Consumer insight on driverless automobile technology adoption via twitter data: A sentiment analytic approach

Citation

KWARTENG, Michael Adu, Alex NTSIFUL, Raphael Kwaku BOTCHWAY, Michal PILÍK, and Zuzana KOMÍNKOVÁ OPLATKOVÁ. Consumer insight on driverless automobile technology adoption via twitter data: A sentiment analytic approach. In: *IFIP Advances in Information and Communication Technology* [online]. vol. 617, Springer Science and Business Media Deutschland, 2020, p. 463 - 473 [cit. 2023-03-06]. ISBN 978-3-03-064848-0. ISSN 1868-4238. Available at https://link.springer.com/chapter/10.1007/978-3-030-64849-7_41

DOI

https://doi.org/10.1007/978-3-030-64849-7_41

Permanent link

Consumer Insight on Driverless Automobile Technology Adoption via Twitter Data: A Sentiment Analytic Approach

Michael Adu Kwarteng[1,2], Alex Ntsiful[1,2], Raphael Kwaku Botchway[1,2], Michal Pilik[1], and Zuzana Komínková Oplatková[1,2]

[1]*Faculty of Management and Economics, Tomas Bata University in Zlin, Mostni 5139, 760 01 Zlin, Czech Republic {Kwarteng,Ntsiful,Botchway,Pilik,Kominkova}@utb.cz*

[2]*Faculty of Applied Informatics, Tomas Bata University in Zlin, Nad Stráněmi 4511, 760 05 Zlin, Czech Republic*

Abstract

Technology has sped up the innovation effort in the automobile industry. Further to this automobile innovation such as intelligent climate control, adaptive cruise control, and others, we find in today's vehicles, it has been predicted that by 2030, there will be driverless vehicles, of which samples are already on the market. The news and the sights of these so-called driverless vehicles have generated mixed reactions, and this motivated our study. Hence the present study focuses on a dataset of tweets associated with driverless vehicles downloaded using the Twitter API. Valence Aware Dictionary and sentiment Reasoner (VADER), a lexicon and rule-based sentiment analysis tool were used in extracting sentiments on the tweets to gauge public opinions about the acceptance and adoption of the driverless vehicles ahead of their launch. The VADER sentiment analysis results, however, show that the general discussion on driverless vehicles was positive. Besides, we generated a word cloud to visually analyze the terms in the dataset to gain further insights and understand the messages conveyed by the tweets in other to enhance the usage and adoption of driverless vehicles. This study will enable self-driving vehicle technology service providers and autonomous vehicle manufacturers to gain more insights on how to transform the transportation sector by investing in research and technology.

Keywords: Driverless vehicle, twitter, sentiment analysis, autonomous, technology, innovation

1 Introduction

Technology has sped up the innovation effort in the automobile industry. A shred of evidence is that most of the latest vehicles we find in town are endowed with technological advancements such as automatic braking systems, crash sensors, cruise control, auto speed control, intelligent climate control, adaptive cruise control, advanced emergency braking system, and many others. Further to these advancements, research indicates that by 2030, the automobile industry could fully introduce unto the market, another dynamic product-driverless vehicle (**Panayiotopoulos and Dimi-trakopoulos 2018**) which could oust the driver from his/her seat literally. With its other variant names such as an un-crewed car, unmanned vehicle, self-drive car, robot car, and the like, driverless vehicle is a type of automobile designed and equipped with artificial intelligence (AI) in such a way that it can self-sense its environment and navigate safely to its destination. It is popularly known in the literature as autonomous vehicles (AVs) but for this paper and many variant audiences in mind, we will use a driverless vehicle. It is interesting to note that there are already some of these vehicles on the market, though most of them are being piloted. **Young (2015)** cites Mercedes Benz F015, General Motors GM ENV, Google self-driving car, Servvan Robotic Vehicle, BMW E-patrol, BMW Honey Comb, and the Zoox

Level 4 Reversible, as examples of driverless vehicles available. Young notes that some of these vehicles are so intelligent that they could sense the driver's capabilities and decide to take over the driving when necessary.

