Happy Driver: Investigating the Effect of Mood on Preferred Style of Driving in Self-Driving Cars

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Figure 1: In an online experiment (N=182), participants experienced three driving styles paired with three moods, with the hypothesis that matched pairings (eg. calm mood - conservative driving style) would increase driver satisfaction. Exemplar still images of the mood videos in the top row from left to right [18, 24, 32].

ABSTRACT

Self-driving cars are around the corner, yet little is known about how users of self-driving cars will react to the car's driving style, and whether the driver's mood affects their driving style preference. This paper explores the impact of users' mood on driving style preference in self-driving cars. An experiment was conducted online (N=182) to investigate participants' preference for three driving styles (conservative, moderate, aggressive) under three induced moods (calm, neutral, excited). Measures of arousal, valence, and driving satisfaction were recorded. Overall, participants scored the aggressive driving style lowest, irrespective of driver mood. Participants' mood impacted preference, where a mismatch between driving style and mood induced prior to the driving style predicted lower driver satisfaction scores. We conclude with the design recommendation that driving styles in self-driving cars should not be overly aggressive, and drivers' mood should be taken into consideration when designing driving styles.

CCS CONCEPTS

• **Human-centered computing** → **User studies**; **Empirical studies in HCI**.

KEYWORDS

Self-driving cars, driving styles, driver mood, user experience.

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1 INTRODUCTION

As self-driving cars advance towards greater levels of automation, an emerging challenge for their adoption is creating a satisfying user experience (UX). In these vehicles, an AI agent replaces the human

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driver; supervising the automation is therefore the primary form of human-agent interaction. Drivers' acceptance of self-driving cars will be largely determined by human-related factors, factors related to the AI partner, and environmental factors [37]. Satisfaction is one such human-related factor. Driver satisfaction is in part determined by qualities of the vehicle's driving style, but the driver's mood may also influence a user's satisfaction with autonomous driving. Designers of automated driving systems therefore face choices regarding how defensively or aggressively the agent should drive. In order to confer a satisfying user experience, autonomous driving agents may need to take the driver's mood into account and modify their driving styles accordingly.

To ensure wide adoption, self-driving cars should provide a driving experience where users are neither frustrated by the car's caution, nor frightened by its aggression. It is unknown whether drivers might prefer a relaxed style when feeling calm or an aggressive style when feeling excited. It has previously been established that drivers' moods influence their driving styles [7, 17] and also that drivers prefer self-driving styles that match their own [38]. This suggests that drivers' preferences in self-driving styles may also vary according to their moods. To date, however, little is known about how the mood of users of self-driving cars influences their preferred driving style. To personalize self-driving technologies, we need to better understand the role of mood in user experience of self-driving cars. It is therefore timely to study whether mood also influences preference of driving style in self-driving cars.

To address this question, we conducted an online experiment (N=182) where participants experienced and rated three driving styles paired with three mood conditions. Specifically, mood videos were used to induce three moods in the participants (calm, neutral, excited). We defined these moods using the dimensions of arousal (i.e., exciting vs boring) and valence (i.e., pleasant vs unpleasant) and measured the induction of the moods using an affective slider [6]. With each mood, participants viewed driving videos simulating three different styles that might be used by a self-driving car (conservative, moderate, aggressive), leading to nine combinations of mood and driving style. We measured satisfaction with the driving styles using an adapted version of the USE satisfaction subscale [29]. To our knowledge, this is the first study to examine the influence of drivers' mood on their preference of style of driving in self-driving cars.

We hypothesize that driver satisfaction will be higher when the driving style matches the participant's mood. Specifically, we expect that participants prefer the driving video that matches the mood video (e.g., calm mood leads to preference of conservative driving video), and that change in mood through watching the driving video negatively correlates with driver satisfaction. 182 participants were recruited through Mechanical Turk to carry out the study.

In summary, our study showed that: (**1**) users generally dislike an aggressive driving style, preferring conservative and moderate driving styles irrespective of their mood, and (**2**) a mismatch between mood and driving style correlates with lower satisfaction with driving style. We conclude that driving styles should match users' moods, but that overly aggressive driving styles should be avoided, even if the car can use such styles safely.

The paper is organized as follows. In the next section, we review earlier research into the user experience of self-driving cars. We then present our experimental design, followed by the results of the study and discussion.

2 RELATED WORK

Self-driving cars use an AI agent to automate some or all of a car's functions, in collaboration with and under supervision of a human. Current vehicles offer a range of self-driving features such as lane assistance, collision avoidance, and automated parking. Numerous car manufacturers are working on higher levels of automation for future vehicles, potentially leading to fully autonomous vehicles.

