacturers in the home country to shift jobs to relatively low-cost regions, resulting in employment decline in the automobile manufacturing sector in that country (e.g., the United States) [9]. Moreover, the introduction of self-driving cars (by Amazon, Google, Tesla, and Uber) has raised concerns regarding upcoming massive technological unemployment [10]. Uber and Google have focused on taxi services [11,12]. Uber tends to develop "software as a service" to reduce the cost of drivers (80% of the total per mile cost) through AVs [11] while Amazon has been working on self-driving technology to deliver goods, potentially cutting expressman jobs [13].

Therefore, the U.S. Department of Commerce estimates that at least one in nine auto workers' careers will be affected by the introduction of AVs [14]. As a result, the public believes that considerable potential job loss will occur in industries involving driving [14]. This caused port cargo drivers at Los Angeles protested the installation of automated cargo trucks at the Los Angeles Board of Harbor Commissioners (https://www.scpr.org/news/2019/04/25/89213/port-workers-rally-against-automation/, access date: 3 September 2021). However, accentuating job creation in the automobile and transportation industries, Ford shared the tweet as "#Ford is investing $1.6 billion to upgrade two plants in Michigan & Ohio—and creating or retaining 650 U.S. jobs", thereby receiving three times more retweets (318) than the average number (90).

Therefore, we are motivated to investigate if communication of job creation (CJC) can improve the diffusion of EVs and AVs. The research question is whether CJC facilitates public acceptance of innovations and improves the diffusion of EVs and AVs in the automobile industry. More specifically, based on diffusion of innovations theory (DOI) and technology anxiety, we explore how the impact of JC in the automobile and transportation industry can be disseminated on social media. In this study, we collect social media engagement data from Twitter because many stakeholders share their views on new technologies on this platform [15]. Twitter has 336 million active users in 2020 (https://www.statista.com/statistics/272014/global-social-networks-ranked-by-number-of-users/, access date: 3 September 2021) and compared with traditional media, new information quickly spreads on Twitter [15]. In this sense, Twitter, one of the most popular social media platforms, benefits from the diffusion of EVs and AVs [16]. Moreover, we investigate the number of retweets to measure public endorsement of EVs and AVs as Twitter users tend to retweet their endorsement of a popular post to attract more followers. Twitter or/and social media users share others' or brands' messages that conform to their personal values [15].

2. Literature Review

2.1. Theoretical Framework

DOI theory takes into account public views on new technologies [17]. DOI is defined as "an innovation is communicated through certain channels over time among the members of a social system" ([18], p. 5). Social media is an ideal space for DOI, because it can spread information to a large number of people, and information can spread and reach more people who would not have been exposed to information [16]. In addition, public attitude toward innovations is measurable on social media. In other words, people can share the message about innovations in such highly competitive and saturated information environments (i.e., social media), which implies that people recognize this message [19]. Previous studies have investigated DOI with social media data, such as Grover, et al. [20]. Based on this view, new technologies (i.e., EV, AV) as innovations can spread steadily through social media [21]. In turn, public opinion plays a crucial role in the wider diffusion and adoption of EV and AV [22]. However, innovations may not be attractive to the majority of consumers due to the lack of cost efficiency and the attributes valued by these consumers perform poorly [23]. We assume that CJC can improve the diffusions of EVs and AVs based on three reasons. Firstly, higher level job creation means that firms have more employees to diffuse new technologies since employees can act as a brand ambassador to facilitate DOI. Secondly, CJC can help deflate such public anxiety while diffusing the EV and AV's innovations through social media. Thirdly, CJC can improve brand image, leading to higher stakeholder engagement.

Firstly, creating more jobs will increase the number of internal stakeholders (i.e., employees) who may act as a brand ambassador to share their firms' messages to the public on social media. Saleem and Hawkins [24] indicated that employee-created social media content affects consumers' perceptions of expertise, which in turn increases Words of Mouth and purchase intention. Furthermore, Matthews, et al. [25] indicated that car dealers play an important role in overcoming resistance to adoption. Employee are familiar with the new products and new technologies so that they can reduce consumers' confusion and improve DOI [26]. Meanwhile, it also reduces the cost of users searching for information related to new technologies, and can improve the tendency of users to use new technologies [27]. Therefore, we predict that an employee could play an important role on DOI. Higher-level job creation means that firms have more employees to diffuse new technologies.

Secondly, as new technologies may cause public anxiety related to jobs, production, and economic growth [5], CJC can help deflate such public anxiety while diffusing the EV and AV's innovations through social media. Lachenmaier and Rottmann [28] argued that product innovation might reduce employment if fewer workers are needed to produce new products than old ones. Acemoglu and Restrepo [29] stated that automation reduces employment and labor share and may even reduce wages because of fixed capital and exogenous technology. For example, AV may replace taxi drivers. During several radical technological advancements in human history, specific groups of the labor force were removed, and their income was transferred from workers to capital owners, which has exacerbated income inequality [30]. Automation enables firms to substitute tasks previously performed by labor with capital since factor prices are determined by the range of tasks performed by capital and labor, and technological changes alter the range of tasks performed by each factor [29]. Therefore, with the rapid development of automation, robotics, and artificial intelligence (AI) technology, people are increasingly worried that new technologies will lead to a labor surplus [29].

Thirdly, firms that emphasize skill empowerment and CJC can generate long-term benefits and strengthen their brand image [31]. Based on Maslow's hierarchy, jobs can satisfy employees' physiological needs (i.e., wages), relationship needs, esteem needs (i.e., a positive management relation with employees), and self-actualization needs [32,33]. Therefore, the public has achieved a consensus that firms should adopt technological progress while continually creating jobs and addressing poverty and low education levels [34,35]. Increasing public awareness of social issues (e.g., employment) has contributed to pressure on corporations to take action to mitigate their negative impacts and report their progress to the public [36]. Social indicators such as JC and employee compensation provided on firms' websites, on social media, and in firms' sustainability reports have received strong public attention [37–39]. Meanwhile, firms' CSR efforts can improve employees' job satisfaction and performance, which in turn engage employees in firms' communication on new technologies [40,41]. Regarding the diffusion of EVs and AVs, lack of trust is one of the barriers [42,43]. On the other hands, trust is a factor in promoting the dissemination of innovation [27]. Firms' operations in line with the CSR concept can obtain greater customer trust [44].