However, it is important to note that driverless vehicles would not replace the traditional vehicles but would rather serve as an addition to the levels of vehicles we have in the automobile industry. In line with this assumption, **SAE international (2016)** explains that there would be five levels of vehicles with level 0 being the fleet of vehicles which is fully operated by humans and level 4 as those vehicles fully driven without any human involvement. The levels of 1-3 vehicles are classified depending on the level of their 'autonomousity' or the amount of human involvement in operating them. Extant studies have argued that the adoption of driverless vehicles on our road comes with a myriad of advantages (**Piao et al. 2016; Sparrow and Howard 2017; Meyer et al. 2017**). Examples of these benefits include a new line of business (**Litman 2017**), reduction in road accidents (**KPMG International 2019; Piao et al. 2016**), and new transport service, and new transport means for the aged and physically impaired (**Sparrow and Howard 2017; Meyer et al. 2017**). For instance, **Piao et al (2016)** explain that driverless vehicles could reduce road accidents by 90% because these accidents are caused by human errors due to factors such as fatigue, alcohol, carelessness, and the influence of drugs. Despite these merits, another stream of research has found that some members of society think that accepting driverless vehicles in our fleet may be problematic. They explain that the challenges, which come with the current level of automobile innovations, mentioned earlier, have not been fully resolved (**Pana-giotopoulos and Dimitrakopoulos 2018**). For instance, studies such as (**Milakis et al. 2017; Van Brummelen et al. 2018**) have found that drivers have trust issues with automated system vehicles and also believe that the automated systems come with some workload and situation awareness issues for the drivers. To this end, researchers have begun to engage the public on their possible acceptance of the incoming technology and also the factors that could influence their adoption (**Payre et al. 2014; Xu et al. 2018**). Thus, to add to this body of initial and pre-driverless vehicle launching research is the main objective of this study. However, we approach this research task with a different method, that is, the sentiment analysis via twitter data. Specifically, the study seeks to gauge the public opinions (positive and negative) about the acceptance and adoption of the driverless vehicles ahead of their launch to offer insights to engineers, product designers, and policymakers of automobile industries, especially those specializing in unmanned vehicles, by using sentiment analysis via twitter.

We believe that both the generation Z and generation alpha, who would be ultimate users of the driverless vehicles, mostly use social media to search for information on the latest technology (**Rathore et al. 2016**), and that a medium such as the twitter could give reach information needed for the study. We also contend that using a survey to ask people 'on the street' about the driverless vehicle, they might have not seen a demo, a method which the previous studies used (e.g. **Daziano et al. 2017; Chowdhury and Ceder 2016**) may not be realistic or the best. With the sentiment analysis, we can extract, from people who have seen a demo of this yet-to-be-launched innovation, rich data of opinions, ideas, challenges, and other sentiments they may have with the technology. We also contend that the sentimental data is richer in that they are not responses to a survey question where a respondent may give socially desirable answers but we are extracting 'post-natural responses to unasked questions. Moreover, this study's population is global, as we do not use twitter sentiments from one location but all users of twitter. Our study is indeed significant for several reasons: First, we argue that, apart from the unique methodological approach highlighted above, the findings of this study will set the tone for further deductive empirical research. Second, the findings can also serve as a guide to policymakers in developing automobiles, and road and traffic management policies. Finally, the results can also guide driverless vehicle engineers to incorporate consumer preferences and challenges into driverless vehicle engineering designs.

The rest of the paper is organized as follows. Next to this introduction is the literature review, followed by a snapshot of sentiment analytic approach. Following that is the analysis of data and findings. We end the paper with a short discussion and conclusion.

2 Literature Review

2.1 Automobile Technology Adoption and Consumer Insights

Like with any other innovation, which comes to the market, customers may be skeptical of the driverless vehicle and would begin to raise questions on several issues. For instance, in **Egbue and Longs (2012)** study involving consumers' attitudes towards the adoption of electric vehicles, it was found that cost and performance were rated higher than environmental and sustainability benefits. Before this finding, **Axsen et al. (2010)** have found that limitations with battery technology and the high cost of the battery were key barriers to electric vehicle adoption. Similarly, the cost has been anticipated to be a potential barrier to adoption when driverless vehicles become fully functional (**Fagnant and Kockelman 2015**). They explain that driverless vehicles require technologies like sensors, software for each automobile, and communication and guidance technology, which are expensive and build up to the total cost of the vehicle. In this regard, **Shchetko (2014)** estimates that Light Detection and Ranging (LIDAR) systems, a common essential device for driverless vehicles, is priced between cost $30,000 to $85,000 and this cost excludes the cost of software, sensors, software, engineering, and extra power and computing requirements.

