Investigating Users' Preferences in Adaptive Driving Styles for Level 2 Driving Automation

ANONYMOUS AUTHOR(S)

Users prefer different styles (more defensive or aggressive) for their autonomous vehicle (AV) to drive. This preference potentially depends on different factors such as the user's trust in AV, and the scenario (pedestrian or car). Predicting a user's preferred driving style and takeover behavior is essential for an efficient and comfortable driving experience. In this research, we designed and ran an experiment to better understand a driver's preferred driving style. In this experiment, participants were asked to complete six automated drives and post-drive surveys in a virtual reality environment. First, we analyze the surveys to understand the effects of different AV driving styles on users. Then, we propose linear and generalized linear mixed effect models for predicting the user's preference and takeover actions under different conditions. Our analysis suggests that trust plays an important role in determining users' preferences and takeover actions. Finally, it shows that scenario, pressing brakes, and AV's aggressiveness level are among the main factors that affect the user's preference. The results provide a step toward developing human-aware driving automation that can implicitly adapt its driving style based on user's preference.

CCS Concepts: • **Human-centered computing → Empirical studies in HCI**; *HCI design and evaluation methods.*

Additional Key Words and Phrases: preferred driving style, trust in automation, autonomous vehicle

ACM Reference Format:

Anonymous Author(s). 2022. Investigating Users' Preferences in Adaptive Driving Styles for Level 2 Driving Automation. In *14th International Conference on Automotive User Interfaces and Interactive Vehicular Applications (AutomotiveUI '22), September 17–20, 2022, Seoul, South Korea.* ACM, New York, NY, USA, 12 pages. https://doi.org/XXXXXXX.XXXXXXX

1 INTRODUCTION AND BACKGROUND

Recent advances in automated driving systems have made it possible for future automated vehicles (AVs) to be driven autonomously without human inputs or even supervision. Developing more advanced autonomous driving technologies can not only provide a secure and comfortable driving experience, but can potentially lead to a socially and environmentally sustainable future [8, 10, 16]. The magnitude of the potential benefits depends on the adoption of these technologies. For user acceptance, which strongly depends on their trust on the system [1, 6], these vehicles will not only have to be reliable, safe, and trustworthy, but should also account for a users' comfort. However, preference and perception of comfort can vary significantly among users as well as within individuals depending on their mental state and the situation. Therefore, systems that adapt and personalize to the user have a better potential for acceptation and adoption.

A primary aspect for perceived comfort is the automation driving style [5, 7]. Drivers have different preferences in driving; some drivers prefer a more defensive, and some prefer a more aggressive driving experience. Even during one course of driving, this preference might change based on different factors such as changes in trust, scenario, and experience of the driver [2, 14]. Previous studies investigated the effects of driving styles on the driver's comfort and trust in using an AV [3, 4, 17]. Lee et al. investigated the effects of defensive, moderate, and aggressive driving style on the trust of the driver in an AV [17]. They measured driver's pressings on the brake and gas pedals to predict driver's trust in the AV. Their study showed that the defensive automated driving style increased the frequency and magnitude of accelerator pedal inputs while the aggressive style increased the brake pedal inputs. Another study by Basu et al. suggests that a personal driving style is not always compatible with the user's preferred driving style, and drivers tend to act more defensively while using an AV [3]. Bellem et al. showed that the change in acceleration and jerk profile helps drivers to distinguish different driving styles [4]. These previous studies mainly focused on non-adaptive driving styles; we propose that adaptive driving styles can result in optimal acceptance and comfort.

Generally, adaptation and personalization in advanced driving assist systems can be classified into two types: explicit and implicit adaptation [12]. Explicit adaptation requires users to state their preferences by selecting the optimal system option. For example, current adaptive cruise control (ACC) systems allow drivers to adjust the distance from the leading vehicle. While such an adaptive system gives users direct control, users have to actively select the option. One of the disadvantages of explicit adaptation is that the user typically has to experience non-optimal driving styles before converging to a final selection. Implicit adaptation, on the other hand, does not openly ask users for their preferences, but instead watches their behavior and determines a preference. However, this requires models for human behavior to predict their preference and appropriately adapt the driving style.A few studies that considered adaptive driving style only considered specific aspects of driving such as acceleration [13]. We propose that a prediction model for preference of the driver in different scenarios of adaptive driving style based on dynamic information—such as user's trust, intention for takeover based on feet movements, and current aggressiveness of the vehicle—can achieve better user acceptance and comfort.