Over 75% of S&P 500 firms will communicate their efforts in social responsibility (such as employment) and environmental policy on their websites [45]. In 2012, 176 major global firms communicate their efforts on sustainability on social media, representing a considerable increase from the 60 firms that did so 2 years earlier [46]. Key firm stake-holders, such as investors, customers, employees, supply chain partners, and government organizations, may collect solid messages regarding firms' efforts on job creation through various channels [47–49]. Moreover, tweets related to employment issues are popular and are more likely to be shared or go viral [50], generating a strong and enduring positive image for the firm. However, as job creation is not a one-off event, a single job creation tweet does not fully reflect a firm's real effort. Job creation is a continual process over time, thus the public shall develop an overall impression about the firms' job creation status.

Figure 1 showed the theoretical framework of this study. We assumed that EVs and AVs may both receive lower stake-holder engagement on social media in the automobile industry. However, Car manufacturers' CJC mitigates the negative effect of EVs and AVs on stakeholder social media engagement.

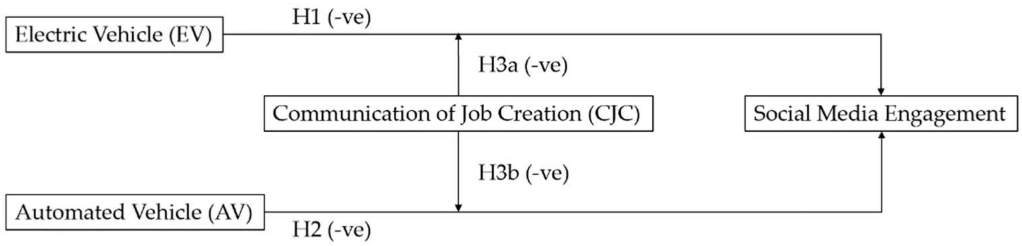

Figure 1. Theoretical framework.

2.2. The Diffusion of Electric Vehicles

Despite the benefits of EVs and their increasing market acceptance, the global sales volume of EVs was slightly higher than 2.1 million in 2019, which only accounted for 2.6% of global car sales (https://www.iea.org/reports/global-ev-outlook-2020, access date: 3 September 2021). According to an automobile industry sales report published prior to the COVID-19 pandemic, among the best-selling cars and sport utility vehicles in the United States in 2019, Tesla Model 3 ranked 19th, with 161,100 units sold (https://www-statista-com.ezproxy.lb.polyu.edu.hk/statistics/276419/best-selling-cars-in-the-united-states/, access date: 8 September 2021). These figures prove that internal combustion vehicles still account for most car sales, which indicates that EVs have a smaller stakeholder base.

The diffusion of EV depends on the attitudes of a wide range of participants, including automobile users, power firms, automobile manufacturers, and governments [51]. To increase the adoption of EVs, the German government provides a purchase grant of at most 4000 € for Battery EVs and 3000 € for Hybrid EVs. (https://www.bundesregierung.de/breg-de/themen/energiewende/kaufpraemie-fuer-elektroautos-verlaengert-369482, access date: 8 September 2021) Yet, the rate of EVs still did not increase greatly [51]. It may be because internal combustion vehicle production is a pillar industry in Germany [51]. Though, the wide diffusion of EVs means that German automobile manufacturers need to give up their existing competencies (e.g., technology, skill, design) around internal combustion vehicles and change to the competencies related to EVs (e.g., battery) [52,53]. Though, as a part of important stakeholders, the German government has not set a timetable for phasing out internal combustion engine vehicles [51]. As an EV has little effect on reducing carbon dioxide emissions, it may not significantly change the government's interest in EV promotion [51]. Power suppliers do not have an efficient operating model for charging services [54]. Most importantly, Biresselioglu, Demirbag Kaplan and Yilmaz [42] indicated that the barriers to the diffusion of EVs are mainly the lack of charging infrastructure, a high price, and lack of trust. Range anxiety hinders car users' confidence in adopting EVs, especially battery EVs [55]. Adopting EVs may create inefficiency for consumers to readjust the vehicles and change their habits [56]. Ball, Vogele, Grajewski and Kuckshinrichs [51] found that car users and car manufacturers may boycott EVs. Therefore, people's acceptance of EVs is still relatively low, which implies that people are less likely to talk about EVs on social media. We develop the first hypothesis as follows:

Hypothesis 1 (H1). Compared with conventional internal combustion vehicles, EVs receive lower stakeholder engagement on social media in the automobile industry.

2.3. The Diffusion of Automated Vehicles

AVs rely on advanced control and sensor systems to transport passengers and goods without human intervention [3,57]. Therefore, the technology behind AVs combines automation and AI. Public opinion plays a significant role on the diffusion of AVs [22]. However, user resistance problem is still one of the challenges of the wide diffusion of AVs [58]. An online survey with 1533 data showed that more than half of the respondents did not want to pay more for autonomous driving technology (https://deepblue.lib.umich.edu/bitstream/handle/2027.42/108384/103024.pdf?sequence=1andisAllowed=y, access date: 25 June2021). Payre, et al. [59] indicated that people who mainly seek novelty may also get tired of AV after a period of time. From the perspective of consumers, distrust of autonomous driving technology remains the main obstacle to diffuse AVs [43]. Some people are also worried about the safety of AVs (http://d2dtl5nnlpfr0r.cloudfront.net/tti.tamu.edu/documents/PRC-15-49-F.pdf, access date: 25 June 2021). Other potential barriers to the diffusion of AVs include ethical issues, privacy concerns, cybersecurity, and legal liability [17]. Moreover, the introduction of AVs may completely destroy employment, which means that the public's attitude towards AVs is uncertain [60,61]. Thus, we develop the second hypothesis as follows:

Hypothesis 2 (H2). Compared with conventional cars' technologies related to safety, performance, and operation, AVs receive lower stakeholder engagement on social media in the automobile industry.

