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Driver Profile Modeling Based on Driving Style, Personality Traits, and Mood States

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***Abstract*— With the advent of advanced safety features and automated vehicles, driver safety has become critical in situations where the human is expected to disengage or drive partially. It is therefore vital to understand driver profiles in the development of systems that can adapt to the user and to which they can trust. Understanding the driving profile is challenging as it is composed of several factors, including driving style, mood states, and personality traits. To fulfill the purpose of modeling driver profiles, this paper proposed a comprehensive framework. A total of 28 licensed male drivers between the ages of 21 and 40 participated in the study; their driving behavior was recorded to create an integrated dataset. Additionally, mood states and personality traits were collected via surveys. The fuzzy logic inference system identified driving styles based on this integrated dataset. The relationship between driving styles, mood states, and a prediction model using random forest was developed for driving styles and personality types (obtained through clustering). Ultimately, findings from prediction can be utilized in risky driving style detection and driver preference sharing for the Mobility-as-a-Service purpose.**

I. Introduction

Recent developments in automated driving technologies will result in road interactions between automated vehicles (AVs) and human-driven vehicles in the foreseeable future. With these advancements, the role of the driver is likely to change. This presents unique challenges to driver safety and driver state assessment. To understand the critical safety issues that drivers may face in the future, it is essential to understand driver profiles.

Driver profiles are critical to improving the understanding of driver preferences, which could lead to providing personalized products with better suggestions (e.g., advanced driver assistant system) [1], boosting user acceptance and trust of AV via shared personality [2], and predicting the behaviors of other drivers [3].

A driver profile is determined by the demographic, physiological, and behavioral characteristics of a driver [4]. The majority of driver profile studies focused on behavioral characteristics, and personality traits, mood states, and driving style are the three most common research subjects. Personality traits usually refer to individual differences in characteristic patterns of thinking, feeling, and behaving [5]. Meanwhile, mood states are defined as emotional state that affects the way people respond to stimuli [6], but unlike mood states and personality traits, there is no agreed-upon definition for driving style [7]. Modeling behavioral characteristics is more complex as they are associated with a variety of temporal factors (e.g., traffic condition, surrounding vehicles, weather, and time of the day) [8]. Additionally, the lack of a consistent and controlled environment for data collection may result in difficulty modeling and validating the behavioral characteristics. This led to the popularity of survey-based studies as a method of choice for recording behavioral characteristics. Survey-based methods are popular as the process of their experiments are stable and have higher replicability. Among young drivers, Wu et al. [9] found a correlation between personality traits and driving styles whilst Zimasa et al. [10] related negative mood states to dangerous driving. Garrity and Demick [11] revealed the relationship among personality traits, mood states, and driving style pairwise but the driving style evaluation of this study may be biased as it was evaluated subjectively by the passengers.

Survey-based approaches may introduce bias to driving style recognition as drivers may not perceive their performance correctly [12]. In the past, studies defined driving style based on research goals with objective methods, which utilize selected vehicle operation states (e.g., speed, acceleration, and angular speed) from the naturalistic driving dataset [13], driving simulators [14], or test vehicles [15]. In addition to the mode of data collection, drivers were classified from mild to aggressive [16], driving performance from bad to good [17], and by analyzing dynamic demand i.e., sports, moderate, and economical driver [15].

While driver profiles have been analyzed in previous studies, few researchers have been able to systematically research driving style, mood states, and personality traits in combination to build driver profiles. As mentioned earlier, past studies assessed the driving style subjectively based on surveys or identified it based merely on vehicle operation states in an inconsistent environment, which changes from time to time due to uncontrolled temporal factors.

Compared to the existing literature on prediction and behavior modeling, our study has made several contributions:

- A comprehensive framework to evaluate driving styles and their corresponding mood states was developed. The driving simulator provided a controlled environment to guarantee all participants experience the same scenarios and well-defined events.
- A longitudinal user study was designed and data collection was conducted to integrate the driving style, personality traits, and mood state of each participant into a single dataset.

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- Alongside a prediction model for driving style that uses mood states and personality traits, an inference model for personality types (obtained by clustering) given mood states and driving style was developed and assessed for accuracy.