Self-driving cars promise numerous benefits ranging over improved safety, accessibility, easier performance of difficult tasks such as parking, as well as improved traffic conditions and introduction of novel types of businesses [23]. Yet as noted by Wintersberger et al., people may not necessarily accept a new technology "just because it is there" [42].

Wintersberger et al. compared the user experience of self-driving cars to manual driving, and found no difference in pleasure. Given the benefits of self-driving cars, it should be possible to do better, motivating the exploration of how to improve user satisfaction in self-driving vehicles.

According to Eyben et al. [17], driving tasks can be classified as *primary* (e.g., steering, accelerating, braking, regulating speed, and maintaining distance to other vehicles), *secondary* (e.g., adjusting lights, operating wipers, and changing gears), or *tertiary* (e.g., using an air conditioner, radio, or phone). In this section, we discuss how the design of self-driving cars across these categories can impact the drivers' user experience.

2.1 Primary Tasks: Driving Style

Recent research has investigated how different self-driving styles influence driver satisfaction, acceptance, and trust. A driving style can be defined by several factors including driving speed, headway (distance to next car), frequency of overtaking other vehicles, and tendency to commit traffic violations [16]. Several studies have previously categorized driving styles under three groups of conservative, moderate, and aggressive [9, 12, 28]. A conservative driving style is characterized by longer deceleration and a larger headway. A moderate driving style is characterized as being neither too conservative nor too aggressive. Finally, an aggressive driving style is characterized by faster acceleration and speed. Drivers determine the trustworthiness of automated systems using both analytic reasoning (i.e., evaluation based on behavioural characteristics) as well as analogic reasoning (i.e., making judgements based on societal norms) [22]. For drivers to trust a self-driving agent, it may need to exhibit personality characteristics similar to those of the driver [27]. Drivers may see a self-driving agent as less trustworthy if it performs poorly, does not share the driver's values (e.g., safety and comfort), or if its behaviour does not conform to the driver's intentions (e.g., obeying the rules of the road) [22, 27]. Therefore, drivers' experiences in self-driving cars may be affected by the automated execution of primary driving tasks.

In a study closely related to ours, Dillen et al. tested four self-driving styles defined by their rates of acceleration [15]. To determine participants' comfort and anxiety while driving, they measured their galvanic skin responses and heart rates. The results indicate that drivers may experience reduced comfort and increased anxiety when the vehicle's self-driving style has greater acceleration and jerk. This shows that more aggressive driving behaviour may not be preferred in a self-driving car. Using a Wizard of Oz procedure, Yusof et al. [43] explored whether people with defensive or aggressive driving styles have a preference for self-driving styles that match their own. For both defensive and aggressive drivers, a preference was found for a defensive driving style in self-driving cars. Similarly, Bellem et al. found that drivers' personality traits were not indicative of their preference of self-driving style [5]. Drivers preferred a driving style characterized by low jerks regardless of their personalities or self-reported driving styles. These results consistently indicate that drivers may prefer a calmer and smoother driving experience regardless of their personalities or their own driving style.

With regards to achieving a more pleasurable driving experience, Sun et al. personalized a vehicle's self-driving style to mimic recordings of the participants' *manual* driving styles [38]. They found that drivers experience greater comfort and trust with a self-driving style that is personalized to their manual driving style compared to either driving manually or a standardized self-driving. These findings seem to contradict with those of Yusof et al. and Bellem et al., but this contradiction may be accounted for by the greater degree of personalization afforded by the approach used by Sun et al. Further, it is possible that both conservative and personalized driving styles are preferred.

Nevertheless, drivers may want to further personalize a self-driving style by influencing its behaviour. Collaborative interfaces, such as those proposed by Wiegand et al. and Frison et al., can enable drivers to collaboratively decide on driving actions with the self-driving agent, which can be more satisfying than fully automated driving [19, 41]. These results indicate that drivers may find a self-driving style more satisfying if it is personalized to their preferences.

2.2 Secondary Tasks: Safety

Secondary driving tasks involve activities geared towards driving safety [17]. In self-driving cars, traditional secondary tasks, such as when to turn on the lights or windshield wipers, may be automated. However, new secondary tasks, such as monitoring and responding to warnings and other prompts, may be introduced through virtual assistants or intelligent user interfaces. In a study by Alpers et al., participants interacted with two virtual assistants, one more and one less human-like [36]. The assistant with human-like characteristics received greater engagement from users when delivering warnings. They were also more confident in the vehicle's abilities and more willing to ride again when interacting with the more human-like virtual assistant. Further confirming these findings, Large et al. conducted a study where participants used a self-driving car equipped with either a touch interface, a voice interface, or an anthropomorphic voice agent [26]. A strong preference was found for the anthropomorphic voice agent as it increased pleasure, trust and sense of control. This shows that drivers may be more receptive to self-driving cars with human attributes.