2.4. Job Creation and the Diffusion of Innovations

2.4.1. The Effect of Communication of Job Creation on the Diffusion of Electric Vehicles

Job creation is one of the decision-making factors related to EVs [51]. Firstly, higher level job creation means that firms have more employees to diffuse new technologies. Employees, as product experts, showed charging technology and demonstration vehicles to consumers, which is more likely to make consumers form a positive attitude towards EVs [62]. Secondly, EVs might cause people's anxiety about employment. Vehicle electrification does not benefit social indicators such as employment, tax, and compensation [8]. From a socio-economic perspective, the widespread adoption of electric vehicles is expected to lead to structural changes in the energy industry (from oil extraction to electricity generation), including changes in employment, income, and profitability [8]. Onat, Kucukvar, Aboushaqrah and Jabbar [8] revealed that internal combustion vehicles have more favorable performance than all other EVs in terms of the generation of employment, compensation of employees, and taxes, which implies that petroleum extraction and all the related supply chains generate higher employment, tax, and compensation. In addition, more EVs mean fewer mechanical jobs, as EVs have fewer moving parts than do internal combustion vehicles [63]. The power system of an internal combustion engine vehicle may have up to 2000 moving parts. By contrast, the parts in electric powertrains may be as few as 20 because EVs do not have multispeed gas tanks, exhaust systems, valvetrains, fuel injectors, transmissions, or radiators [6,64]. However, building a conventional powertrain is the most labor-intensive part of building a car, which creates numerous jobs [65]. For instance, 150,000 U.S. jobs were related to building engines, transmissions, and axles at U.S. factories in 2018 [65]. According to some estimates, 75,000 jobs related to building engines and transmissions will be eliminated in Germany by 2030 [65]. In general, EVs can be regarded as an electric motor with a large battery [6], which can be easily imported from areas with a low labor cost rather than being built by an automaker or supplier in developed areas with a high labor cost [6]. At present, large-scale and low-cost battery production is concentrated in Asia [52]. As a result, with the production of EVs, standard blue-collar jobs in the automobile industry in developed areas have been reduced. The stakeholder base of EV decreased further, which has reduced people's desire to diffuse EVs. Therefore, firms need to create more jobs to reduce people's anxiety and meet people's needs. Without the threat of unemployment, people will be more likely to engage in the diffusion of EVs. We propose the following hypothesis:

Hypothesis 3a (H3a). Car manufacturers' CJC mitigates the negative effect of EVs on stakeholder social media engagement.

2.4.2. The Effect of Job Creation on Automated Vehicles

AVs rely on advanced control and sensor systems to transport passengers and goods without human intervention [3,57]. Therefore, the technology behind AVs combines automation and AI. The automation of transportation will create momentum for economic growth; however, it will considerably affect many occupations and jobs [66]. Dixon and Lim [67] pointed out that automation and relative factor increase rate are the key factors for the decline of labor share in the United States since the 2000s, and they are also important reasons for the rise of enterprise market forces (whether product market or labor market). Large-scale layoffs are inevitable among drivers in truck transportation, taxi and bike-sharing services, express delivery services, and food distribution industries because of AVs. Workers in related sectors such as manufacturing and warehousing may also be affected [60]. Cirera and Sabetti [68] proved that automation has a significantly negative effect on employment in the service industry. AVs may significantly reduce the need for human drivers. Predictions suggest that 1.7 million drivers might be replaced by Uber's "Otto" program, which involves installing AI in 16-wheeler trucks [69]. Moreover, AV accelerates the emergence of shared mobile platforms that enable the use of cars without ownership, which may fundamentally change the mode of car ownership and operation as well as the employment structure of the automobile and transportation industries [1]. AVs potentially increase existing labor market inequalities [70]. The development and application of intelligent machines may reduce the employment rate and wages of low- and medium-skilled workers (i.e., taxi and bus drivers) [71]. On the other hand, occupations in the key link of information flow may gain greater structural strength and may result in higher wages because computers transform work into knowledge-intensive activities [72]. Although workers in traditional occupations may attempt to improve their skills, they find it challenging to balance rest and skill improvement (i.e., receiving a college education) [73,74]. In addition, new technologies may make it unnecessary to provide long-term jobs, which undermine labor standards [75]. More seriously, new technologies may concentrate power within global technology multinationals, making it more difficult for employees to negotiate [75]. Most people indicated that firms adopting AVs must bear the responsibility of job creation [58]. The impact of AV on employment reduces people's acceptance of AV, which does harm to the diffusion of AVs. In contrast, JC can reduce people's anxiety and give them the opportunity to start accepting AVs, which are helpful to diffuse AVs. In addition, it is beneficial for the diffusion of AVs when firms employ more people to develop communication and marketing campaigns for AVs [58]. We propose the following hypothesis:

Hypothesis 3b (H3b). Car manufacturers' CJC mitigates the negative effect of AVs on stakeholder social media engagement.

3. Methods

3.1. Data Collection

For sample selection, we mainly focused on mainstream brands from the top 10 global auto groups in 2020 (https://www.focus2move.com/world-car-group-ranking/, access date: 20 June 2021). To standardize our data and to ensure our data authenticity, we firstly obtained employment data from annual reports of the selected brand's parent group. We did not use tweets about job creation due to a couple of reasons. Firms hardly talk about their JC on Twitter platforms. Therefore, we could not find a sizable sample of tweets about job creation of our selected brands. Moreover, as firms' job creations are continual processes instead of one-off events, the public's impression of firms' efforts in creating new jobs have developed over time. Thus, compared to tweets about job creation, more precise data for job creation are from the firms' annual reports as our conservative measurement of a firm's job creation communication to the public. If we could not get employment data in an annual report, we checked the parent groups' U.S. Securities and Exchange Commission (SEC) Form 10-K or 20-F, which is also a trustable resource. For some old employment data (e.g., the number of employees in 2012), we checked the data on www.statista.com (access date: 3 September 2020) and www.martrend.net (access date: 3 September 2020). To be specific, the fiscal years of Toyota, Honda, Nissan, and Tata end on 31 March each year, while others end on 31 December each year. However, Hyundai and Kia were excluded, as they surprisingly do not disclose specific employment data in their annual reports or any other resources. In addition, we excluded supercar brands (i.e., Ferrari and Aston Martin) because their customers comprise a minority of the public. Tesla was included, as its market capitalization is $245 billion, indicating its position as the world's most valuable automaker [76]. Finally, based on the aforementioned considerations, we collected tweets from the 33 brands listed in Table 1.

Table 1. Brands included in the study sample.