In this work, we take the first step toward adaptive driving styles for AVs by evaluating heuristic-based adaptive drives that uses explicit adaptation based on users' trust and preference. We collected data from 36 participants while they interacted with a SAE Level 2 automated driving [22] in an urban scenario using a medium fidelity driving simulator. We analyzed the survey results to understand the effects of each heuristic-based adaptive driving style on drivers preference, trust, and workload. We also developed predictive models for users' driving style preference and takeover behavior to assess which factors need to be considered while developing an implicit adaptation strategy.

This paper is organized as follows. Section 2 summarizes our hypotheses. Section 3 describes the driving simulation study used to collect human subject data. The analysis of the driving questionnaire is presented in Section 4. Predictive models for drivers' preference and takeover behavior are presented in Section 5 and 6, respectively, followed by concluding statements in Section 7.

2 HYPOTHESES

In this work, we investigate the effects of multiple adaptive driving styles on users for a sample of 36 participants and build two predictive models: 1) for user preferences in driving and 2) for user's takeover behavior. We hypothesized that users' trust in AV affects their preferred driving style and takeover behavior. In addition to trust, we hypothesized that users' experience with AV and the specific driving scenario are important factors in the users' selection of their preferences. We also tested the hypothesis that the mismatch between the user's preference and AV's aggressiveness level of driving affects the takeover behavior of the user. Ultimately, our six hypotheses are as follows:

- H1: User trust during the course of driving an AV directly affects the user's driving preference.
- H2: Users' preference is affected by the presence of pedestrians or vehicles in the driving context.

- H3: User's takeover behavior is informative for predicting the preference of the user.
- H4: Users' preference is affected by the length of interaction with the AV.
- H5: User's trust in AV affects the user's takeover behavior.
- H6: A mismatch between the user's preference and AV's aggressiveness in driving affects the user's takeover behavior.

We will address our primary objective and test the hypotheses above by analyzing a randomized experiment on a sample of users using both linear and generalized mixed effect regression models [9, 23]. Our models will incorporate predictor variables for trust, scenario, length of interaction, and other factors that may affect driving preference.

3 METHOD

3.1 Participants

Thirty six participants (mean age = 22.86, standard deviation =5.487, range: 18 − 38) were recruited for this study, including 16 females, 19 males, and 1 non-binary. All participants were required to 1) be in possession of a valid driver's license 2) be aged from 18 to 65; 3) have no self-reported sensory deficiency. The entire experiment lasted two hours, and participants were compensated with either a $20 gift card or a two-hour (course) credit. The study was approved by ANONYMIZED Institutional Review Board (approval ID: ANONYMIZED).

3.2 Apparatus

3.2.1 Driving simulator. The experiment was conducted on a medium-fidelity driving simulator which includes a Logitech (G29) steering wheel, brake pedal, and accelerator pedal (Figure 1). There were three 45-inch TV screens with an angle of 50 degrees and 42 inches perpendicular to the driver's field of vision, displaying the dashboard of the vehicle and the driving environment separately. The dashboard includes a speedometer showing the speed, a navigation arrow presenting the direction the vehicle needs to drive to, and an indication of whether the driving automation is on or off. The driving environment was rendered with the Unreal Engine[1], simulating an urban area, which includes traffic lights, other vehicles, pedestrian crossing intersections, stop signs, and roundabouts.

3.2.2 Additional equipment. A web camera was placed to capture the side view of the throttle and brake pedals to determine participants' takeover intentions. We manually annotated the instances where a participant moves their foot to the brake pedal without pressing it as their takeover intention.

3.3 Design

Participants experienced six driving sessions with six types of driving style adaptations: two fixed and four adaptive. In each session, an AV passes through sixteen urban intersections; every other intersection had either of two different event types: 'pedestrian' and 'traffic-related'. Therefore, there were a total of eight event intersections per session. Pedestrian-related events include pedestrians on the sidewalk, crossing at the crosswalk, at the intersection, and walking at the intersection. Traffic-related events included right turns at a red light, following a lead vehicle, yield and left turns, and a two-way stop. All eight events randomly occurred in each driving session. Figure 2 shows screenshots of some events during the session. Participants were asked to to takeover by pressing throttle or brake pedals whenever they anticipated unsafe driving. The AV resumed control once the participant removed their input to both the throttle and

[1] https://www.unrealengine.com

Fig. 1. Medium-fidelity driving simulator with three screens, steering wheel, brake pedal, and accelerator pedal

(a) Pedestrian-related event with a pedestrian crossing at the crosswalk

(b) Traffic-related event at a two-way stop

Fig. 2. Screenshots showing example events during the session.

brake for a period of two seconds. For a given event, if the participant pressed the brake anytime during the event, we annotated that as $\text{takeover}_{\text{brake}}$ for that event. Similarly, if the participant pressed the throttle during the event, we annotated that as $\text{takeover}_{\text{throttle}}$ for that event.