The findings from this study are applicable in two major implementations. 1) Driving style prediction- A risky driving style can be predicted to adopt a new Advanced Driver Assistant System (ADAS) strategy, given the personality traits and mood states of the driver, and the mood states can be determined by smart devices and/or a driver-monitoring camera. 2) Personality type inference can help personalize the product setup when drivers use other mobility anywhere (i.e., Mobility-as-a-Service), by observing users' driving style and mood states. In this study, such inference is used interchangeably with prediction.

II. Problem Formulation

Tenets of personality traits, mood states, and driving style were assumed as follows: 1) Personality traits are enduring attributions of each participant and consistent during the experiment period. 2) Mood states are affected by participants' experience near the experiment day, which can be different per experiment session. 3) While each participant's baseline driving style (e.g., aggressive) is enduring, it is influenced by mood states.

In this section, the experimental design, data collection, and metrics used for the analysis are discussed.

A. Experiment Design

A total of 28 individuals between the ages of 21 and 40 (Mean = 27.53 years, SD = 5.06 years) were recruited in California's San Francisco Bay Area by way of online advertisements as well as at physical locations. All participants were male, fluent in English, and had a valid U.S. driver's license. Prior to the user study, each participant took a personality traits assessment. During it, they would visit the test site four times altogether with a one-week interval between each visit. In every visit, participants experienced two driving simulator sessions: an urban city and a highway driving scenario. A mood check was required afterwards. For two out of four visits, each participant was asked to write down their happy and angry experiences and played an audio track. This was done to facilitate mood manipulation as music, imagination, and recall have been found to induce mood [18]. A sum of 224 driving session runs was carried out.

B. Integrated Dataset Construction

1) Personality Traits: To assess personality traits, the NEO Personality Inventory-3 (NEO-PI-3) questionnaire developed by McCrae et al. [19] was employed. This test is modeled upon the Five-Factor Model [20] as the basis of human personality. The five traits (i.e., Big-Five Scores) are Neuroticism, Extroversion, Openness, Agreeableness, and Conscientiousness. The evaluation of each personality trait is based on six sub-scores, evaluated by eight survey questions. The raw scores of the five factors and their sub-scores were calculated based on the survey response, and then for each trait, standardized T scores [21] were used. The T score represented the standardized values for each personality trait, where a score of 50 represents the mean and a difference of 10 from the mean is the difference of one standard deviation.

2) Profile of Mood States: The mood profile of a driver was assessed using the Profile of Mood States 2nd Edition-Adult Short (POMS 2-A Short) survey, developed by Terry et al. [22]. This 24-item questionnaire was adopted because of its ability to capture transient and fluctuating feelings. The responses of the assessment produced eight factors, including scores for six mood clusters: Anger-Hostility (Anger), Confusion-Bewilderment (Confusion), Depression-Dejection (Depression), Fatigue-Inertia (Fatigue), Tension-Anxiety (Tension), and Vigor-Activity (Vigor). Two general scores were also generated: Total Mood Disturbance (TMD) and Friendliness.

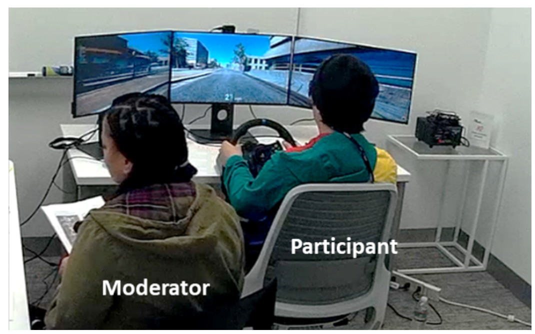
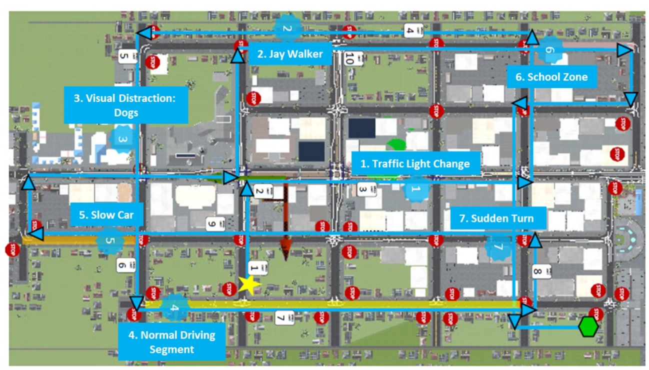
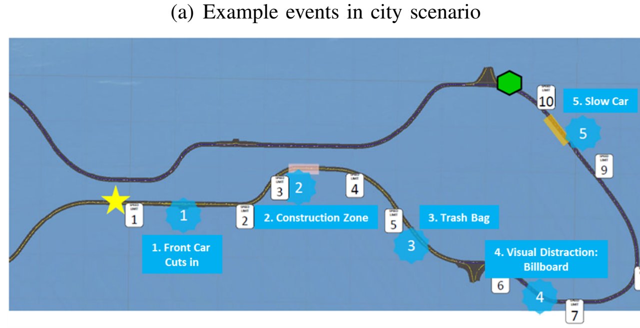


