Twitter users are not a representative sample of the population [44]. As our analysis is based on English tweets, the main population analyzed might be located in the U.S. and should not be considered a representative global or U.S. sample [45]. In addition, only a small fraction of tweets in our dataset contain a geolocation so that we could not differentiate between different regions, which remains an ongoing issue in Twitter research [46]. As the training dataset plays an important role for training and evaluating the SVM, results depend on its quality. As described in the previous section, we found indications that the training data is of high quality but further robustness checks could provide additional evidence for the quality of the training data. Considering these limitations, however, we found interesting results that we carefully discuss in this section. This allows us the get valuable insights about people's perceptions as previous Twitter research has [14].

The RR and BR values calculated in this study indicate that people have reservations regarding self-driving cars. People tweet about risks of self-driving cars almost three times as much than about the benefits. Even if the difference might not be as big as this number suggests due to the limitations of our analysis, technology acceptance would not be guaranteed in the current state, making a disruption of individual mobility seem unlikely in the near future. This presents a problem that needs to be tackled before self-driving are sold to the public. We calculated the BR and RR values of separate years, to analyze the tweets over time and could find a small increase in RR from 0.5581 to 0.5290 (+5.2%). This might indicate that the impressive recent technical developments do not affect risk and benefit perceptions much and communication strategies should be reconsidered.

Suggestions for improvement can be derived by going over the tweet contents of the classified tweets, and trying to understand the reasons behind both risk and benefit perceptions towards self-driving cars. Among the different risk-related tweets, most of the tweets displayed concern towards the vehicles' accident, for example: "[…] Google's driverless cars have been involved in four car accidents" or "CAR CRASH Google Self Driving Cars to Decide if You Live or Die […]". This might be a case of a distorted perception of a risk as it contradicts current research. Experts argue that 93% of car accidents are due to driver error [23] and the use of self-driving cars could reduce car accidents by that exact amount [6].

People also display distrust towards the manufacturing companies and conveyed their love for driving, for example: "Sorry @google not going to buy a self driving car I like driving and don't trust your technology". In this case, benefit perception might be distorted. While driving can be enjoyable in certain situations, we find ourselves often confronted with less enjoyable aspects of driving such as traffic congestions, long monotonous highways with speed limitations, or on the search for a parking space in increasingly crowded cities. The author of this tweet might not be aware of this perspective, which could be used in communication strategies to improve benefit perceptions.

Furthermore, people also displayed fear for their own safety and privacy (e.g., "[…] Can #driverless #cars be made safe from hackers?"), where hacking someone's car could allow others to take control of your vehicle. Hackers might even go as far as writing viruses that could be transmitted from car to car. This is a risk that could proof to be real. We already see hacker attacks on current cars. These hacking attacks could cause physical harm to the passengers, which might be perceived more severe than having a personal computer hacked even if the consequences can be severe, too (e.g., huge financial losses, loss of private documents, publication of sensitive data). Manufacturers of self-driving cars need to be aware of that and provide strategies of how to avoid hacking of their vehicles.

Regarding the tweets that were classified as benefits of self-driving cars, many users were especially attracted to the fact that they could save time through self-driving vehicles, for example: "Sleepy time in the car for a in back seat. Wish I had a self driving car & I coulda joined em……". This is also might be a case of distorted benefit perception since only full self-driving automation or level 4 automation [21] allows sleeping while driving. The current level of automation is 2 and it is likely to take some years until we arrive at level 3 or even level 4 automation. Meanwhile, many drivers are misusing current self-driving, for example by even leaving the driver's seat entirely while driving on a public road using the Autopilot feature of a Tesla Model S [20]. People expecting to soon be able to sleep while driving might become disappointed if such systems will not be released soon as suggested by some developers of self-driving cars.

In general, people are impressed by the innovation put into the self-driving concept, for example: "[…] That hyper-futuristic driverless Mercedes has been spotted in San Fran – again […]". Most benefit tweets reflected that people were simply excited to try something new, for example: "[…] A perk of living near Google… We saw the self-driving car today on the highway!" Developers of self-driving have recognized that people are excited about this new technology and the benefits it could provide. Consequently, they are investing in the development of self-driving cars and already promise features that will first be implemented in several years. If communication strategies are not adjusted, this excitement could cause exaggerated risk perceptions and a misunderstanding of the benefits self-driving cars are going to provide. Focusing only on the benefits and even generating exaggerated benefit perceptions could have adverse effects on public acceptance of self-driving cars.

6 Conclusion

The results indicate the need for developers and manufacturers to listen to the voice of customers of self-driving cars and probably rethink their communication strategy. By analyzing 601,778 tweets using supervised machine learning classification, we identified the need to clearly reassure the public of their risk perceptions. People tweet more about risks of self-driving cars than about the benefits. Many of the supportive tweets indicated that the benefit perceptions neglect the actual state of the technology and, thus, could be dangerous or lead to disappointment when trying the new technology for the first time. Getting potential customers to perceive the objective benefits of self-driving cars such as increased safety and increased comfort might increase benefit perception sustainably. This would lead to less disappointment with self-driving cars when they become available to the broad public and, thus, lead to higher acceptance. It is not likely that self-driving cars will disrupt individual mobility in the near future due to the lack of acceptance.

This analysis focused only on Twitter. Further research could replicate this approach using different machine learning algorithms, datasets, and other new technologies. It was not in the scope of this paper to optimize the machine learning text classification to reach the best possible classification accuracy of the SVM. By tuning the parameters of the SVM or generating additional training data, analyses could be improved. Further research of self-driving cars could be based on other keywords and use other approaches such as topic modeling [47] instead of supervised machine learning to remove the effortful manual classification of Tweets.

With the applied optimizations for text classification we could achieve sufficient accuracy of the text classification. Combined with manual inspection of the classified tweets to identify the cause for certain developments of risk and benefit perceptions, we could make well-founded suggestions for improving the public acceptance of self-driving cars. We identified a promising metric, risk rate *RR*, which can be used to study risk and benefit perceptions in social media. Furthermore, we identified issues in the communication strategies of self-driving car developers.

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