2.3 Tertiary Tasks: Comfort

Tertiary driving tasks are concerned with comfort [17]. As the autonomy of self-driving cars advances, drivers will be progressively converted to passengers, enabling them to use time while "driving" to perform other tasks. In self-driving cars, this tertiary category may expand to include elements of the car that serve to enhance the experience of the ride without explicitly controlling the driving itself. A Wizard of Oz study was conducted by Detjen et al. to investigate how non-driving activities relate to trust and acceptance of self-driving cars [13]. They found that internet access, a music system, and the interiors of the vehicle are important factors for comfort. Using a driving simulator combined with virtual reality, Lakier et al. demonstrated the possibly of playing games with passengers from nearby cars in virtual reality [25]. These systems illustrate other factors to improve comfort while "driving".

While secondary and tertiary tasks are not directly related to our study, these are other aspects of the driving experience that can influence satisfaction. However, the primary driving task creates the foundation of the user experience in driving as it entails setting the speed, acceleration, and steering. Emotional factors have been found to influence driving behaviour [11]. Given this, we have focused on the role that mood plays in predicting driver satisfaction for the primary driving task (e.g., driving style). While prior literature has explored various driving styles for self-driving cars, none have yet explored how drivers' moods affect their driving style preferences.

3 EXPERIMENTAL DESIGN

We performed a Mechanical Turk experiment (N=182) to investigate the impact of mood on driving style preferences in self-driving cars. Our primary question was whether drivers have higher satisfaction with self-driving styles that match their mood.

In determining the apparatus to use to simulate a driving experience for participants, this study faced several constraints including an online format (due to the COVID-19 pandemic), a large sample size (to provide sufficient power), and the need to create an aggressive driving experience without endangering participants or other drivers. As Gerber et al. describe, methods for conducting self-driving user studies include real-world driving videos, real world simulations, rapid prototyping simulators, driving simulators, and VR headset-based simulators [21]. However, our constraints precluded the use of any of these options. Specifically, the virtual format ruled out the ability to use real-world simulations or driving simulators. The need for a large number of participants operating from their own home made impractical the use of VR headset simulations. The ability to create an aggressive driving style prevented us from creating real-world driving videos, which may have endangered the researchers or other drivers. In light of these constraints, we opted to create videos presenting conservative, moderate and aggressive driving experiences through screen recordings of the driving simulation game City Car Driving [14].

As can be seen in Figure 2, participants completed nine experimental conditions which covered all combinations of the three

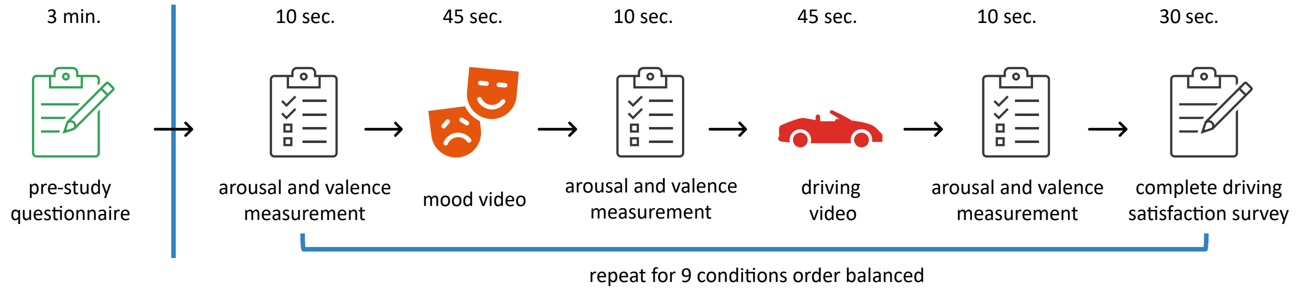

Figure 2: Experiment Procedure.

Table 1: Hypotheses of Satisfaction with Driving Styles.

Style / Mood	Conservative Driving	Moderate Driving	Aggressive Driving
Calm	High	Mid	Low
Neutral	Mid	High	Mid
Excited	Low	Mid	High

moods (calm, neutral, excited) and three driving styles (conservative, moderate, aggressive). Under each condition, we took an initial measure of arousal and valence, presented a mood video, took a pre-driving measure of arousal and valence, presented a driving video, took a post-driving measure of arousal and valence, and measured satisfaction with the presented driving style.

3.1 Hypotheses

We hypothesize that there are positive effects on driver satisfaction when the car's driving style matches the person's mood. More specifically:

H1: Driver satisfaction of participants will be higher when the driving style matches the participant's mood (as induced by the mood videos).

H2: Large differences in the participant's mood before the driving video and the participant's mood following the driving video will predict poorer driver satisfaction with the driving style.

These hypotheses are summarized in Table 1. Following advice from Cockburn et al. [10], the study was registered prior to data collection following guidelines. Some minor changes in terminology were made between registering the study and writing this paper.