By giving a fair idea of how much driverless vehicles may cost, we refer to **Dellenback (2013)** estimates of the cost of 2013 civilian and military driverless vehicles, which stood at $100,000 in 2013. Further, earlier studies have also found other adoption challenges for driverless vehicles including trust (**Bansal et al. 2016; Kyriakidis et al. 2015**). **Although Paden et al. (2016)** have highlighted high carbon emission, excessive traffic and accidents as the challenges we have with the conventional vehicles, problems which are not found with the driverless vehicle, **Fagnant and Kockelman (2015)**'s findings of security, trust, privacy, reliability, and liability with the autonomous vehicle cannot be discounted. By shedding more light on these concerns, **Fagnant and Kockelman (2015)** argue that there is the need to worry about electronic security as there are possibilities of computer hackers, terrorist organizations, and demotivated employees who could sabotage driverless vehicle and that could result in accidents and traffic on the roads. When the driverless vehicle becomes operational, data and information sharing become a common ritual and that is where privacy issues set in (**Fagnant and Kockelman (2015)**. Despite these drawbacks, **Kaur and Rampersad (2018)** argue that there may be certain situations, which would make some consumers opt for driverless vehicles as compared to others, and that further research is needed to uncover those situations.

2.2 Overview of Driverless Automobile Technology

The definition for driverless vehicle ranges from a vehicle that operates without human driver (**Paden et al. 2016**), to a vehicle whose critical control functions such as steering, braking, throttling is managed without the driver's support (**NHTSA 2013**). It is envisaged that the introduction of the driverless vehicle can help reduce about 1.2 million road fatalities, which according to **WHO (2015)**, occurs every year. Interest in this driverless automobile technology is said to have started as far back as 1939 during the World's Fair held in New York (**Levy 2016**). However, **LeValley (2013)** reports that fully developed autonomy occurred in the early 21st Century. Levy explains that the developer of these autonomous technologies took inspiration from the Defense Advanced Research Projects Agency (DARPA), which developed driverless technology for the military. According to DARPA (2014), the military driverless vehicle was intended to reduce the number of soldiers who lose their lives on the war front. Gradually, DARPA continued to develop this concept until they had a breakthrough (called the DRAPA's first Urban Challenge) in 2007 when they have autonomous vehicles, which were capable of navigating through city-like terrain, obey traffic regulations, change and merging lanes while avoiding road obstructions.

Since that breakthrough, interest in autonomous vehicles has surged up. Extant studies have it that technology giants like Google, Testa, and Uber, and well-known automobile firms like General Motors, Ford (all in the US) together with their European and Japan counterparts have made significant progress in this regard (**Chehri and Mouftah 2019**). As the tech and automobile giants make progress, governments and legislative bodies begin to develop strategies, promulgate laws and regulation, and build infrastructure like smart cities, to support and in ahead of the launch of the driverless vehicles. Infrastructures are very essential to its success because, according to **Chehri and Mouftah (2019)** autonomous vehicle uses a different range of technologies including radar, cameras, radio antennas, and the support of artificial intelligence, 5G network to safely navigate on roads. This suggests that for a country to adopt driverless vehicles certain infrastructures must be in place as well as amendments to its laws, especially those relating road and traffic issues.

To this end, **Johnsen et al. (2017)** indicate that German Bundestag has reviewed their Road Traffic Act given this new paradigm shift in the automobile industry. A section of the amended Road Traffic Act reads: *'The driver may turn his attention away from the traffic situation and vehicle operation if the car is in an automated or autonomous driving mode, but she/he must in principle remain vigilant so that he can immediately take control of the vehicle again, if necessary (**Johnsen et al. 2017**, p. 49)*. Moreover, many other countries are preparing well for the task ahead in automobile technology and this has led to a periodic compilation of countries' readiness, known in literature now as Autonomous Vehicle Readiness Index (AVRI) by KPMG international since 2018. Thus, according to **KPMG (2019)**'s Autonomous Vehicle Readiness Index (AVRI), there are about 25 countries that are ready to embrace the driverless vehicles' agenda with Netherland leading the chart. The AVRI has four key measures and these include policy and legislation, technology and innovation, infrastructure, and consumer acceptance. Netherland leads the 2019 chart because it had 1st position in the infrastructural ranking, 2nd on consumer acceptance, 5th on policy and legislation, and 10th in technology and innovation category, culminating to total points of 25.05. Four other countries following Netherland include Singapore (2nd 24.32 points), Norway (3rd, 23.75). United States (4th, 22.58 points), and Sweden (5th, 22.48 points). For the comprehensive list of the ranking, see the KPMG AVRI report 2019.