Fig. 1: Data collection setup



(a) Example events in city scenario



(b) Example events in highway scenario

Fig. 2: Driving style evaluation events

3) Driving Simulation: Unlike mood states and personality traits, driving style is evaluated objectively from participants' driving behavior. To understand driving style, the driving trajectories for each participant were observed using an in-house driving simulator built with AirSim [23], a plug-in for Unreal Engine 4. The participants controlled the vehicle using a Logitech G29 steering wheel and pedals as shown in Fig. 1. Three 24-inch displays represented the front and side views of the simulation environment.

The driving simulations presented urban city and highway scenarios to participants, as shown in Fig. 2. In each scenario, drivers experienced five critical events which included sudden danger (e.g., sudden cut-in behavior), speed limit signs, a slow preceding vehicle, visual distractions, and normal driving. Driving trajectories included vehicle coordinates, principal axes (yaw, pitch, rotation in degrees), speed (miles per hour), throttle and brake (0for no throttle/brake to 1 full throttle/brake), steering angle (0 to 1), distance from lane center(in meters), and the distance from surrounding vehicles (m). Combining driver reactions under different events, each session was classified into a certain driving style by the proposed fuzzy-logic inference system, which will be introduced in Section III-A.

4) Data Analysis: The driving trajectories in each session were classified into different driving styles, and the mood states and personality traits were processed. Principal Component Analysis (PCA) was applied for feature selection of the mood data. In assessing personality traits, Hierarchical Clustering Analysis (HCA) helped to cluster drivers with similar personalities. This was done because initial analysis found (1) regression for five-dimensional traits on a small-sample dataset was impractical and (2) a large number of combinations of five continuous traits were infeasible for classification. Furthermore, data cleaning was executed to filter out unrealistic sessions (e.g., driving on the sidewalk at city scenario) and 201 out of 224 data points remained in the dataset.

III. Methodology

In this section, the algorithms for profiling the mood states, personality traits, and driving styles of participants are described. As shown in Fig. 3, this study consists of a data collection phase and a modeling phase. In the data collection phase, each participant followed the experimental procedures as their mood states, driving trajectory, and personality traits were collected. As the one important part of driver profile modeling, the correlation between mood states and personality traits was investigated using their scores.

In the modeling phase, training and test datasets were split. For the assessment of mood states, three principal components from mood states explained 93% of mood states, and based on the contribution to three principal components, five out of eight significant features (i.e., Tension, Vigor, Fatigue, Friendliness, and TMD) were selected. Four driving styles were determined by the fuzzy logic inference system based on driving trajectories and three personality types were clustered by HCA. Eventually, a prediction model was trained and validated by random forest, enabling the prediction of (1) driving style with mood states and personality traits and (2) personality types with mood states and driving style.

A. Enhanced Fuzzy logic Inference System for Driving Style Recognition

In this study, four driving styles were defined based on definitions given by [14], and they were aggressive, anxious, keen, and sedate. Economical type was excluded because the behavior based on fuel consumption could not be replicated in a simulator study, also participants did not feel time efficiency concerns. The driving styles are not mutually exclusive, but there were predominant styles. The recorded 201 sessions were classified into one of the four styles. To utilize prior knowledge of driving trajectory, the fuzzy logic inference system was adopted to classify driving styles by interpreting the fuzzy linguistic terms given by the definitions. To ensure separation between driving styles, the weights used in the fuzzy logic inference systems were optimized.