3.2 Participants

Participants were recruited through Amazon Mechanical Turk [1] and completed the experiment using the web-based Qualtrics survey tool [33]. The study was made available to participants who met these attributes: age 18 years or older, located in Canada or the United States, number of prior Mechanical Turk tasks completed greater than 1,000, with approval rate higher than 95%. Additionally, participants were screened to ensure possession of an active driving license in the US or Canada, having driven a car in the past 12 months, not having consumed alcohol six hours prior to the study or marijuana fourteen hours prior to the study, and using a tablet or computer to provide immersive display of the videos used in the study.

202 participants completed the survey to completion and were paid 6 USD. Participants were given the opportunity to opt out of the study at any point by exiting their browser window. A frequent problem with Mechanical Turk studies is participants who do not engage with the study, but instead answer all questions with the same value [4]. Participants meeting both of two exclusion criteria were removed from the data pool: driving satisfaction scores that are at least two standard deviations from the mean and driving satisfaction scores with very low variance (less than 0.25) across all conditions. Of the 202 participants, 20 were excluded, and 182 participants remained.

Of the included participants, 105 were male, 75 female, 1 non-binary, and 1 preferred not to list their gender. The median self-reported age of participants fell between 35 and 39 years old and mean years of driving experience was 14.

3.3 Measures

Moods are characterized in terms of two orthogonal dimensions of *arousal* and *valence* [35]. Arousal denotes level of physiological activation. For example, excitement corresponds with high arousal and boredom with low arousal. Valence denotes level of pleasure. For example, depression corresponds with low valence and happiness with high valence. Consequently, specific moods can be located in this 2-dimensional continuous space, represented by their intensity of arousal and valence. Participants' mood was captured using two affective sliders for valence and arousal [6]. Valence was measured on a scale from unpleasant to pleasant; arousal was measured from bored to excited. Images from EmojiGrid [39] were used to mark the slider endpoints.

To measure driving satisfaction, each participant completed the Satisfaction subscale of the Usefulness, Satisfaction, and Ease of Use (USE) questionnaire [29] following each viewing of a driving video (see Figure 2). The Satisfaction subscale uses a 7-point Likert scale for seven attributes including satisfaction, recommending to a friend, fun to use, works as desired, wonderful, desire to have the system, and pleasant to use [29].

3.4 Mood Videos

As shown in Figure 2, participants watched 45-second video clips to induce a calm, neutral, or excited mood. We use arousal and valence to define the three moods (calm, neutral, and excited moods) induced by the mood videos. A calm mood has low arousal and moderately positive valence; a neutral mood has moderate arousal and valence, and an excited mood has high arousal and valence [35].

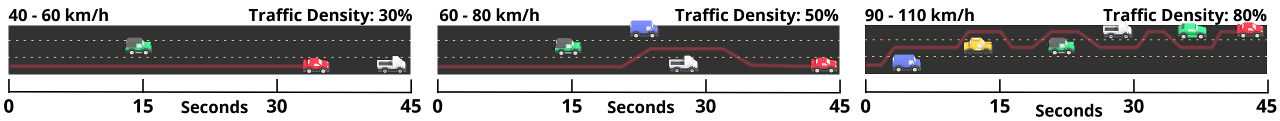

Figure 3: Driving conditions and exemplar paths taken for the conservative, moderate and aggressive driving videos.

We paired these mood conditions with three driving conditions of a calm, neutral and aggressive driving style.

Still images that are representative of the mood videos are shown in Figure 1. The calm video shows a scenic nature scene with relaxing music [34]; the neutral video shows a walk through downtown London [40], and the exciting video shows a come-from-behind victory in a running race with energetic commentary [2]. The selection procedure and validation of these videos are described in Appendix A.

3.5 Driving Videos

As described in Figure 2, participants viewed driving videos to give them the experience of being driven in a self-driving car. Three 45-second videos were created, giving the experience of conservative, moderate, and aggressive driving styles. The conservative driving video was characterized by lower arousal and high valence; the moderate driving video was characterized by moderate arousal and moderate valence, and the aggressive driving video was characterized by moderate valence and high arousal.

The videos were created using *City Car Driving*, a driving simulation game [14]. We used City Car Driving because of its realism and ability to customize density and behaviour of other vehicles, as well as its successful use in earlier studies [3, 31]. For consistency, we recorded all three driving styles using the same stretch of highway within the game's "New City - Business District" scenario.

Our driving styles manipulated three factors described in Section 2.1. These are: driving speed, overtaking of other vehicles, and lane changes (which indirectly affected headway). Additionally, we altered the traffic density parameter in City Car Driving to allow for more frequent lane changes. Changes to other parameters indirectly changed headway – for example, frequent lane changes in busy traffic led to tailgating behaviour. Our definition of conservative, moderate, and aggressive driving styles using these attributes is shown in Figure 3.