2.3 A Snapshot of Sentiment Analytic Approach via Twitter

Sentiment analysis, popularly known as opinion mining, has been long studied in both academia and the industry (**Grover and Akar 2017; Kar and Dwivedi 2020**). It employs computational algorithms in the form of natural language processing bent on identifying sentiment polarity, intensity, and topics, particularly where the so-called sentiments apply (**Liu et al. 2005; Chamlertwat et al. 2012**). Sentiment analysis in practice turns out to automate opinion discovery and classification systems that deal with a huge amount of data by purposefully extracting and understanding complex humangenerated content/judgment. (**Lake 2011**)

In the last decade, the concept of sentiment analysis has become one of the most topical and researched areas in machine learning (see, **Agarwal et al. 2011; Whitelaw et al. 2005**). Technically, sentiment analysis applies to different levels of text granularity (**Agarwal et al. 2011**). Thus, the scope of the sentiment analysis process involves document-level classification task to a finer-grain level of a sentence and then to the phrase level for execution. (**Wilson et al. 2005**). However, there are two main approaches used in sentiment analysis, and these can be categorized under the machine learning approach and Lexicon based approach. The machine learning approach works as a supervised learning approach where the training process involves classifies input into output manually. Once training data with sentiment values are captured by the process, the corresponding domain data will generate results. On the other hand, the lexicon-based approach used in this study works as an unsupervised learning approach. It works based on the features fed by the encoded sentimental lexicon score to analyze the polarity whether it is positive or negative.

Over the years, sentiment analysis has been used extensively in several areas such as deducing opinions of customers' in the banking sector (**Botchway et al. 2020**), products review data analysis (**Fang and Zhang 2015**), gaining insights in telecommunication usage in Ghana (**Nabareseh et al. 2018**)

2.4 Research Questions

Extant literature has shed more light on user-generated content on social media (**Afful-Dadzie et al. 2016; Feldman 2013; Aggarwal et al. 2011**). This paper employed opinion mining/sentiment analysis to do a rigorous analysis using unstructured textual information on Twitter sites (data). The following research questions guided the study.

1. What are the characteristics of driverless vehicle adoption tweets? Are there any patterns of negativity or positivity associated with the adoption and usage of driverless cars on twitter sites?
2. What are the sentiments of driverless vehicles tweets? How do customers feel about the use of driverless cars?

3 Methodology

3.1 Data Collection and Pre-processing

Twitter has become the most preferred social media channel with 330 million monthly active users according to **Statista (2019)**. The dataset consists of 11,000 tweets collected between May, 20, 2020, and June 29, 2020, using the Twitter streaming Application Programming Interface (API). With the help of the python library Tweepy (**Feldman 2013**), we collected tweets that contained the keyword "self-driving cars" on Twitter (**Fig. 1**).

We then proceeded to clean the text by removing duplicate tweets, punctuations, stop words, URLs, slangs, @ symbol used to mention usernames and converted all text to lowercase. Additionally, we omit terms with low frequency and filter out meaningless words. Consequently, 9590 documents (tweets) were stored as a corpus in a comma separated value (CSV) format after the cleaning process.

3.2 Document Analysis

We used a lexicon-based sentiment analysis approach for our work (**Grover et al. 2018**). Although the lexicon approach is considered an unsupervised method, it is a major sentiment analysis technique that categorizes text documents into a set of predefined sentiment classes. The Valence Aware Sentiment Dictionary and Reasoner (VADER), a lexicon and rule-based tool specifically attune to sentiments expressed on social media (**Hutto and Gilbert 2014**) were deployed from the python NLTK 3.4.1 toolkit.