Given the driving trajectories collected in the simulator, the fuzzy logic inference system estimated the probability of how each trajectory could be classified into a predefined driving style. The classification was done based on the highest probability. To be specific, the fuzzy logic inference system evaluated drivers' reactions to well-defined events and final probability was calculated by the weighted sum of each reaction. For example, an average speed of 110 mph in a session would be labeled as Very High, and the probability that the driving style is typified as aggressive may increase, and at the same time that the probability of it being anxious may decrease.

Considering the difference in driving trajectories between city and highway scenarios, two corresponding sets of fuzzy rules were developed for each scenario type to analyze the reactions in events, including normal driving (cruising without surrounding vehicle), car following [24], stop sign approaching and departure [14], and lane change [25]. In the city scenario, intersections and normal driving accounted for the majority of the scene. To evaluate how the participants performed on city roads, four key features were selected: 1) average speed near speed limit signs, 2) minimum speed at stop signs, 3) maximum acceleration after stop, and 4) maximum deceleration when approaching stop signs [26]. In the highway scenario, driving style was analyzed by its interaction with surrounding vehicles and normal driving, and hence four features selected from different events were evaluated: 1) average speed near speed limit signs, 2) maximum brake force when another vehicle cuts in, 3) minimum time headway to the preceding vehicle [27], and 4) lane change rate (i.e., lane change occurrence per mile) [28]. Based on predefined fuzzy rules, the inference system quantified linguistic probability (i.e., from not likely to very likely) into probability values. Due to article length restrictions, only 7 of 30 example fuzzy rules were shown in Table I.

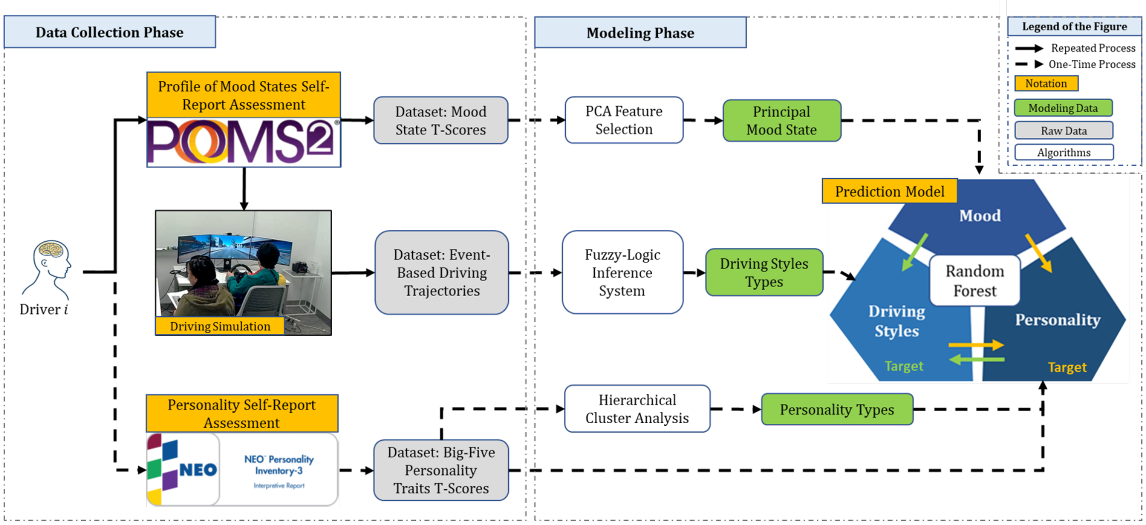


Fig. 3: System workflow of the driver profile modeling [data collection and modeling]

TABLE I: Example Fuzzy-Rules for Highway Scenario

		Agg.	*Anx.*	*Kee.*	*Sed.*
Speed	*Low*	NL	VL	HL	L
	Medium	HL	HL	VL	VL
	High	L	NL	L	NL
	VeryHigh	VL	NL	NL	NL
Brake	*Light*	VL	HL	HL	L
	Medium	L	NL	VL	HL
	High	HL	VL	L	NL

**Agg.* - Aggressive, *Anx.* - Anxious, *Kee.* - Keen, *Sed.* - Sedate
NL - Not Likely, HL - Hardy Likely, L - Likely, and VL - Very Likely.