Brand	Parent Group	American Brand	Parent Group
Mercedes Benz	Daimler AG	Buick	General Motors Company
Smart		Cadillac	
BMW	Bayerische Motoren Werke AG	Chevrolet	
MINI		Corvette	
Volkswagen	Volkswagen AG	GMC	
Audi		Ford (incl. Ford Trunk)	Ford Motor Company
Porsche		Lincoln	
Toyota	Toyota Motor Corporation	Chrysler	Fiat Chrysler Automobiles
Lexus		Dodge	
Honda	Honda Motor Co Ltd.	Jeep	
Acura		Ram	
Nissan	Nissan Motor Co Ltd.	Tesla	Tesla Inc.
Infiniti			
Jaguar	TATA Motors Ltd.		
Land Rover			
Peugeot	Peugeot SA		
Citroen			
Renault	Renault SA		
Fiat	Fiat Chrysler Automobiles		
Alfa Romeo			
Maserati			

Then, we ran Twitter's Application Programming Interface (i.e., REST API) on Python 3.7 to obtain tweets from each brand. We downloaded tweets from 25 September 2015 to 25 September 2019. We collected 57,294 tweets from 33 automobile brands. We only included original tweets by the brands, and the brands' replies to others (i.e., the tweets starting with "@") were excluded. Replies were excluded because replies cannot represent the car maker's intention. Firms' retweets (sharing others' posts) were included in the sample for analysis as retweeting indicates the tweets are in line with firm values. Finally, 32,006 tweets were processed for data analysis.

3.2. Rule-Based Classification

In rule-based classification, experts develop some rules (i.e., keyword) to label the text [77]. The advantage of rule-based classification is that expert opinions are integrated into the classification process [77]. It is widely adopted in social media studies, such as those by Chau, Li, Wong, Xu, Yip and Chen [77], and Grover, et al. [78]. To construct our rule-based classifier, we created a lexicon consisting of words related to EVs, AVs, and other features of vehicles (Appendix A). The lexicon was reviewed for completeness by experts who are researchers in the field of transportation.

3.3. Data Analysis

We used hierarchical linear regression for data analysis. We used the number of retweets as a measure of Twitter reactions because retweeting indicates a positive reaction to the firm's message [50]. Compared with liking and commenting, retweeting reflects a stronger countersignaling response. The retweets will appear on peoples' personal profile. Therefore, people may share the tweets when people believe that the firm's message contains information that matches their personal values, and they believe that the information is valuable to their personal network of followers when they share the messages [50]. In addition, people tend to express their position on a topic through social media to improve their personal image [79]. Therefore, retweeting is a behavior related to self-discourse, which implies that people need to pay more cognitive efforts to it. A higher number of retweets indicates that the original tweet has higher social media engagement as well as wider diffusion. [80]. Consumers are more likely to buy from brands that reflect their personal values and beliefs [81]. Because the number of retweets is strictly non-negative and exponential, we then used the common logarithm of the number of retweets as the dependent variable to reduce distribution conflict and to include the tweets with extremely high retweeting frequency [82]. As Lg(x) requires $x > 0$, we must adjust the zero value in the number of retweets [82]. Because normal distribution does not change when the variable contains a constant, we adjusted the number of retweets by adding one to every number (https://blogs.sas.com/content/iml/2011/04/27/log-transformations-how-to-handle-negative-data-values.html, access date: 9 October 2021) and created the dependent variable "Ln (Adjusted Retweet Count)" for regression analysis.

First, we tested the relationship between the tweets regarding EVs and social media engagement and the relationship between the tweets regarding AVs and social media engagement. Second, we examined how CJC moderates these two relationships. For the independent variable CJC, we adopted the difference between the parent group's total employees in the current year and its average employee numbers in the previous years. We then tested the job creation in the 1 year (JC1), 2 years (JC2), and 3 years (JC3) prior to the tweet.

To explain the content level and environment level heterogeneity, we also created serial control variables, including rate of asset (ROA), total assets in billion USD (TA), text length (TL), brand dummies, year dummies, and variables related to the basic features of the vehicle. First, for the tweets related to basic car features, we followed the method of Keith, et al. [83] and applied the price, performance, emission, and range as our control factors to mitigate the effect of other performances of vehicles. ROA controlled for the effect of firm profitability, and TA controlled for firm size. TL was used to control for the effect of a tweet's length on stakeholder social media engagement, which has been proven to be correlated with the likelihood of retweeting. Finally, year dummies were used to reduce the yearly economic impact on social media, and brand dummies were used to control for the effect of brand reputation on stakeholder social media engagement. Detailed notations and explanations of variables are listed in Table 2.

Table 2. Details of study variables.

Variables	Explanation
	Dependent variable
Lg (Adjusted Retweet Count)	Ln of total adjusted number of retweets on a tweet
	Independent variables
EV	Tweets concerning electric vehicles
AV	Tweets concerning automated vehicles
JC1	Changes in the number of global employees of the parent group in the current year compared with that in the last year
EV × JC1	The moderating effect of the change in the number of employees within 1 year on social media engagement about electric vehicles
AV × JC1	The moderating effect of the change in the number of employees within 1 year on social media engagement about automated vehicles
JC2	Changes in the number of global employees of the parent group in the current year compared with the average in the previous 2 years
EV × JC2	The moderating effect of the change in the number of employees within 2 years on social media engagement about electric vehicles
AV × JC2	The moderating effect of the change in the number of employees within 2 years on social media engagement about automated vehicles
JC3	Changes in the number of global employees of the parent group in the current year compared with the average in the previous 3 years
EV × JC3	The moderating effect of the change in the number of employees within 3 years on social media engagement about electric vehicles
AV × JC3	The moderating effect of the change in the number of employees within 3 years on social media engagement about automated vehicles
	Control variables
Price	Tweets about price
Performance	Tweets about performance
Emission	Tweets about emission
Range	Tweets about range
ROA (%)	$ROA = \frac{Operations\ Income\ Before\ Depreciation}{Total\ asset}$
TA (billion USD)	Firm's total asset in billion USD
TL	Number of words in a tweet
Brand dummies	Distinguish different brands' tweets
Year dummies	Distinguish tweets in different years

In the main analysis, model 1 was used to test the effects of control variables on social media engagement, and models 2–4 were used to test the moderating effect of job creation in different years. To ensure that our results were consistent, we conducted two robustness checks. First, we conducted the analysis without Tesla, as their CEO, Elon Musk, is a very active Twitter user; thus, Tesla's data would have skewed the model. Then, we changed to use the number of likes as the dependent variable in the robustness check.

4. Results

4.1. Descriptive Analysis

Figure 2 shows the distribution of tweets by brand and tweets contributed by brands with retweeting number in the top 100 number. Among 32,006 tweets, Nissan accounted for the largest proportion (11.98%), with 3833 tweets, followed by Mercedes Benz (3209 tweets; 10.03%) and Volkswagen (1815 tweets; 5.67%). The lowest number of tweets was noted for GMC (168 tweets; 0.52%). Among 472 tweets from Tesla, the retweeting number of 78 (16.53%) tweets ranked in the top 100.