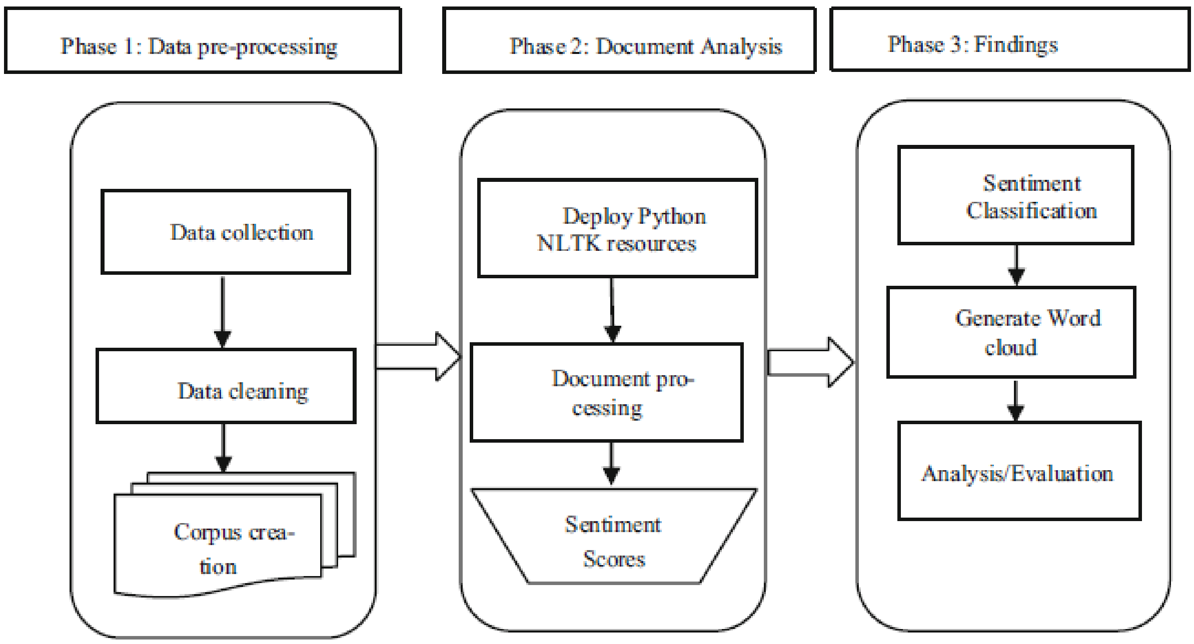

Fig. 1. Model framework of our Study

Given a document, VADER examines its lexical features to determine an initial sentiment score before applying five different rules based on grammatical conventions and syntax to amend that score. These rules handle capitalization and exclamation marks as sentiment amplifiers. Besides, they also handle negations and contrastive conjunctions well. VADER produces positive, negative, neutral, and compound scores for each tweet in the dataset. The positive, negative, and neutral scores are ratios for proportions of text that lie in these categories whereas the compound score sums up all the lexicon ratings which have been normalized between -1(most extreme negative) and +1(most extreme positive).

3.3 Findings

Our initial experiments reveal that VADER with a threshold value of 0.2 produces the best values of precision and recall, with an improvement in both classification directions (positive and negative) in terms of metrics. Hence documents (tweets) with VADER scores greater than 0.2 were classified as positive, documents with scores between 0 and 0.2 are classified and neutral with all other tweets with scores less than zero classified as negative. Out of 9590 documents (tweets), 4014, 1976, and 3600 were classified as positive, negative, and neural respectively. **Figure 2** shows the proportion of sentiment classes. We generate a word cloud based on the frequencies of the words used in the dataset to determine the size of the words to gain further insights into the opinions expressed in the tweets.