We designed four levels of driving styles: 1) highly aggressive (HA), 2) less aggressive (LA), 3) less defensive (LD), and 4) highly defensive (HD). The automated driving was implemented using a modified intelligent driver model (IDM) and Stanley controller based on the parameters defined in [20]. The driving style was varied by changing the parameters of the IDM model in real time such that there was variation in vehicle's maximum and minimum driving speed, and the smallest distance that the vehicle starts to stop from pedestrians and other cars across the different driving styles [20]. The two fixed driving style adaptations used the less aggressive (LA) and the less defensive (LD) driving styles throughout all events in a driving session. For the four sessions of adaptive driving styles, two included trust-based adaptation and the other two included preference-based adaptation; the system adaptively chose driving aggressiveness from above-mentioned four levels based on the participant' response.

In the trust-based adaptive mode, the driving style changed based on a single-item survey that measures the change in trust in the system. The survey question was presented on the screen as shown in Figure 3(a). There were five options: greatly increase (+2); slightly increase (+1), stay the same (0), slightly decrease (-1), and greatly decrease (-2). Each time after participants made the selection, the system recorded the numeric value. Once the accumulative values changed by 2, the driving style would change (+2 led the driving style to be more aggressive, and -2 would change the driving style to be more defensive). For example, two consecutive choices of "slightly increase" (+1 and +1) or a one-time selection of "greatly increase" (+2) would lead to changing the driving style to a more aggressive style. Similarly, in the preference-based adaptive mode, the driving style would change based on the preference measurement survey on the screen (Figure 3(b)), and each change from the previous choice made by participants would result in a change in the driving style. Specifically, three options were provided on participants' preferred AV driving style: drive more aggressively, stay the same, or drive more defensively. For example, if a participant chose "drive more defensively" when the vehicle driving style was less defensive (LD), then the AV driving style would drop one level to be highly defensive (HD). Finally, the fixed mode was included as the baseline which presented either the LD or LA driving style (but not adaptive). The trust-based and preference-based adaptive drives either started with LD or LA as their initial driving styles. This resulted in six automated driving style: fixed_{LD}, fixed_{LA}, trust_{LD}, trust_{LA}, pref_{LD}, and pref_{LA}.

3.4 Procedure

Upon arrival, participants were required to sign two consent forms, including the COVID-19 protection protocols, followed by a demographic questionnaire, which included information such as age, driving behavior, driving history, and their historical use of AV. Participants were then presented with an overview of the experimental procedures, as well as the definitions for trust in automation [18] and trust in AVs [22]. For the actual experiment, there were a total of seven 10-minute drive sessions, which entailed one manual drive and six automated drive (i.e., SAE Level 2 automation) sessions. A 10-minute break was allotted in between the sessions, resulting in the overall experiment duration being approximately two hours. Participants were asked to keep their dominant hand on the steering wheel and their foot on or near the pedals during the experiment. Each automated drive session included two separate driving routes to avoid participants memorizing the driving environment and road events. Automated drives were presented in a counterbalanced order, including two routes in fixed mode (i.e., fixed_{LA} and fixed_{LD}) along with two routes for each adaptive mode (trust_{LD}, trust_{LA}, pref_{LD}, and pref_{LA}). The manual drive and each automated drive set consisted of all eight events (four pedestrian- and four traffic-related events) in a randomized order. During the automated drive, the simulator would occasionally pause the drive to present questions measuring participants' real-time trust levels and preferred driving styles between each two events (Figure 3). After each drive, participants were asked to fill a questionnaire survey. This questionnaire survey first reminds the participants of the definition of trust and then measures 14 categories of interest on a rating scale adapted from [15] and NASA-TLX [11]. These categories are trust in vehicle's response trust in the vehicle's display, overall trust in vehicle, reliability/competence, understanding/predictability, familiarity, the propensity to trust, trust in automation, mental demand, physical demand, temporal demand, performance, effort, and frustration. Once all drives were finalized participants were debriefed and the experiment was completed.