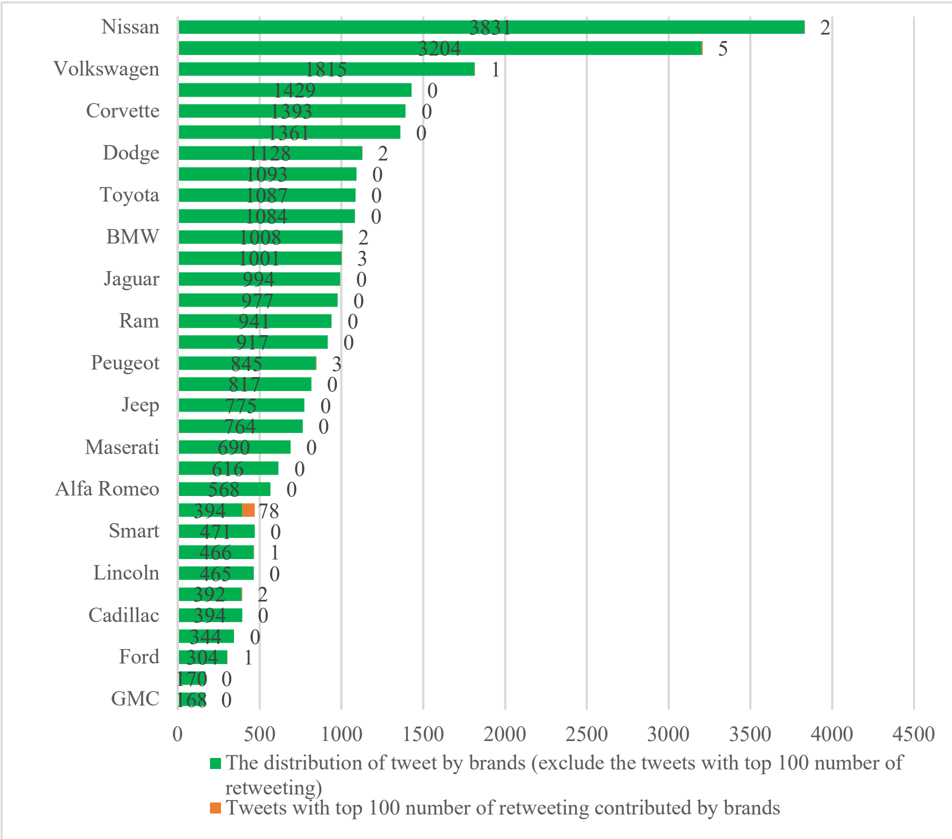

Figure 2. Distribution of tweets by brand and tweets contributed by brands with retweeting number in the top 100 number.

4.2. Linear Regression

This study used SPSS 25.0 to test the hypotheses. Descriptive statistics and correlations are presented in Table 3. Collinearity should not be a major concern in our analysis, as most variables' variance inflation factors were less than five, except for TA as it correlated with ROA.

Table 4 displays the regression analysis results with the Lg (Retweet) as the dependent variable. Model 1 was used to test the effect of control variables on social media engagement. Regarding the basic features of vehicles, performance (0.108, $p < 0.01$) and emission (0.127, $p < 0.01$) had positive effects on social media engagement, whereas price (−0.155, $p < 0.05$) had negative effects on social media engagement. Range was not significant. This implies that people focus on vehicle performance and emission, with negative consumer perception of price. TA (0.001, $p < 0.01$) and ROA (0.024, $p < 0.01$), as financial indicators, had significantly positive effects on social media engagement. TL (−0.001, $p < 0.01$) negatively affected social media engagement, which means that excessively long tweets have negative effects.

Table 3. Descriptive statistics and correlations; *N* = 32,006.

	Variables	Mean	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	LG (RETWEET)	1.54	0.53																			
2	EV	0.07	0.25	0.015 **																		
3	AV	0.02	0.13	−0.064 **	0.272 **																	
4	JC1	1.05	14.21	−0.0073 **	0.059 **	0.010																
5	EV × JC1	0.28	3.08	0.024 **	0.340 **	−0.029 **	0.211 **															
6	AV × JC1	0.04	1.72	0.003	−0.022 **	0.159 **	0.120 **	0.159 **														
7	JC2	2.18	16.73	−0.095 **	0.085 **	0.018 **	0.915 **	0.208 **	0.108 **													
8	EV × JC2	0.51	3.98	0.028 **	0.473 **	−0.001	0.191 **	0.913 **	0.133 **	0.225 **												
9	AV × JC2	0.08	2.09	−0.009	0.006	0.280 **	0.105 **	0.141 **	0.888 **	0.120 **	0.160 **											
10	JC3	3.79	19.32	−0.091 **	0.095 **	0.016 **	0.850 **	0.196 **	0.097 **	0.977 **	0.225 **	0.115 **										
11	EV × JC3	0.73	4.91	0.028 **	0.544 **	0.013 *	0.171 **	0.829 **	0.110 **	0.215 **	0.966 **	0.145 **	0.231 **									
12	AV × JC3	0.11	2.41	−0.013 *	0.023 **	0.332 **	0.094 **	0.125 **	0.807 **	0.116 **	0.156 **	0.976 **	0.116 **	0.150 **								
13	Price	0.00	0.03	−0.015 **	0.004	−0.004	0.002	0.003	−0.001	0.006	0.003	−0.001	0.008	0.007	−0.001							
14	Performance	0.01	0.09	0.006	0.040 **	0.000	0.017 **	0.019 **	−0.004	0.020 **	0.030 **	−0.005	0.021 **	0.035 **	−0.003	−0.003						
15	Range	0.00	0.01	0.005	0.010	−0.001	0.000	−0.004	0.000	0.001	−0.003	0.000	0.002	−0.003	0.000	0.000	−0.001					
16	Emission	0.02	0.13	0.051 **	0.027 **	−0.013 *	0.022 **	−0.001	−0.002	0.024 **	0.007	−0.004	0.025 **	0.012 *	−0.005	−0.004	0.034 **	0.023 **				
17	TA (billion)	207.94	130.64	−0.075 **	−0.047 **	−0.034 **	0.329 **	0.070 **	0.004	0.413 **	0.081 **	0.001	0.456 **	0.084 **	0.002	0.029 **	0.019 **	−0.001	0.062 **			
18	ROA (%)	8.10	2.33	0.014 *	−0.269 **	−0.154 **	−0.423 **	−0.093 **	−0.017 **	−0.468 **	−0.125 **	−0.037 **	−0.472 **	−0.142 **	−0.047 **	−0.016 **	−0.019 **	−0.005	−0.105 **	−0.326 **		
19	TL (no. of characters)	130.11	52.62	−0.195 **	0.213 **	0.156 **	0.073 **	0.028 **	0.014 *	0.121 **	0.075 **	0.047 **	0.125 **	0.100 **	0.061 **	0.024 **	0.057 **	−0.001	0.125 **	0.088 **	−0.337 **	

Remark: *. Correlation is significant at the 0.05 level (two-tailed). **. Correlation is significant at the 0.01 level (two-tailed).