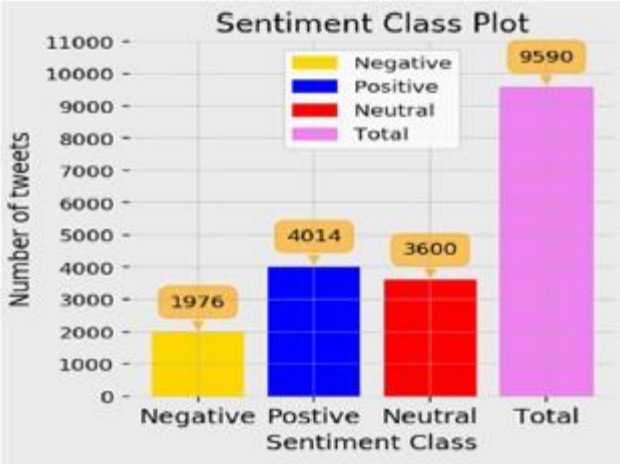

Fig. 2. Sentiment class graph

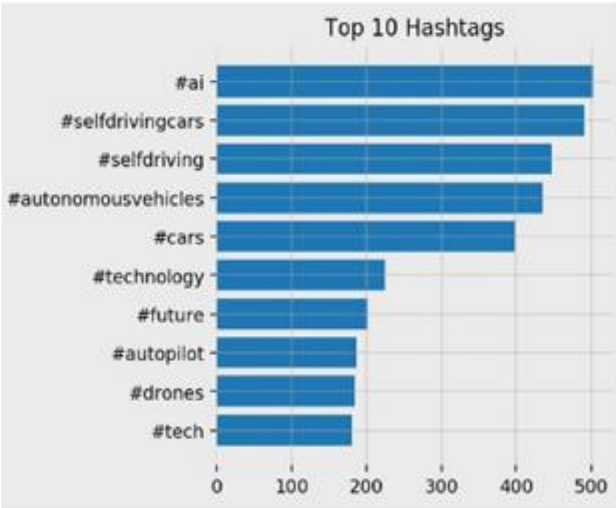

Fig. 3. Top 10 hashtags from the dataset

4 Short Discussion and Conclusion

In this study, we performed the sentiment analysis of 9590 tweets using the VADER lexicon. The tweets were classified into three classes namely: positive, negative, and neutral. VADER classified 4014 tweets as positive while 1611 and 3965 tweets were classified as negative and neutral respectively. The sentiment analysis results indicate that the overall discussion on self-driving cars in terms of usage and adoption involving stakeholders on Twitter was positive. This is quite encouraging judging from the increasing popularity self-driving vehicle technology is currently enjoying coupled with its huge potential to transform the transportation system (and by extension the economy and society). Analysing **Fig. 3** (Top 10 hashtags) and **Fig. 4** (word cloud of negative sentiments) provides further insights from different perspectives. Artificial intelligence (AI) tops the list in **Fig. 3** which shows the significant impact and pioneering role of AI in autonomous vehicle development (**Maayan-Wainstein 2020**). An example is deep reinforcement learning (DRL), which combines strategies of deep learning and reinforcement learning to enhance the automation of training algorithms in applications used for lower-level vehicle automation. Since the bigger and bolder a word appears in a word cloud depicts the importance and frequency with which the word is mentioned within a given context, prominent words like "car", "people", "crashes", "ai", "problem" found in the negative sentiment word cloud raises safety and technology issues that require attention. Investigating the tweets containing these terms to find out the actual message they carry will go a long way to enhance the usage and adoption of autonomous vehicles. In our view, the explanation provided above adequately answers research questions 1 and 2, which also collaborates with recent studies performed by researchers (**Botchway et al. 2019; Nabareseh et al. 2018; Ibrahim and Wang 2019**). Ignoring non-English tweets was a major limitation to this study since their inclusion could potentially enrich the work by providing further insights that could be exploited. In the future, methods such as topic modeling and time-series amongst others could be applied to improve the analysis of tweets in the dataset.

Fig. 4. Negative sentiments word cloud

References

Afful-Dadzie, E., Nabareseh, S., Oplatková, Z.K., Klimek, P.: Framing media coverage of the 2014 sony pictures entertainment hack: a topic modelling approach. In: Proceedings of the 11th International Conference on Cyber Warfare and Security: ICCWS 2016, p. 1 (2016)

Agarwal, A., Xie, B., Vovsha, I., Rambow, O., Passonneau, R.J.: Sentiment analysis of Twitter data. In: Proceedings of the Workshop on Language in Social Media (LSM 2011), pp. 30-38, June 2011

Axsen, J., Kurani, K.S., Burke, A.: Are batteries ready for plug-in hybrid buyers? Transp. Policy **17**(3), 173-182 (2010). **https://doi.org/10.1016Zj.tranpol.2010.01.004**

Bansal, P., Kockelman, K.M., Singh, A.: Assessing public opinions of and interest in new vehicle technologies: an Austin perspective. Transp. Res. Part C Emerg. Technol. **67**, 1-14 (2016). **https://doi.org/10.1016/j.trc.2016.01.019**

Botchway, R.K., Jibril, A.B., Kwarteng, M.A., Chovancova, M., Oplatková, Z.K.: A review of social media posts from UniCredit bank in Europe: a sentiment analysis approach. In: Proceedings of the 3rd International Conference on Business and Information Management, pp. 74-79, September 2019. **https://doi.org/10.1145/3361785.3361814**

Botchway, R.K., Jibril, A.B., Oplatková, Z.K., Chovancová, M.: Deductions from a Sub-Saharan African Bank's Tweets: a sentiment analysis approach. Cogent Econ. Finance **8**(1), 1776006 (2020). **https://doi.org/10.1080/23322039.2020.1776006**

Chamlertwat, W., Bhattarakosol, P., Rungkasiri, T., Haruechaiyasak, C.: Discovering consumer insight from Twitter via sentiment analysis. J. UCS. **18**(8), 973-992 (2012)