The probability of each driving style could be expressed as (1), where a weight factor $w_{ds,f}$ was introduced to define how much a feature (f) contributes to a particular driving style [14]:

$$p(ds) = \sum_{f \in \, features} w_{ds,f} \cdot p(ds \mid f) \tag{1}$$

where $ds \in DS$={Aggressive,Anxious,Keen,Sedate}, and $\sum w_{ds,f} = 1$.

To avoid ambiguities in classification between similar driving styles (e.g., aggressive with keen, anxious with sedate), Non-Dominated Sorting Genetic Algorithm II (NSGA-II) [29] was adopted to optimize the weights $w_{ds,f}$. As presented in (2), two objective functions were maximized by tuning the weights. F_1 is the sum of the probability difference between each pair of driving styles, and F_2 is used to find the probability of the most probable driving style. This optimization process improved classification certainty by maximizing both F_1 and F_2.

$$\begin{gathered} F_1 = \sum_{i=1}^{3} \sum_{j=i+1}^{4} \left\| P\left(DS_i\right) - P\left(DS_j\right) \right\|_2 \\ F_2 = \underset{ds \in \mathrm{DS}}{\operatorname{argmax}} \left(\sum_{k=1}^{N} p_k(ds)/N \right) \\ F(w) = \operatorname{maximize}(F_1(w), F_2(w)) \\ \text{s.t.} \quad 0 \leq w_{ds,f} \leq 1 \end{gathered} \tag{2}$$

where $P(DS_i)$ is the combination of probabilities of i-th driving style in each session for all participants, $P(DS_i) = \{p_1(DS_i), ..., p_i(DS_i), ..., p_n(DS_i)\}$, N is the number of sessions to be evaluated, and $p_k(ds)$ is the probability of ds at k-th session.

B. Prediction Based on Random Forest

For this study, the prediction was formulated as a classification problem with the characteristics of the dataset taken into consideration; Random Forest [30] was used as the classifier as it could process inputs with categorical variables where input data was a synthesis of categorical variables (i.e., types) and continuous variables (i.e., score values). Random forest can, moreover, reduce over-fitting in a small-sample dataset with Bootstrap Aggregating (Bagging) [31]. Also, because the participants were all young male drivers, the dataset was unbalanced with an unequal distribution of mood states and driving styles. By weighting each class, random forest can account for unbalanced datasets effectively. Additionally, the results from classification are voted by multiple decision trees, thereby improving their robustness.

As shown in the prediction model in Fig. 3, when the prediction target was driving style, the inputs were personality traits, personality types (obtained from the HCA), and mood states. When predicting personality types, the inputs were driving styles and mood states. To improve prediction accuracy, grid search (exhaustive search) with 5-fold cross-validation was used to tune the hyper-parameter of the random forest model. Specifically, three major parameters were tuned: the number of decision trees (n_{tree}), maximum depth of the tree(d_{max}), and the number of features to randomly investigate (n_f). As a result, 1) for driving styles prediction, n_{tree} was 100, d_{max} was 50, and n_f was 3, and 2) for personality types prediction, n_{tree} was 42, d_{max} was 70, and n_f was 3.

IV. Result

A. Correlation Analysis for Personality Traits and Mood State

Correlations between personality traits and mood states are represented in a heat map created from the correlation matrix.

As shown in Fig. 4, Neuroticism has a positive correlation (correlation coefficient > 0.3) with Tension, Fatigue, and Total Mood Disturbance (TMD). It, however, also has a strong negative correlation with Vigor (r=-0.49, p <.001) and Friendliness (r=-0.41, p <.001). Extraversion has a positive correlation with Depression, Vigor, and Confusion. Compared with other traits, Conscientiousness is associated with all mood states ($|$coefficients$|$ > 0.3), plus it is positively associated with Vigor(r=0.3, p <.001) and Friendliness(r=0.35, p <.001). It also has a strong negative correlation with Confusion (r=-0.54, p <.001) and TMD (r=-0.52, p <.001). Not to mention, weak correlations (correlation coefficient < 0.3) are detected for Openness and Agreeableness with mood states. Openness has a weak positive correlation with Vigor and Friendliness but displays a weak negative correlation with Tension, Anger, Fatigue, and TMD. Agreeableness has a weak negative correlation with all mood states.