Table 4. Regression analysis with Lg (Retweet) as the dependent variable.

Independent Variables	Model 1			Model 2			Model 3			Model 4		
	Coefficient	*SE*	*p*	Coefficient	*SE*	*p*	Coefficient	*SE*	*p*	Coefficient	*SE*	*p*
EV				−0.034 **	0.009	0.000	−0.049 **	0.010	0.000	−0.058 **	0.010	0.000
AV				−0.190 **	0.016	0.000	−0.199 **	0.016	0.000	−0.203 **	0.017	0.000
JC1				0.000 *	0.000	0.021						
EV × JC1				0.004 **	0.001	0.000						
AV × JC1				0.008 **	0.001	0.000						
JC2							0.000	0.000	0.113			
EV × JC2							0.004 **	0.001	0.000			
AV × JC2							0.007 **	0.001	0.000			
JC3										0.000 *	0.000	0.009
EV × JC3										0.004 **	0.000	0.000
AV × JC3										0.006 **	0.001	0.000
Price	−0.155 *	0.061	0.012	−0.158 *	0.061	0.010	−0.160 **	0.061	0.009	−0.162 **	0.061	0.008
Performance	0.108 **	0.021	0.000	0.107 **	0.021	0.000	0.107 **	0.021	0.000	0.107 **	0.021	0.000
Range	−0.070	0.194	0.720	−0.080	0.193	0.680	−0.070	0.193	0.718	−0.063	0.193	0.743
Emission	0.127 **	0.015	0.000	0.124 **	0.015	0.000	0.123 **	0.015	0.000	0.123 **	0.015	0.000
TA	0.001 **	0.000	0.000	0.000 **	0.000	0.000	0.000 **	0.000	0.000	0.001 **	0.000	0.000
ROA	0.024 **	0.002	0.000	0.023 **	0.002	0.000	0.019 **	0.002	0.000	0.018 **	0.002	0.000
TL	−0.001 **	0.000	0.000	−0.001 **	0.000	0.000	−0.001 **	0.000	0.000	−0.001 **	0.000	0.000
Brand dummies	Included			Included			Included			Included		
Year dummies	Included			Included			Included			Included		
F	1113.134			1010.915			1011.938			1012.767		
R^2	0.5996			0.6029			0.6032			0.6034		
Adjusted R^2	0.5991			0.6023			0.6026			0.6028		
RMSE	0.33550			0.33413			0.33403			0.33395		
N	32006			32006			32006			32006		

Remark: + $p < 0.1$; * $p < 0.05$; ** $p < 0.01$.

Table 5. Regression analysis with Lg (Retweet) as the dependent variable.

Independent Variables	Model 1			Model 2			Model 3			Model 4		
	Coefficient	*SE*	*p*	**Coefficient**	*SE*	*p*	**Coefficient**	*SE*	*p*	**Coefficient**	*SE*	*p*
EV				−0.035 **	0.009	0.000	−0.047 **	0.010	0.000	−0.054 **	0.010	0.000
AV				−0.199 **	0.016	0.000	−0.209 **	0.016	0.000	−0.212 **	0.017	0.000
JC1				0.000 *	0.000	0.044						
EV × JC1				0.003 **	0.001	0.000						
AV × JC1				0.008 **	0.001	0.000						
JC2							0.000 *	0.000	0.044			
EV × JC2							0.004 **	0.001	0.000			
AV × JC2							0.007 **	0.001	0.000			
JC3										−0.001 **	0.000	0.002
EV × JC3										0.003 **	0.001	0.000
AV × JC3										0.007 **	0.001	0.000
Price	−0.162 **	0.062	0.009	−0.165 **	0.062	0.008	−0.167 **	0.062	0.007	−0.168 **	0.062	0.006
Performance	0.113 **	0.021	0.000	0.113 **	0.021	0.000	0.113 **	0.021	0.000	0.113 **	0.021	0.000
Range	−0.005	0.236	0.983	−0.010	0.235	0.966	−0.002	0.235	0.992	0.001	0.235	0.997
Emission	0.129 **	0.015	0.000	0.126 **	0.015	0.000	0.125 **	0.015	0.000	0.124 **	0.015	0.000
TA	0.001 **	0.000	0.000	0.000 **	0.000	0.000	0.001 **	0.000	0.000	0.001 **	0.000	0.000
ROA	0.024 **	0.002	0.000	0.023 **	0.002	0.000	0.019 **	0.002	0.000	0.019 **	0.002	0.000
TL	−0.001 **	0.000	0.000	−0.001 **	0.000	0.000	−0.001 **	0.000	0.000	−0.001 **	0.000	0.000
Brand dummies	Included			Included			Included			Included		
Year dummies	Included			Included			Included			Included		
F	995.596			903.038			903.856			904.481		
R^2	0.5704			0.5741			0.5743			0.5745		
Adjusted R^2	0.5698			0.5735			0.5737			0.5739		
RMSE	0.33300			0.33160			0.33151			0.33145		
N	31534			31534			31534			31534		

Remark: + $p < 0.1$; * $p < 0.05$; ** $p < 0.01$.

Table 6. Regression analysis with Lg (Like) as the dependent variable.