Chehri, A., Mouftah, H.T.: Autonomous vehicles in the sustainable cities, the beginning of a green adventure. Sustain. Cities Soc. **51**, 101751 (2019). **https://doi.org/10.1016/j.scs.2019. 101751**

Chowdhury, S., Ceder, A.A.: Users' willingness to ride an integrated public transport service: a literature review. Transp. Policy **48**, 183-195 (2016). **https://doi.org/10.1016/j.tranpol.2016. 03.00**

Daziano, R.A., Sarrias, M., Leard, B.: Are consumers willing to pay to let cars drive for them? Analyzing response to autonomous vehicles. Transp. Res. Part C Emerg. Technol. **78**, 150164 (2017). **https://doi.org/10.10167j.trc.2017.03.003**

Dellenback, S.: Director, intelligent systems department, automation, and data systems division, southwest research institute. Communication by email, 26 May 2013

Egbue, O., Long, S.: Barriers to widespread adoption of electric vehicles: an analysis of consumer attitudes and perceptions. Energy policy **48**, 717-729 (2012)

Fagnant, D.J., Kockelman, K.: Preparing a nation for autonomous vehicles: opportunities, barriers and policy recommendations. Transp. Res. Part A Policy Pract. **77**, 167-181 (2015). **https://doi.org/10.10167j.tra.2015.04.003**

Fang, X., Zhan, J.: Sentiment analysis using product review data. J. Big Data **2**(1), 1-14 (2015). **https://doi.org/10.1186/s40537-015-0015-2**

Feldman, R.: Techniques and applications for sentiment analysis. Commun. ACM **56**(4), 82-89 (2013). **https://doi.org/10.1145/2436256.2436274**

Grover, P., Kar, A.K.: Big data analytics: a review on theoretical contributions and tools used in literature. Glob. J. Flex. Syst. Manag. **18**(3), 203-229 (2017). **https://doi.org/10.1007/s40171-017-0159-3**

Grover, P., Kar, A.K., Davies, G.: "Technology enabled Health"-insights from Twitter analytics with a socio-technical perspective. Int. J. Inf. Manag. **43**, 85-97 (2018)

Hutto, C.J., Gilbert, E.: Vader: a parsimonious rule-based model for sentiment analysis of social media text. In: Eighth International AAAI Conference on Weblogs and Social Media, May 2014

Ibrahim, N.F., Wang, X.: Decoding the sentiment dynamics of online retailing customers: time series analysis of social media. Comput. Hum. Behav. **96**, 32-45 (2019). **https://doi.org/10. 1016/j.chb.2019.02.004**

Johnsen, A., Strand, N., Andersson, J., Patten, C., Kraetsch, C., Takman, J.: D2. 1 Literature review on the acceptance and road safety, ethical, legal, social and economic implications of automated vehicles (2017)

Kar, A.K., Dwivedi, Y.K.: Theory building with big data-driven research-moving away from the "What" towards the "Why". Int. J. Inf. Manag. **54**, 102205 (2020)

Kaur, K., Rampersad, G.: Trust in driverless cars: Investigating key factors influencing the adoption of driverless cars. J. Eng. Tech. Manag. **48**, 87-96 (2018). **https://doi.org/10.1016/j.jengtecman.2018.04.006**

KPMG International: 2019 Autonomous Vehicle Readiness Index, Assessing countries preparedness for autonomous vehicles (2019)

Kyriakidis, M., Happee, R., de Winter, J.C.: Public opinion on automated driving: Results of an international questionnaire among 5000 respondents. Transp. Res. Part F Traffic Psychol. Behav. **32**, 127-140 (2015). **https://doi.org/10.1016/jjengtecman.2018.04.006**

Lake, T.: Twitter Sentiment Analysis. Western Michigan University, Kalamazoo (2011)

LeValley, D.: Autonomous vehicle liability—application of common carrier liability (2013)

Levy, J.: No need to reinvent the wheel: why existing liability law does not need to be preemptively altered to cope with the debut of the driverless car. J. Bus. Entrepreneurship Law **9**, 355 (2016). **http://digitalcommons.pepperdine.edu7jbel7vol9/iss2/5**

Litman, T.: Autonomous vehicle implementation predictions. Victoria Transport Policy Institute, Victoria, Canada (2017)

Liu, B., Hu, M., Cheng, J.: Opinion observer: analyzing and comparing opinions on the web. In: Proceedings of the 14th International Conference on World Wide Web, pp. 342-351, May 2005