4 ANALYSES OF DRIVING QUESTIONNAIRES

We first analyzed the post-drive questionnaires to understand the effects of different driving style adaptations on the user. We use Bayesian linear mixed effects regression models for different categories of the questionnaire and a preference mismatch variable. Based on the results from regression models, we present the probability of the effect of each drive type on outcome variables.

(a) On-screen survey to measure trust

(b) On-screen survey to measure preference

Fig. 3. On-screen survey to measure trust and preference after each event.

4.1 Outline of Analyses

We utilize Bayesian mixed effects regression models to analyze the questionnaire results. More specifically, the focus of this Bayesian analysis is to find the probability of the drive types affecting the score of all 14 questionnaire categories and the cumulative preference mismatch. The cumulative preference mismatch counts the drives in which the driver preference is different from the AV aggressiveness level. In this model the participant variable is considered as a random effect variable and the fixed effects are drive type (i.e., the type of driving style adaptation) and drive number.

This Bayesian linear mixed effects regression model was implemented by the `brm` function in the `brms` package in R[2]. This analysis was performed to provide insights into the relationships between the independent and dependent variables. We used the weakly informed default priors for the model parameters, which correspond to half Student-t prior with 3 degrees of freedom, and obtained 2000 posterior draws of the parameters from a single chain after a burn-in of 200 and thinning draws by 2. Three chains of draws were obtained.

4.2 Results

	Preference mismatch	Trust vehicle's response	Trust display	Trust overall	Reliability/ competence	Understanding/ predictability	Familiarity	Propensity to trust	Trust in automation	Mental demand	Physical demand	Temporal demand	Performance	Effort	Frustration
Fixed_{LD}	−0.97	−0.71	−0.78	−0.62	0.82	0.5	0.69	0.99	0.87	−0.69	−0.97	−1.00	−0.60	−0.81	−0.91
Pref_{LA}	−0.69	−0.63	−0.74	0.75	0.96	−0.74	−0.53	0.87	0.88	−0.54	−0.88	−0.91	−0.93	−0.74	−0.87
Pref_{LD}	−0.87	0.64	−0.64	0.58	0.94	0.60	0.86	0.93	0.81	−0.99	−1.00	−0.99	0.80	−0.78	−0.81
Trust_{LA}	−0.92	0.51	0.83	0.58	0.80	−0.79	0.67	0.83	0.56	−0.84	−0.92	−0.53	−0.96	0.67	−0.58
Trust_{LD}	−0.97	0.93	0.64	0.80	0.86	0.95	0.82	0.89	0.92	−0.99	−0.93	−0.96	−0.70	−0.83	−0.97

Fig. 4. Analysis of post-drive questionnaire. Each row represent one driving style and each column shows one category of the questionnaire. Each cell answers the question of how likely its corresponding driving style affects driver's score in the corresponding category. Positive (negative) values shows a positive (negative) effect. Darker cells represent higher probabilities.

[2] https://www.r-project.org/

Figure 4 summarizes the results of the analyses for preference mismatch variable and the 14 categories of questionnaire items obtained from the Bayesian regression analysis. Variables, which are related to trust: 'trust vehicle's response', 'trust display', 'trust overall', 'propensity to trust', and 'trust in automation' are the changes we observe in their values in two most recent drives. In these Bayesian analyses, we compared the score of each drive type with the baseline drive type of fixed_{LA}. The darker colored squares indicate the pairwise contrasts with high posterior probabilities of being active. The red and green colors show a negative and positive effects, respectively. The negative effects also can be identified by a negative sign in the square cell indicating that a particular drive type yields lower outcome values than the baseline drive type. For example, the cell corresponds to 'trust_{LD}' and 'trust vehicle's response' on bottom left (green) indicates a 93% posterior probability that drive type trust_{LD} yields a higher score on the trust in vehicle response question: "Your degree of trust in the vehicle to respond accurately" compared to the baseline drive type fixed_{LA}. Similarly, the bottom most right cell (red) indicates there is a 97% posterior probability that drive type trust_{LD} yields a lower score on the 'frustration' questions than the baseline drive type. If we consider those outcomes whose estimated probabilities are greater than 90% to be highly likely events, then these results indicate that users are highly likely to experience less frustration in drive types fixed_{LD} and trust_{LD} compared to drive type fixed_{LA}. Furthermore, we observe that perceived performance is estimated to decrease in drive type pref_{LA} as compared to the baseline fixed_{LA}, and that it is estimated to decrease for trust_{LA}. In addition, all three mental, physical, and temporal demands are inferred to decrease under drive type pref_{LD} and trust_{LD}. Trust in automation increases across different drive types: propensity to trust is greater for trust_{LD}, pref_{LD}, and fixed_{LD}. Understanding and predictability are greatest for trust_{LD}. Reliability and competence are greatest for pref_{LD}, pref_{LA}, and fixed_{LD}. Trust in vehicle's response is greatest for trust_{LD}. Finally, we are highly likely to observe fewer preference mismatches in drive types for trust_{LD}, trust_{LA}, and fixed_{LD}.