Properties of these driving videos were explored in a small pilot study to confirm their suitability for this study; this procedure is described in Appendix B.

3.6 Method

This study used a 3x3 within-subjects design with 3 mood conditions (calm, neutral, excited) and 3 driving style conditions (conservative, moderate, aggressive). The resulting nine conditions were order-balanced using an imbalanced Latin Square [30] to reduce learning effect.

Participants began by completing a demographic questionnaire. This included questions on the frequency and type of driving, years of driving experience, enjoyment of driving, driving skill and perception of self-driving cars.

Participants then followed the steps illustrated in Figure 2 for each of the nine conditions. First, participants provided a *initial* assessment of their mood through arousal and valence measures. They then watched a mood video to induce a calm, neutral, or excited mood. A second mood measurement of arousal and valence was then taken to capture the participant's mood prior to watching the driving video (*pre*-driving video measurement). Participants watched the driving video, after which mood was measured again using arousal and valence measures (*post*-driving video measurement). Finally, participants completed the driving satisfaction questionnaire.

Mild deception was used in recruiting and when instructing participants about the study. The study was advertised as investigating different driving styles, without mentioning that these referred to self-driving. This was to avoid biasing our sample population to enthusiasts of autonomous vehicles. The mood videos were explained as a short break between trying the driving styles, and it was not revealed that the videos were intended to induce specific moods. At the end of the study, participants received a debriefing form that explained the deception and the real purpose of the study. This study received approval from the Queen's University General Research Ethics Board of the authors' university.

4 RESULTS

We present our results in terms of the hypotheses stated in Section 3.1: (H1) participants prefer the driving video when it matches their mood, and (H2) greater differences in pre- and post-measurements of mood negatively correlate with driver satisfaction – i.e., people dislike driving styles that are vastly different from their mood. These hypotheses both test how mood influences preference in driving style, but triangulate through the use of different measures.

4.1 H1: Preferred Driving Styles vs Mood

We assessed whether participants' moods, as induced by the mood videos, affected their ranked satisfaction with the driving videos. The independent variable was the choice of mood video (calm, neutral, exciting) and the dependent variable was the participants' rating of driving satisfaction (Satisfaction subscale of USE questionnaire [29]). As shown in Figure 1, we hypothesized that driver satisfaction would be higher when the induced mood was closer to the mood expressed by the driving style – e.g., a calm mood would best match the conservative driving style and an excited mood would best match the aggressive driving style.

Since we had no prior beliefs about the distribution of participants' mood or satisfaction scores, a Friedman test was used for each of the three mood types to compare participants' satisfaction under that mood with the three driving styles. As shown in Table 2, all three Friedman tests were significant ($p < .05$). Wilcoxon Signed Rank Tests were subsequently used to conduct post-hoc pairwise comparison of the driver satisfaction levels for each driving style (also shown in Table 2). The p-values of the Wilcoxon tests were adjusted using the Holm-Bonferroni method [20] to control for multiple tests performed. For all three mood videos, significant

Table 2: H1 Results. Satisfaction of driving styles based on induced mood condition. A "∗" marks significance ($p < .05$).

Mood	Driving Style	Driving Satisfaction Median	Friedman Test	Wilcoxon Signed Rank Test
Calm	Conservative (CC)	1.29	$X^2(2)$=50.76	CC vs. CM: p<0.781
	Moderate (CM)	1.14	p<0.001*	CM vs. CA: p<0.001*
	Aggressive (CA)	1.00		CA vs. CC: p<0.001*
Neutral	Conservative (NC)	1.29	$X^2(2)$=51.34	NC vs. NM: p<0.080
	Moderate (NM)	1.21	p<0.001*	NM vs. NA: p<0.001*
	Aggressive (NA)	1.00		NA vs. NC: p<0.001*
Excited	Conservative (EC)	1.29	$X^2(2)$=24.31	EC vs. EM: p<0.720
	Moderate (EM)	1.29	p<0.001*	EM vs. EA: p<0.001*
	Aggressive (EA)	1.00		EA vs. EC: p<0.001*

differences were found when comparing the conservative vs aggressive driving style and moderate vs aggressive driving style ($p < .05$). These results are shown in Figure 4.

The results show that the mood video did not impact participants' preference of driving video. For all mood video conditions, participants ranked the conservative and moderate driving styles equally, while ranking the aggressive driving style lower.