Independent Variables	Model 1			Model 2			Model 3			Model 4		
	Coefficient	*SE*	*p*	**Coefficient**	*SE*	*p*	**Coefficient**	*SE*	*p*	**Coefficient**	*SE*	*p*
EV				−0.058 **	0.009	0.000	−0.074 **	0.010	0.000	−0.087 **	0.010	0.000
AV				−0.230 **	0.015	0.000	−0.240 **	0.016	0.000	−0.240 **	0.017	0.000
JC1				0.001 **	0.000	0.000						
EV × JC1				0.004 **	0.001	0.000						
AV × JC1				0.007 **	0.001	0.000						
JC2							−0.000	0.000	0.951			
EV × JC2							0.004 **	0.001	0.000			
AV × JC2							0.007 **	0.001	0.000			
JC3										0.000	0.000	0.138
EV × JC3										0.004 **	0.000	0.000
AV × JC3										0.006 **	0.001	0.000
Price	−0.173 **	0.061	0.005	−0.176 **	0.061	0.004	−0.178 **	0.061	0.003	−0.180 **	0.061	0.003
Performance	0.106 **	0.021	0.000	0.106 **	0.021	0.000	0.106 **	0.021	0.000	0.106 **	0.021	0.000
Range	−0.002	0.193	0.990	−0.016	0.192	0.934	−0.006	0.192	0.975	0.002	0.192	0.992
Emission	0.119 **	0.015	0.000	0.115 **	0.015	0.000	0.114 **	0.015	0.000	0.114 **	0.015	0.000
TA	0.000 **	0.000	0.000	0.000	0.000	0.327	0.000	0.000	0.137	0.000 +	0.000	0.085
ROA	0.016 **	0.002	0.000	0.015 **	0.002	0.000	0.012 **	0.002	0.000	0.011 **	0.002	0.000
TL	−0.001 **	0.000	0.000	−0.001 **	0.000	0.000	−0.001 **	0.000	0.000	−0.001 **	0.000	0.000
Brand dummies	Included			Included			Included			Included		
Year dummies	Included			Included			Included			Included		
F	1871.285			1705.404			1706.061			1707.558		
R^2	0.7157			0.7192			0.7193			0.7195		
Adjusted R^2	0.7153			0.7188			0.7189			0.7191		
RMSE	0.33394			0.33190			0.33185			0.33175		
N	32,006			32,006			32,006			32,006		

Remark: + $p < 0.1$; * $p < 0.05$; ** $p < 0.01$.

Models 2–4 were used for the main analysis. First, variables related to EV and AV were significantly negative in models 2–4, which implies that stakeholders have negative social media engagement for the tweets about EVs and AVs. Thus, H1 and H2 were supported. Then, we also observed that EV × JC and AV × JC had positive effects on retweeting in models 2–4, which implies that JC mitigates the negative effect of EVs and AVs on stakeholder social media engagement. This result indicates that stakeholder technology anxiety is indirectly caused by job loss. Thus, H3 was fully supported. Furthermore, we noted that the moderating effect of JC on EVs was stronger when firms create jobs in the longer term. By contrast, firms' short-term JC can stimulate to a greater extent the moderating effect of JC on AV. Finally, R^2 (0.6034) in model 4 was the highest, indicating that model 4 was the optimal model, and EV × JC3 and AV × JC3 explained most of the moderating effects.

4.3. Robustness Check

To ensure the robustness and consistency of the research results, we conducted two robustness checks of our results. First, we re-ran the model, excluding Tesla's data (Table 5) in the robustness check. Model 4 was still the optimal model. The findings remained the same, suggesting that the model was not influenced by bias from Tesla's tweets. In addition, the findings also remained the same when we changed to use "Lg (Like)" as dependent variables (Table 6). Therefore, the category of social media engagement did not influence our findings. Both forwarding and likes can reflect public opinions. Furthermore, R squared in the model with "Lg (Like)" as the dependent variable was larger than that in the model with "Lg (Retweet)" as the dependent variable. People need to put more cognitive effort on retweeting instead of giving likes, which implies that more people may give likes to a tweet rather than retweet it. However, people may get engaged more deeply when they retweet.

5. Discussion

Our results indicate that a tweet about EV is less likely to retweet, compared to all other non-EV tweets. Social media engagement is negative for AVs compared with traditional cars' technologies on safety, performance, and operations. This explains that the diffusions of EVs and AVs are considerably inert on social media channels. Moreover, we find car manufacturers' CJC moderates the negative effect of EVs and AVs on social media engagement.

5.1. Implications for Theory

To the best of our knowledge, this is the first study that employed social media datasets to indicate that CJC improves DOI in the automobile industry. Social media is an ideal platform to examine DOI since everyone can express their opinions easily and freely on social media. In addition, people's attitudes towards innovations are measurable (i.e., social media engagement) on social media. In Twitter, social media engagement includes giving likes, providing comments, and retweeting. We use retweeting, as the highest engagement, to represent social media engagement since the tweets will appear on their personal profile and become one of users' self-presentations when people share the tweets [84]. Compared with the data collected using other methods (e.g., survey and interviews), social media analytics is more suitable for investigating public opinion and is much more suitable in our research context. Our findings indicate that social media engagement should receive greater attention from both academics and senior management for promoting DOI among the public.

First, we adopt social media data to provide evidence that the diffusions of EV and AV are still passive, which is consistent with previous studies [31,32,81]. Ball, Vogele, Grajewski and Kuckshinrichs [51] and Biresselioglu, Demirbag Kaplan and Yilmaz [42] argued that obstacles for the diffusion of EVs (e.g., charging infrastructures) are substantial rather than incentives for the diffusion of EVs (e.g., ecological awareness, allowance). On the other hand, Biresselioglu, Demirbag Kaplan and Yilmaz [42] claimed that a lack of consumer acceptance is still taking a big toll as the barrier to diffuse AVs. Tesla is more adept at communicating with the public regarding its technologies, but our robustness test revealed that our prediction applies to all other brands, which is that stakeholders react negatively to EVs and AVs on social media platforms.

CJC, as a moderator, can reduce stakeholders' negative reactions and improve DOI. CJC is one part of firms' communications on their CSR practices. Previous studies overlooked that job loss may be one of the barriers to the diffusion of EVs and AVs [17]. According to Maslow's hierarchy of needs, employment is one of people's significant needs. Thus, job creation is a significant social issue. Consumers tend to identify with firms that they think are socially responsible and recommend them to their friends and others [85]. The CEO of Tesla, Elon Musk, emphasizes CSR, for example, by transforming conventional energy sources into renewable energy and reusing space rockets to minimize wastage, which attract greater public media engagement. This extends the research by Wiengarten, et al. [86], which indicates that CEOs who focus on CSR might enhance firms' financial performance. In addition, social influencer CEOs are more likely to post CSR messages on Twitter to engage stakeholders strategically [78]. CSR is a long-term investment that can bring benefits not only to the local community, but also to the enterprise itself, which requires that firms' innovations be responsible [44]. Therefore, in our study, the results indicate that CJC that fulfills key sustainable development goals helps brands win public approval of innovations. Our study provides evidence to the relationship between CSR efforts and DOI, which extends the CSR literature.

In addition, firms' new technologies can reach widely and quickly through employees, who are seen as ambassadors. Moreover, employees are also product experts who can answer people's questions about new technologies, share their own experience on new technologies, and release people's anxiety about new technologies.