To summarize, these results suggest a trade-off among the different drive types. For example, perceived reliability/competence is more likely to be increased under the Pref_{LA} and Pref_{LD} drive types, but at the cost of decreased trust in display. These concurrent advantages and disadvantages should lead us to build new models that are more informative in terms of understanding the nature of driver preferences and takeover behaviors. In the next sections we proceed to introduce these models and uncover the important variables that should be considered for designing an effective adaptive AV driving style.

5 A PREDICTIVE MODEL FOR USER'S PREFERENCE

We now build a model for predicting users' preference in each drive's event. First, we propose a linear mixed effect regression model for predicting the user's preference. Then, we present the results and explains the statistically significant ($p < 0.05$) factors that change the driving style preference of the user.

5.1 Outline of the model and analyses

This section builds a linear mixed model for predicting the preference change of the driver. Table 1 describes the variables that are considered in building this model. The first step is testing if we need to include 2-way interactions between variables by building two models: 1) Model 'A' that includes all main effects; 2) Model 'B' that includes all main effects plus all two-way interactions. Then, by using R's `anova` function, we compare these two models. Based on this comparison (Table 2), we can conclude that there are two-way interactions that have a significant effect ($p < 0.05$) on the dependent variable and needs to be included in the model. However, it does not give us any information on which interactions need to be included.

Variable	Effect	Var type in model	Variable class	possible values
preference change	-	DV	ordinal	-1 < 0 < 1
participant	random	IV	categorical	p1, p2, ... , p36
aggressive level	fixed	IV	continuous	0 < x < 5
event type	fixed	IV	categorical	pedestrian (EP), traffic (EC)
drive number	fixed	IV	ordinal	1 < 2 < 3 < 4 <5 < 6
drive type	fixed	IV	categorical	LA, LC, pref_LA, pref_LC, trust_LA, trust_LC
$\text{takeover}_{\text{throttle}}$	fixed	IV	categorical	0, 1
$\text{takeover}_{\text{brakes}}$	fixed	IV	categorical	0, 1
trust	fixed	IV	continuous	-15 < x < 15
takeover intention	fixed	IV	categorical	0 , 1
route	fixed	IV	categorical	1, 2, 3, 4, 5, 6

Table 1. Information about variables in the model.

Model	AIC	Log likelihood	χ^2	Pr(> χ^2)
Model A	2062.7	-1011.4		
Model B	2031.6	-903.8	215.11	7.332e-12 ***

Table 2. Likelihood Ratio (LR) test of Model A (includes all main effects) and Model B (includes all main effects plus all 2-way interactions).

The next step is variable selection from all main effects and 2-way interactions. For doing this, we used the Elastic Net method from the package `GLMnet` in R. Elastic Net is preferred over other methods because it addresses the over-regularization problem by balancing between the penalties of LASSO and ridge regression [19]. We fitted the elastic net algorithm to the data. The tuning parameter $\lambda = 0.067$ were identified by using 20 fold cross validation. The resultant interaction effects are included in the model. Based on this result, including the main effect of the selected interaction terms, and adding participant and participant:drive number (to consider the correlation between the output of each participant during all 6 drives), the following model is finalized below:

$$
\begin{aligned}
\text{pref change} \sim\ & (1|\text{participant}) + (1|\text{participant:drive number}) + \text{aggressive level} + \text{event type} + \text{route} + \text{drive number} \\
& + \text{drive type} + \text{takeover intention} + \text{takeover}_{\text{brake}} + \text{takeover}_{\text{throttle}} + \text{trust} \\
& + \text{aggressive level:takeover intention} + \text{drive type:takeover intention} + \text{route:takeover intention} \\
& + \text{drive number:takeover intention} + \text{takeover}_{\text{brake}}\text{:takeover intention} + \text{takeover}_{\text{throttle}}\text{:takeover intention} \\
& + \text{takeover}_{\text{brake}}\text{:takeover}_{\text{throttle}} + \text{takeover}_{\text{brake}}\text{:trust} + \text{drive type:event type}
\end{aligned}
$$

Then, the model is run in "R" by using the package `lme4` and function `lmer`.