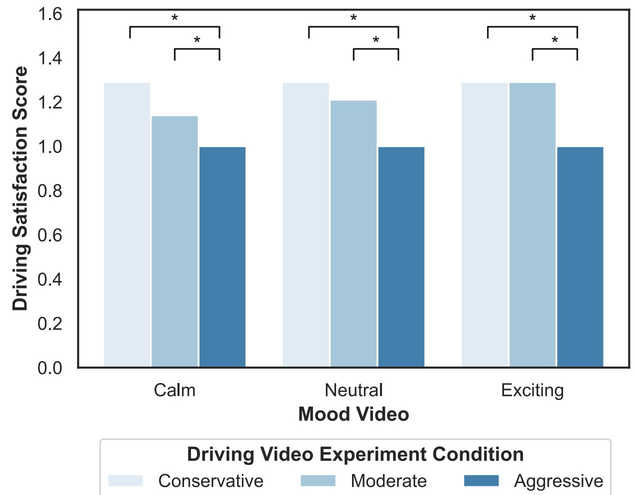

Figure 4: Satisfaction with driving style based on prior induced mood condition; a "∗" indicates significance ($p < .05$).

4.2 H2: Mismatch in Driving Style to Mood as Predictor of Driving Dissatisfaction

The previous section (hypothesis H1) asks the coarse-grained question of how well mood videos match driving videos. Under hypothesis H2, we ask the finer-grained question of whether a mismatch between the participant's mood before and after viewing the driving video leads to lower driving satisfaction.

More precisely, with reference to the procedure of Figure 2, we compare the pre-measure of mood (after mood induced, before watching driving video) to the post-measure of mood (after watching driving video.) We hypothesized that larger differences in these two measures of mood would predict lower driving satisfaction.

Since mood is measured in terms of arousal and valence, our analysis therefore asks whether mismatch in valence and/or arousal correlates with lower driver satisfaction, and how strong this correlation is for each of arousal and valence.

Specifically, we used multiple regression to establish the degree to which difference in arousal and difference in valence predict participants' rating of driving satisfaction. For H2, the independent variables are the magnitudes (i.e. absolute values) of participants' change in arousal and valence as measured before and after watching the driving video. The dependent variable is the participants' rating of driving satisfaction using the Satisfaction subscale of the USE questionnaire [29].

The multiple regression was significant for both arousal ($p < .001$, $\beta = -.157$) and valence ($p < .001$, $\beta = -.356$) variables. These results suggest that greater dissatisfaction with the driving style occurs when there is greater change in participants' arousal or participants' valence as a consequence of watching the driving video.

5 DISCUSSION

The results of H1 show that across all mood conditions, participants preferred the conservative and moderate driving styles over the aggressive driving style. These results lend evidence to findings by Dillen et al. [15], Yosuf et al. [43] and Bellem et al. [5] which indicate that drivers generally prefer conservative driving styles. However, we found that mood affects preference for driving style, albeit not enough to be the sole determining factor (H2). In this section, we discuss the implications of our findings for the design of self-driving cars. Finally, we present an exploratory analysis hinting that people may like driving styles that lower their arousal levels and dislike driving styles that raise their arousal levels.

As seen in Table 2, the aggressive driving style had the lowest driving satisfaction (DS=1.00) across all conditions ($p < .001$). The conservative driving style had the highest driving satisfaction across all conditions (DS=1.29). However, no significant difference in preference was found between the conservative and moderate driving styles, indicating that these styles may be equally preferred over the aggressive style. This result is consistent with earlier studies that found a preference for defensive over aggressive driving styles [43], and studies that found that defensive driving styles can provide a feeling of comfort with these novel technologies [13]. These earlier studies treated peoples' preferences for driving style as a static personality trait; we advance this research by confirming this result even when participants' moods change. We observe that preferences do change with mood, but not enough to modify this basic preference toward defensive (i.e. conservative and moderate) styles. With our finding that conservative and moderate driving styles are preferred to the aggressive style, our primary design lesson is that even if self-driving cars can safely drive with an aggressive style, these styles should be avoided.

It is notable that mood affected preference for driving style. In particular, mismatch of both valence and arousal with driving style negatively influence driving satisfaction. While these changes were not large enough to influence our primary outcome, they did have an impact. Designers of self-driving cars should be aware that mood does impact preference in driving style.

Given the novelty of self-driving cars and consequently participants' limited experience with them, it may be that drivers' preference of self-driving styles will change as this technology becomes