Maayan-Wainsten, L.: Four Innovations Taking Autonomous Vehicle AI to the Next Level, 6 July 2020 (2020). **https://www.enterpriseai.news/2020/07/06/4-innovations-taking-autonom ous-vehicle-ai-to-thenext-level/**. Accessed 7 July 2020

Meyer, J., Becker, H., Bosch, P.M., Axhausen, K.W.: Autonomous vehicles: the next jump in accessibilities? Res. Transp. Econ. **62**, 80-91 (2017). **https://doi.org/10.1016/jjetrec.2017.03.005**

Milakis, D., Van Arem, B., Van Wee, B.: Policy and society related implications of automated driving: a review of literature and directions for future research. J. Intell. Transp. Syst. 21(4), 324-348(2017)

Nabareseh, S., Afful-Dadzie, E., Klimek, P.: Leveraging fine-grained sentiment analysis for competitivity. J. Inf. Knowl. Manag. **17**(02), 1850018 (2018)

National Highway Traffic Safety Administration. NHTSA: Preliminary statement of policy concerning automated vehicles, Washington, DC (2013)

Paden, B., Čáp, M., Yong, S.Z., Yershov, D., Frazzoli, E.: A survey of motion planning and control techniques for self-driving urban vehicles. IEEE Trans. Intell. Veh. **1**(1), 33-55 (2016)

Panagiotopoulos, I., Dimitrakopoulos, G.: An empirical investigation on consumers' intentions towards autonomous driving. Transp. Res. Part C Emerg. Technol. **95**, 773-784 (2018)

Payre, W., Cestac, J., Delhomme, P.: Intention to use a fully automated car: attitudes and a priori acceptability. Transp. Res. Part F Traffic Psychol. Behav. **27**, 252-263 (2014). **https://doi.org/10.1016/j.trf.2014.04.009**

Piao, J., McDonald, M., Hounsell, N., Graindorge, M., Graindorge, T., Malhene, N.: Public views towards implementation of automated vehicles in urban areas. Transp. Res. Procedia **14**, 2168-2177 (2016). **https://doi.org/10.1016/j.trpro.2016.05.232**

Rathore, A.K., Ilavarasan, P.V., Dwivedi, Y.K.: Social media content and product co-creation: an emerging paradigm. J. Enterp. Inf. Manag. **29**, 7-18 (2016)

SAE International: Taxonomy and definitions for terms related to driving automation systems for on-road motor vehicles. SAE International (J3016) (2016)

Shchetko, N.: Laser eyes pose price hurdle for driverless cars. Wall Street J. (2014)

Sparrow, R., Howard, M.: When human beings are like drunk robots: driverless vehicles, ethics, and the future of transport. Transp. Res. Part C Emerg. Technol. **80**, 206-215 (2017). **https://doi.org/10.1016/j.trc.2017.04.014**

Statista. Number of monthly active twitter users worldwide from 1st quarter 2010 to 1st quarter 2019 (in millions) (2019). **https://www.statista.com/statistics/282087/number-of-monthly-active-twitter-users**

Van Brummelen, J., O'Brien, M., Gruyer, D., Najjaran, H.: Autonomous vehicle perception: the technology of today and tomorrow. Transp. Res. Part C Emerg. Technol. **89**, 384-406 (2018). **https://doi.org/10.1016/j.trc.2018.02.012**

Wilson, T., Wiebe, J., Hoffmann, P.: Recognizing contextual polarity in phrase-level sentiment analysis. In: Proceedings of Human Language Technology Conference and Conference on Empirical Methods in Natural Language Processing, pp. 347-354 (2015)

Whitelaw, C., Garg, N., Argamon, S.: Using appraisal groups for sentiment analysis. In: Proceedings of the 14th ACM International Conference on Information and Knowledge Management, pp. 625-631, October 2005

WHO: Global Status Report on Road Safety 2015. World Health Organization (2015). **http://www.who.int/violence_injury_prevention/road_safety_status/2015/en/**. Accessed 27 June 2020

Xu, Z., Zhang, K., Min, H., Wang, Z., Zhao, X., Liu, P.: What drives people to accept automated vehicles? Findings from a field experiment. Transp. Res. Part C Emerg. Technol. **95**, 320-334 (2018). **https://doi.org/10.1016/j.trc.2018.07.024**

Young, M.: From Motorist-Monitoring Autos to Self-Driving Trucks (2015). **https://www.trendhunter.com/slideshow/autonomous-vehicles**. Accessed 26 June 2020