5.2 Results

The significant effects ($p < 0.05$) obtained from the linear mixed effects regression model are shown in Table 3. These results address the first four research hypotheses. First, we observe a significant effect of a user's trust during the course of driving an AV on their driving preference. This effect is estimated to be positive, which indicates that as trust increases a driver is expected to prefer more aggressive driving styles. Second, the event type (i.e., whether there is pedestrian or vehicle traffic) has a statistically significant effect on driver preference, with drivers expected to drive less

predictors	estimate	std error	t value	Pr(>|t|)
trust	3.613e-02	6.826e-03	5.292	1.41e-07 ***
event_EP	-1.215e-01	5.094e-02	-2.385	0.017221 *
drive number	3.055e-02	1.254e-02	2.436	0.015242 *
brakes	-2.766e-01	4.474e-02	-6.183	8.03e-10 ***
aggressive level	9.530e-01	3.520e-02	27.071	< 2e-16 ***
throttles:brakes	-1.263e-01	4.310e-02	-2.930	0.003438 **
drive_fixed$_{LD}$:event_EP	2.756e-01	7.197e-02	3.829	0.000134 ***
drive_pref$_{LA}$:event_EP	2.801e-01	7.168e-02	3.908	9.74e-05 ***
drive_pref$_{LD}$:event_EP	1.817e-01	7.162e-02	2.537	0.011280 *
drive_trust$_{LA}$:event_EP	2.444e-01	7.131e-02	3.428	0.000626 ***
drive_trust$_{LD}$:event_EP	2.299e-01	7.263e-02	3.166	0.001579 **
Intention:route2	-1.691e-01	8.224e-02	-2.056	0.039984 *
Intention:route5	-1.980e-01	8.292e-02	-2.388	0.017066 *
Random effects:				
Groups	Variance	Std.Dev.		
participants:drive number	0.01972	0.1404		
participants	0.04911	0.2216		
Residual	0.17393	0.4170		

Table 3. Results of the model. Only significant ($p < 0.05$) rows are reported. Note: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

aggressively when they encounter pedestrians compared to encountering other vehicles. Third, there is a significant association between drive number and driver preference. Specifically, users tend to prefer more aggressive driving styles as the amount of time that they are engaged in the AV driving increases. Fourth, those drivers who used the brake are inferred to prefer a more defensive driving style compared to those drivers that did not press the brake.

Besides the four research hypotheses of interest, the results of the fitted model indicate that AVs with higher levels of aggressive driving are more highly preferred by the user, and that significant two-factor interactions exist between throttles and brakes, drive types and event types, and takeover intentions and routes. The two-factor interactions between drive types and event types imply that the differences in driver preferences across the different drive types depend on the type of event. Similarly, the two-factor interaction between throttles and brakes suggests that the number of throttles can have a significant effect on user preferences depending on the number of times that brakes are used in the drive, and that the number of throttles by itself may not have a significant effect on preferences. Finally, the two-factor interactions between takeover intention and the indicators for routes 2 and 5 imply that one should account for routes when attempting to infer the effects of driver takeover intention on preference.

predictors	estimate	std error	z value	Pr(>|z|)
trust	-0.29129	0.05105	-5.706	1.16e-08 ***
preference_change.Q	0.73829	0.19552	3.776	0.000159 ***
Random effects:				
Groups	Variance	Std.Dev.		
participants:drive number	0.3899	0.6244		
participants	4.7159	2.1716		

Table 4. Results of the predictive model for takeover. Only significant ($p < 0.05$) rows are reported.

6 A PREDICTIVE MODEL FOR USER'S TAKEOVER BEHAVIOR

Now, to test the hopethesis H5 and H6, we build a model for predicting takeovers of the user. We use a generalized linear mixed effect regression model and analyze the statistically significant ($p < 0.05$) factors that predicts takeover actions.