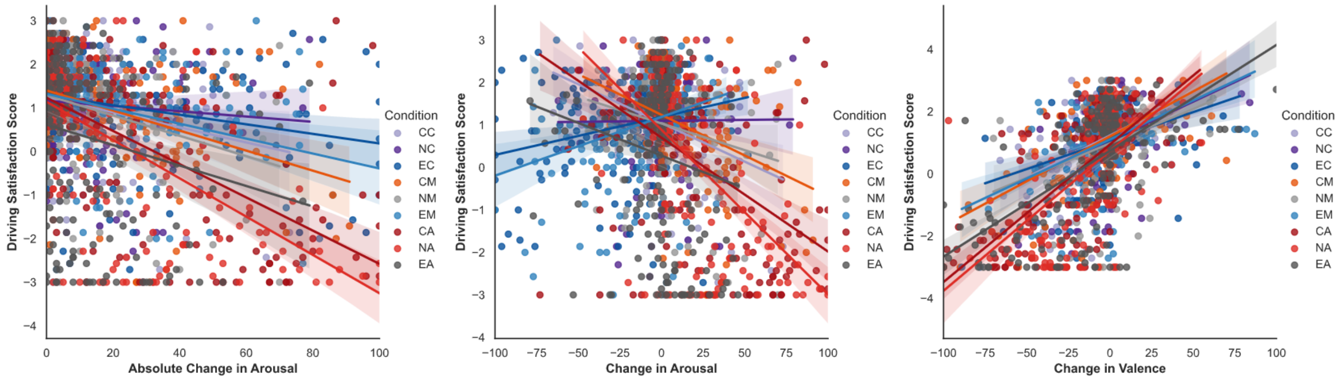

Figure 5: Magnitude (left) and Directionality (center & right) of difference in arousal and valence on driver satisfaction.

more widely used. Particularly, as users of self-driving cars become more comfortable with the car's safety and with having given up control over driving, they may become more comfortable with more aggressive driving styles. Driving styles that seem aggressive to people who have grown up with manual driving may eventually be perceived as moderate to future users of self-driving cars. However, the reported results are important to the introduction of self-driving cars and likely the first years of their deployment.

5.1 Exploratory Analysis: Effect of Mood on Driver Satisfaction

The analysis of driver satisfaction with the moderate driving style (Table 2) provides an example of how mood affects driver satisfaction. Participants' satisfaction with the moderate driving style increased progressively from the calm (DS=1.14), inducing an increase in arousal, to the neutral (DS=1.21) to the excited mood (DS=1.29), inducing a decrease in arousal. This result is surprising as the mismatched excited mood-moderate driving style (EM) pairing leads to higher driving satisfaction than the matched neutral mood-moderate driving style (NM) pairing.

To better understand this trend, we considered the scatter plot of all participants' scores showing change in mood versus driving satisfaction score (Figure 5). Conditions in which the driving video was expected to increase participants' arousal (e.g. CA & NA) are drawn in red and conditions in which the driving video was expected to decrease arousal (e.g. EC & EM) are drawn in blue. In this figure (left), red points have lower satisfaction, while blue points have higher satisfaction. This suggests that participants satisfaction with a driving style may be negatively correlated with the change in arousal it induces.

A possible cause of this unexpected finding is revealed by plotting the difference in participants' arousal and valence. As seen in the regression lines in Figure 5(Right), driving satisfaction increased as valence increased. Conversely, participants' satisfaction increased when their arousal decreased (Figure 5(Center)). This, however, was not the case in conditions EC, EM and NC wherein change in arousal was positively correlated with driving satisfaction. These results suggest that increasing the valence of the user of a self-driving car increases their driving satisfaction. Changing the arousal of the user can either increase or decrease their satisfaction. This trend is consistent with our result that according to the standardized β-values reported in section 3.1, valence has a stronger effect on driver satisfaction than arousal. Note that the analysis of this trend was not part of our registered protocol, instead emerging as the data was analyzed. This post-hoc analysis should therefore be viewed as suggestive of trends rather than statistically valid, and as such no statistical analysis is provided.

6 LIMITATIONS

Due to the COVID-19 pandemic, our study was conducted online and restricted to using videos of self-driving styles and affective sliders for measuring participants' moods. Every effort was made to provide an experience of different driving styles, although videos are not as visceral as driving in a real car or a simulator. In place of biometric approaches, we used possibly less accurate affective sliders which could be administered online using Mechanical Turk. Further details on the validation of mood and driving videos, as well as potential limitations, are discussed in the Appendix.

7 CONCLUSIONS AND FUTURE WORK

To explore the role of driver mood on preference and satisfaction for driving styles in self-driving cars, we performed an online experiment (N=182) where different moods (calm, neutral, excited) were induced in participants prior to their watching and scoring self-driving videos of different styles (conservative, moderate, aggressive). The results show a consistent preference for a conservative or moderate driving style as well as a dislike for an aggressive driving style. Moreover, our results indicate that drivers' moods do play a role in determining preference for driving style. We conclude with the design recommendation that self-driving styles be personalized to the moods of drivers, so long as the driving style is not overly aggressive.

