Brandon Ables

Article Critique

Full article citation:

Basu, C., Yang, Q., Hungerman, D., Singhal, M., & Dragan, A. D. (2017). Do You Want Your Autonomous Car To Drive Like You? Proceedings of the 2017 ACM/IEEE International Conference on Human-Robot Interaction, 417–425. https://doi.org/10.1145/2909824.3020250

Description of the problem the research aims to solve:

The research aims to solve the problem of what the driving style of autonomous cars should be and how that style should compare to the driving style of the user of the autonomous car. The assumption in the field previously has been that users want the autonomous car to drive the way the user drives e.g. aggressively or defensively. The authors point out that the idea of being a "backseat driver" is to get the person driving to drive the way you do. The authors of this paper hypothesized that users actually want an autonomous driving style that is different than their own.

The gap in the existing theory the research will contribute to filling:

In the related work section, the authors mention several studies on metrics for determining driving style. The authors state they determine driving style by degree of defensiveness, which they determine through an aggregate of driving features and scenarios. The gap in the field is only five studies (at the time of publishing) relating to autonomous cars and driving styles. One of the studies relates autonomous driving style with the comfort of the passenger. The other four studies involve teaching autonomous cars how to drive from human demonstration. All five papers link the autonomous car's driving style to the user's driving style. This study addresses the gap that an autonomous car's driving style can and should be different from the user's driving style.

The research question:

The research question was their hypothesis: Users of autonomous cars prefer a driving style that is significantly different than their own.

The theoretical framework driving the paper:

No theoretical framework is mentioned in the paper. The authors state they "design and conduct a user study to start analyzing potential differences between how users drive and how they want to be driven" (Basu et al., 1).

The specific model guiding the research:

No specific model is stated guiding the paper. The authors do mention Inverse Reinforcement Learning has previously assumed that drivers want cars to match their driving style. This study challenges that assumption and the model.

The research design:

The researchers performed a two-part mixed-methods study for users to experience and evaluate autonomous cars with different driving styles. In the first part of the study the researchers collected driving data in a simulator. In the second part, the researchers used the collected data from the simulator to allow the participants to experience their own driving (and other driving styles) as passengers.

Research instruments:

An open-ended three-question interview was given after the participant used the driving simulator to understand if the simulation resembled everyday driving. The researchers also used open-ended responses to have participants think aloud during the autonomous driving passenger experience. The main subjective measures were preference and perceived similarity to their own driving style on a 7-point Likert scale.

The main objective measures were driving style features and overall defensiveness calculated from the following features: Mean distance to lead car, Mean time headway, Time headway during lane change, Distance headway during lane change, Distance headway merge back, Braking distance from the intersection, Time to stop, Maximum turn speed, Speed at intersection, Average speed for 20 meters before intersection.

Task 1 was calculated using mean distance to lead car, mean time headway, time headway during lane change, distance headway, and distance headway merge back. Task 2 was calculated using mean distance to lead car, mean time headway, time headway during lane change, and distance headway. Task 3 was calculated using braking distance from the intersection, average speed for 20 meters before intersection, time to stop, speed at the intersection, and maximum turn speed. Task 4 was calculated using speed at the intersection and maximum turn speed.

Variables:

The manipulated variables used for driving style were aggressive, defensive, own style, and a distractor style (another driver's style). The defensiveness score was calculated for each participant by averaging their scores from the four tasks listed above. The authors also performed a manipulation check on the aggressive and defensive styles and found they were meaningful.

Population:

It was a within-subjects allocation. 15 participants were a mix of graduate and undergraduate students. The mean driving experience was 5.46 years with a standard deviation of 4.5 years. 3

Participants were between 30 and 31, the other 12 were between 28-24. 46% of participants claimed to be well experienced in driving and 20% claimed to be experienced.

The major findings:

9 out of 15 participants preferred a different driving style to their own. 80% of participants preferred a style they thought was their own, but really it was more defensive than their own style. This shows that people think they drive safer than they really do. The research also found that users prefer more defensive driving while passengers, and there was a correlation between the driving style users prefer and their own perceived driving style, but there was no correlation between what they thought was their driving style and what was actually their own style.

Plausible alternative interpretations of the observations:

Participants might have felt like they were driving the simulator better than they really were. Even a slight delay in learnability could skew the results. The simulator could have also been too manageable and safe feeling, leading to more comfort especially as a passenger. Another interpretation is that most passengers nowadays are usually on their phones or looking out a side window, not focused on what the driver is doing. This means that the simulation could be creating a new passenger experience instead of recreating a regular passenger experience.

Limitations and delimitations:

Only using participants under 31 could limit the relevancy of the data. Most autonomous car owners will be in an older demographic as they will cost more than an average car. Another limitation is that the simulator did not simulate different weather conditions. Variables for calculating defensive driving degree such as “mean distance to lead car” could have been left out of consideration. For the passenger experience, seeing the same road area multiple times could breed a familiarity and comfort with the surroundings that could affect the results. Another limitation could be that there was no actual car that could influence the way they drive or how they feel as a passenger. People buy nice cars to look cool and people drive aggressively to look cool as well. These feelings were not considered in the article.

Theoretical contribution of the work to the literature:

This research contributes the new view that different autonomous car users will want different autonomous car driving styles. People attach a lot of significance to how they drive, and it is a new area to think about how your car drives you. If the relationship between autonomous car driving style and user driving style aren’t compatible, it could result in a negative user experience and other societal and economic ramifications.

The key references:

The key references involved how the researchers calculated the driving style features for the four tasks. They used the following studies on naturalistic lane changes and turning:

Lee, S. E., Olsen, E. C. B., & Wierwille, W. W. (2004). A Comprehensive Examination of Naturalistic Lane-Changes: (733232011-001) [dataset]. https://doi.org/10.1037/e733232011-001

Hong, J.-H., Margines, B., & Dey, A. K. (2014). A smartphone-based sensing platform to model aggressive driving behaviors. Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, 4047–4056. https://doi.org/10.1145/2556288.2557321

Banovic, N., Buzali, T., Chevalier, F., Mankoff, J., & Dey, A. K. (2016). Modeling and Understanding Human Routine Behavior. Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems, 248–260. https://doi.org/10.1145/2858036.2858557

New hypotheses arising that could be pursued in future work:

How can showing a person their true driving style affect changing their driving style to become safer? How does driving context affect driving style? How do the driver and passenger experiences differ when in a luxury car?