6.1 Outline of the model and analyses

We fit a generalized linear mixed effects model for predicting the takeover behavior of the driver as a function of the factors in the experiment. The outcome variable is an indicator for takeover, with value "1" indicating that either the brake or the gas pedal were pressed in the drive and value "0" indicating that the driver did not press any pedals during the drive. As the outcome variable is binary, the specific model that we fit is a logistic mixed effects regression model. The random effects correspond to participants and the different drives nested within participants. These random effects are introduced into the analysis so as to capture the correlations that may exist between the probabilities of takeover across the different drives for each participant. The fixed effects that we enter into the model are the main effects of trust, drive number, drive type, event type, route, preference change, preference, and aggressive level. Additional details about these variables are provided in Table 1. Due to the complexity of this model, and the relatively limited number of participants involved in the study relative to this model, we focus only on inferences for the main effects, and do not consider two-factor interactions. This generalized linear mixed effects regression model is fitted in `R` via the `glmer` function in the `lme4` package. When fitting this model we used the BOBYQA optimization method [21] to improve the convergence of the model fitting procedure. The model is given by

$$\begin{aligned} takeover \sim\ & (1|\text{participant}) + (1|\text{participant:drive number}) + \text{trust} + \text{drive number} + \text{drive type} + \text{event type} \\ & + \text{route} + \text{preference change} + \text{preference} + \text{aggressive level}\,. \end{aligned}$$

6.2 Results

The significant effects ($p < 0.05$) from the logistic mixed effects regression model are summarized in Table 4. The fitted model indicates that trust has a negative effect on the probability of takeover, and that preference mismatch has a positive effect on the probability of takeover. These results correspond to hypotheses 5 and 6 in Section 2, in that higher values of trust are associated with smaller proportions of takeover actions by the user, and that users takeover action have a non-linear (quadratic) relation with the mismatch between user's preference and the AV's aggressiveness level.

In summary, the analysis of the questionnaire showed that although explicit driving style adaptation based on heuristics can have better perceived trust and reliability, but there is a trade-off across different heuristics. Therefore, an optimal drive type could be identified based on the specific goals and context. Also, we identified critical factors that is needed to develop models for implicit driving style adaptation using the predictive models. Specifically, we found that apart from trust, situational factors such as presence of pedestrian can significantly impact drivers' preference. Additionally, the interaction between some of these factors is also necessary to model drivers' preference. Furthermore, the two predictive models could be used to dynamically adapt driving style that leads to the lowest number of takeover actions. The takeover predictive model suggests that users with a lower mismatch between the driver's preference and AV's aggressiveness level tend to have fewer takeover actions. Therefore, we expect to reduce the user's takeover actions by using the first predictive model, constantly predicting the user's preference in each event, and changing the AV's aggressiveness level based on the user's preference. Finally, both predictive models of preference and takeover validate the importance of trust in driving an AV.

7 CONCLUSION

This work investigated the effects heuristic-based adaptive driving styles on user trust, preference, and takeover intentions in SAE level 2 driving automation. We conducted a driving simulator study and collected data from 36 participants while they interacted with different driving style adaptations. The results showed that driving style adaptation can have better perceived trust and reliability. The data analysis validated our hypotheses that 1) user preference is affected by surroundings, length of interaction, and trust; 2) users' takeover is informative to predict preference, and it can result from users' trust change and mismatch of driving styles. We also built predictive models to estimate the users' preferred adaptive driving style and takeover behavior. The built predictive models hold great potential to identify optimal driving styles based on user inputs and operation goals. Although this work is limited to explicit driving style adaptation based on user responses, future work will include augmenting the current regression models with more advanced models as well as validating implicit adaptation techniques of driving style based on these models. This work is a step toward developing human-aware automation that can improve the acceptance of and comfort in automated vehicles.

REFERENCES

[1] Nadia Adnan, Shahrina Md Nordin, Mohamad Ariff bin Bahruddin, and Murad Ali. 2018. How trust can drive forward the user acceptance to the technology? In-vehicle technology for autonomous vehicle. *Transportation research part A: policy and practice* 118 (2018), 819–836.

[2] Kumar Akash, Neera Jain, and Teruhisa Misu. 2020. Toward adaptive trust calibration for level 2 driving automation. In *Proceedings of the 2020 international conference on multimodal interaction*. 538–547.

[3] Chandrayee Basu, Qian Yang, David Hungerman, Mukesh Sinahal, and Anca D Draqan. 2017. Do you want your autonomous car to drive like you?. In *2017 12th ACM/IEEE International Conference on Human-Robot Interaction (HRI*. IEEE, 417–425.

[4] Hanna Bellem, Thorben Schönenberg, Josef F Krems, and Michael Schrauf. 2016. Objective metrics of comfort: developing a driving style for highly automated vehicles. *Transportation research part F: traffic psychology and behaviour* 41 (2016), 45–54.