For future work, approaches to personalizing self-driving styles to the drivers' moods should be investigated. As the autonomy levels of self-driving cars progressively advances, the drivers will transition into a passenger role. With this transition, a new question may be raised on how to adapt the driving style of a self-driving car to multiple passengers whose preferences may differ. Finally, we have considered the user experience of self-driving cars to span multiple categories of driving tasks (i.e., primary, secondary, and tertiary). As new user experiences develop in each of these categories, it will be valuable to investigate the combination of these new developments and how they can collectively provide a cohesive and enjoyable driving experience.

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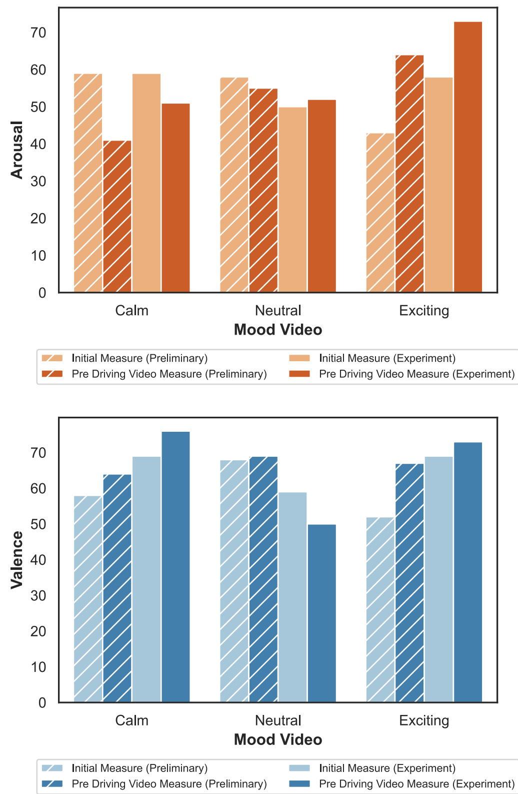

Figure 6: Change in arousal and valence as a result of watching mood video. Preliminary measures were obtained during our validation study. Experimental measures show change in mood in the experiment itself.

APPENDICES

A SELECTION AND VALIDATION OF MOOD VIDEOS

As described in section 3.6, this study required a stimulus to induce three desired moods (calm, neutral, excited) in participants. Braun et al. [8] suggested that asking participants to watch music videos can induce an emotion with dwell time of two minutes, which matches the amount of time required to complete one of our study's conditions. This inspired the use of short videos to induce moods in this study. Following the methodology of Braun et al., we selected videos from YouTube expected to induce the desired mood state and validated the videos through in-lab testing. Although Braun validated the effectiveness of the DEAP dataset, we had concerns that the popularity of the music videos used in this dataset might lead participants to have prior associations with these videos that may have changed since validation.

We collected data from seven participants to determine whether the selected videos induce the desired arousal and valence in participants. The videos used are shown in Table 3. For each of the three videos, presented in random order, the following procedure was used. First, arousal and valence were measured, the mood video was watched, and arousal and valence were measured again. These values are shown as the "preliminary" values in Figure 6. Participants were then shown a list of 14 adjectives and asked to select any that described their mood.

The success of the mood videos in altering participants arousal and valence levels can be seen in Figure 6 which shows how participants arousal and valence levels change based on watching the mood videos in both the preliminary experiment as well as the survey. The figure also shows the effect of the mood videos during the main study itself (listed as "Experiment" values), showing that the trends seen in the preliminary test held during the study.

B VALIDATION OF DRIVING VIDEOS

As described in section 3.6, we created videos using the City Car Driving simulation game [14] to illustrate three driving styles. An in-lab test was run to confirm that the driving videos were effective in conveying the desired conservative, moderate and aggressive driving styles. Two rounds of surveys were administered to 8 and 4 participants respectively. Participants viewed each of the three driving videos in a randomized order. They then selected an adjective from a list of 14 adjectives to describe the driving style. Participants were also asked to rate the strength of the adjective they selected and were asked an open question to note if any notable incidents occurred in the driving video. The mood induced by the mood and driving videos, as shown in Tables 3 and 4, have significant overlap. However, there were some difference in the descriptors used by participants, for example, the reckless term appears in the aggressive driving video, but not the exciting mood video.

Table 3: Validation of mood video through in-lab study. Values show the number of participants who assigned the given descriptors to each video.

Mood	Video	Start Time	Descriptors
Calm	Deep Sleep [34]	16m30s	calm (6/7) peaceful (6/7) serene (2/7)
Neutral	City Person Walking [40]	04m00s	neutral (3/7) normal (3/7) typical (2/7)
Excited	Race Comeback [2]	00m20s	interesting (7/8) excited (6/8) assertive (3/8)

Table 4: Validation of driving video through preliminary studies.

Driving Style	Descriptors
Conservative	calm (4/8) normal (4/8) boring (3/8)
Moderate	calm (4/8) normal (4/8) neutral (3/8)
Aggressive	aggressive (3/4) reckless (2/4) exciting (2/4)