5.2. Implications for Practice and Policy

We observed the failure of the diffusion of EVs and AVs on social media, which implied that firms need to put more effort into social media communication. Communication on social media exceeds the limit of time and space. Therefore, social media allows firms to achieve wider and more immediate DOI. We suggested that CJC is a benefit for firms' DOI. Firms may get higher social media engagement when they communicate their efforts on job creation in the topics related to EVs and AVS. Among 32,006 tweets, we only found that there were less than 100 tweets that mentioned job creations on the topic of EVs and AVs. Car manufacturers generally neglect to mention job creation in the diffusion of EVs and AVs. However, when firms mention job creation, they can get higher social media engagement. For example, "#Ford is investing $1.6 billion to upgrade two plants in Michigan & Ohio—and creating or retaining 650 U.S. jobs" received three times more retweets (318) than the average number (90). "#MercedesBenz goes #electric in America—bringing 600 U.S. jobs & a $1 billion investment to #Alabama #switchtoEQ http://benz.me/dmCASE" (https://t.co/9HZjQkkV3M, 19 August 2020) received 160 retweets, approximately 60% more than the average number (97).

Furthermore, job creation is one aspect of CSR practices. In particular, the firm's commitment to job creation is conducive to establishing a responsible public image. Consequently, people may engage more in these firms, which improves the diffusions of innovations in these firms.

In addition, this study provides evidence of the significance of employees as ambassadors, which also illustrated that firms need to maintain a high level of employee satisfaction. Employees who have satisfactory working experience are more likely to share their firms to their friends and relatives. In particular, firms' efforts on CSR have potential to improve employee satisfaction [40,41].

Additionally, as promoting innovations is the long-term goal of the government, we suggest that policy makers should promote new labor policies while promoting technology and innovation policies related to EVs and AVs. For instance, Singapore's Ministry of Transport suggests that full AV adoption will only occur in approximately 15 years because social issues must first be addressed, including job displacement and reskilling as well as impacts on revenue collection (road tax); measures to resolve these matters can reduce citizens' anxiety when AVs are adopted [87]. Policymakers should communicate new training programs to ease people's anxiety about unemployment caused by new technologies. Currently, AVs still need to run under human supervision. There are still many accidents caused by automatic cars, resulting in people's fear of new technology. Training can educate drivers to become more familiar with AVs and improve the adoption rate (http://agelab.mit.edu/files/publications/2016_6_Autonomous_Vehicles_Consumer_Preferences.pdf., access date 20 June 2021). In addition, service front-line personnel with more professional knowledge will be able to engage consumers in the experience of EV and AV, thus improving DOI [24].

5.3. Limitations and Future Research Directions

First, although retweeting is assumed to represent positive engagement, which is also largely supported by the literature, some retweeting may denote negative sentiments. Future research could use sentiments from Twitter followers as the dependent variable. Second, this study covers the majority of global brands in the auto industry. However, some brands from developing countries may have been neglected (i.e., China). Third, it is not clear how social media engagement affects firm performance, as the sentiment of tweets regarding supply chain problems could affect stock market prices (Schmidt, Wuttke, Ball and Heese [15]). Such effects may also affect firms' innovation and should be investigated. Future studies should measure how public opinion regarding EVs and AVs on social media affects auto firms' stock returns.

In addition, we noted that several international brands communicated the number of jobs they created for the U.S. on Twitter. These car makers obtained several reactions from stakeholders. For instance, "#MercedesBenz goes #electric in America—bringing 600 U.S. jobs & a $1 billion investment to #Alabama #switchtoEQ http://benz.me/dmCASE" (https://t.co/9HZjQkkV3M, 19 August 2020) received 160 retweets, approximately 60% more than the average number (97). Therefore, we assume that the U.S. public may prefer locally produced brands because of the desire to support local employment or because they show a larger commitment to supply products and components made in the local market [88]. Future studies can adopt the number of employees in American subcompanies as a variable and replicate the current study. The current research team could not locate adequate U.S. employment information of most European car makers; thus, this study only focused on the topic in the global context.

Furthermore, future studies can extend the hypothesis and compare the differences between stakeholders' reaction to local manufacturing in different markets. For example, Tesla established new factories in China and Germany to manufacture new models for Chinese and European markets. Tesla's actions corroborate our empirical findings. In particular, the Tesla Shanghai Gigafactory is a wholly owned subsidiary of Tesla, which is the first foreign car manufacturer with 100% foreign capital in China. The factors (e.g., new job creation on local supply chains and lower prices) affecting the Chinese government's decision to allow Tesla to set up a wholly owned factory should be investigated. However, Tesla's foreign investment may limit new job creation in the United States. Therefore, how to maintain the balance between foreign investment and local investment in the scenario of EVs and AVs requires further investigation.

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Appendix A

Table A1. Lexicon.

Category	Keyword	Category	Keyword
	electric	AV	intelligentmobility
	ev		intelligent mobility
	evs		automate
	ev.		automateddriving
	#ev		fullyautomated
	allelectric		highlyautomated
	formulae		automated
	formula e		selfdriving
	i3		selfdrivinglaw
	#i3		selfdrivingtechnology
	i8		autopilot
	#i8		self driving
	ipace		self-driving
	#ipace		driverless
	i-pace		autonomous
	#i-pace		automation
	prius		
	#prius	Price	price
	etron		prices
	#etron		dollar
	Model 3		rent
	#model3		lease
	model y		installment
	#modely		
	model s	Performance	0–100
	#models		0–60
	model x		accelerate
	#modelx		accelerated
	#TeslaCharging		accelerates
	e-Golf		accelerating
	#e-golf		acceleration
	#egolf		top speed
EV	egolf		maximum speed
	etron		max speed
	EQC		turbo “
	#EQC		horse power
	VOLT		hp
	LEAF		v8
	EQS		#v8
	#EQ		v6
	#EQC		#v6
	#EQV		w12
	#EQS		#w12
	EQV		nm
	EQC		kw
	taycan		
	ehybrid	Range	mile range
	PLUG-IN		range anxiety
	PLUG IN		
	plugin	Emission	co2
	Charging system		co2emissionen

Table A1. *Cont.*

Category	Keyword	Category	Keyword
	Charging station Charging point Charging network #ChargedWithExcitement #ReadyForElectric Tesla Destination Charging supercharging supercharger electrification battery batteries Tesla charging section roadster		co2emissions emission NO2 diesel g/km l/100km

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