[5] Hanna Bellem, Barbara Thiel, Michael Schrauf, and Josef F Krems. 2018. Comfort in automated driving: An analysis of preferences for different automated driving styles and their dependence on personality traits. *Transportation research part F: traffic psychology and behaviour* 55 (2018), 90–100.

[6] Jong Kyu Choi and Yong Gu Ji. 2015. Investigating the importance of trust on adopting an autonomous vehicle. *International Journal of Human-Computer Interaction* 31, 10 (2015), 692–702.

[7] Andre Dettmann, Franziska Hartwich, Patrick Roßner, Matthias Beggiato, Konstantin Felbel, Josef Krems, and Angelika C Bullinger. 2021. Comfort or not? Automated driving style and user characteristics causing human discomfort in automated driving. *International Journal of Human–Computer Interaction* 37, 4 (2021), 331–339.

[8] Anders Eugensson, Mattias Brännström, Doug Frasher, Marcus Rothoff, Stefan Solyom, and Alexander Robertsson. 2013. Environmental, safety legal and societal implications of autonomous driving systems. In *International Technical Conference on the Enhanced Safety of Vehicles (ESV). Seoul, South Korea*, Vol. 334.

[9] Julian J Faraway. 2016. *Extending the linear model with R: generalized linear, mixed effects and nonparametric regression models*. Chapman and Hall/CRC.

[10] Christian Gold, Moritz Körber, Christoph Hohenberger, David Lechner, and Klaus Bengler. 2015. Trust in automation–before and after the experience of take-over scenarios in a highly automated vehicle. *Procedia Manufacturing* 3 (2015), 3025–3032.

[11] Sandra G Hart and Lowell E Staveland. 1988. Development of NASA-TLX (Task Load Index): Results of empirical and theoretical research. In *Advances in psychology*. Vol. 52. Elsevier, 139–183.

[12] Martina Hasenjäger and Heiko Wersing. 2017. Personalization in advanced driver assistance systems and autonomous vehicles: A review. In *2017 ieee 20th international conference on intelligent transportation systems (itsc)*. IEEE, 1–7.

[13] Arne Kesting, Martin Treiber, Martin Schönhof, and Dirk Helbing. 2007. Extending adaptive cruise control to adaptive driving strategies. *Transportation Research Record* 2000, 1 (2007), 16–24.

[14] Lucienne Kleisen. 2011. *The relationship between thinking and driving styles and their contribution to young driver road safety*. University of Canberra Bruce, Australia.

[15] Moritz Körber. 2018. Theoretical considerations and development of a questionnaire to measure trust in automation. In *Congress of the International Ergonomics Association*. Springer, 13–30.

[16] Rico Krueger, Taha H Rashidi, and John M Rose. 2016. Preferences for shared autonomous vehicles. *Transportation research part C: emerging technologies* 69 (2016), 343–355.

[17] John D Lee, Shu-Yuan Liu, Joshua Domeyer, and Azadeh DinparastDjadid. 2021. Assessing drivers' trust of automated vehicle driving styles with a two-part mixed model of intervention tendency and magnitude. *Human factors* 63, 2 (2021), 197–209.

[18] John D. Lee and Katrina A. See. 2004. Trust in Automation: Designing for Appropriate Reliance. *Human Factors: The Journal of the Human Factors and Ergonomics Society* 46, 1 (2004), 50–80.

[19] Tongyu Liu, Shao-Wei Lin, Su Lin, Lin Yang, Haizhou Ji, Jianping Zou, and Rong Xie. 2019. Exploration of high-risk factors for pulmonary embolism in patients undergoing postoperative anti-thrombotic therapy among gynecologic oncology surgery: a retrospective study. *Annals of Translational Medicine* 7, 7 (2019).

[20] Manisha Natarajan, Kumar Akash, and Teruhisa Misu. 2022. Toward Adaptive Driving Styles for Automated Driving with Users' Trust and Preferences. In *Proceedings of the 2022 ACM/IEEE International Conference on Human-Robot Interaction*. 940–944.

[21] Michael JD Powell. 2009. The BOBYQA algorithm for bound constrained optimization without derivatives. *Cambridge NA Report NA2009/06, University of Cambridge, Cambridge* 26 (2009).

[22] SAEInternational. 2021. Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles. *J3016_202104* (2021).

[23] Walter W Stroup. 2012. *Generalized linear mixed models: modern concepts, methods and applications*. CRC press.