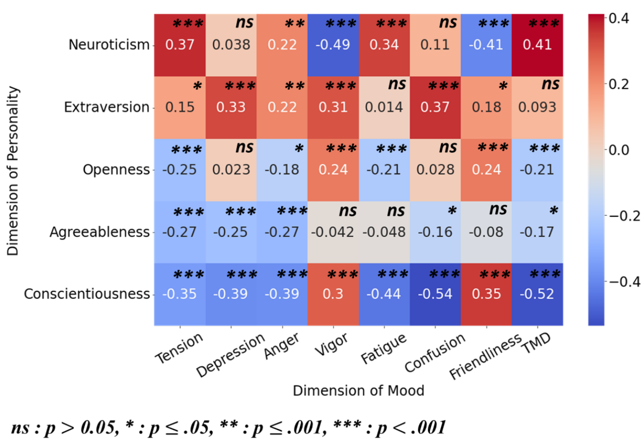


Fig. 4: Correlation matrix between mood states and personality traits

B. Personality Types Clustering

Besides the 28 participants, a total of 92 responses to the NEO-PI-3 personality survey were collected online. After applying HCA on personality traits, a dendrogram that represented the euclidean distance between each data point in a tree-based diagrammatic representation was obtained. This dendrogram suggested a three-cluster result, as shown in Fig.5, where three personality types are colored in orange, green, and red. Notably, not all 92 evaluated participants are shown in Fig.5. The participant count was, respectively, 34, 31, and 27 for the Type 1, Type 2, and Type 3 personality. The average Big-Five personality traits for the three types of personality are shown in Fig. 6. Compared to the other two, Type 1 has the lowest scores for Agreeableness and Openness but its score for Neuroticism is high. Type 2 personalities have the lowest Neuroticism scores and high Conscientiousness, Extraversion, and Openness. The scores on Extraversion and Conscientiousness are low for Type 3 personalities, who also have high Agreeableness and Openness.

The averages of each mood state for the three personality types are presented in Fig. 7. The difference between mood states for Type 1 is smaller than it is for Type 2 and Type 3. Type 2 personalities have the highest scores for Vigor and Friendliness, and the lowest scores for Tension, Depression, Anger, Fatigue, Confusion, and TMD. Type 3 personalities have the lowest scores for Vigor and Friendliness.

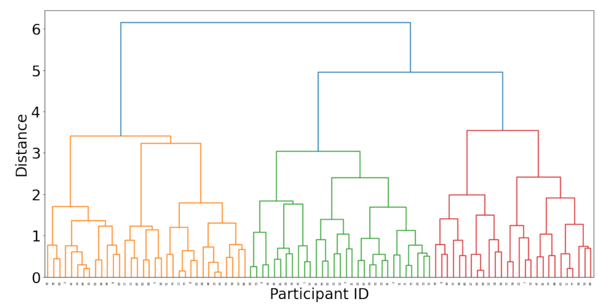


Fig. 5: Personality type clustering dendrogram using HCA

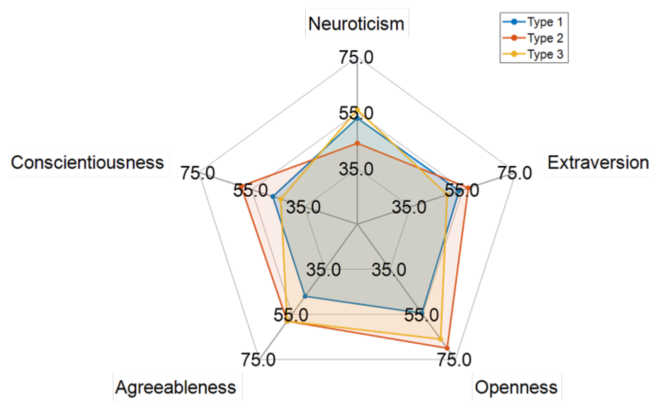


Fig. 6: Average scores of three personality types

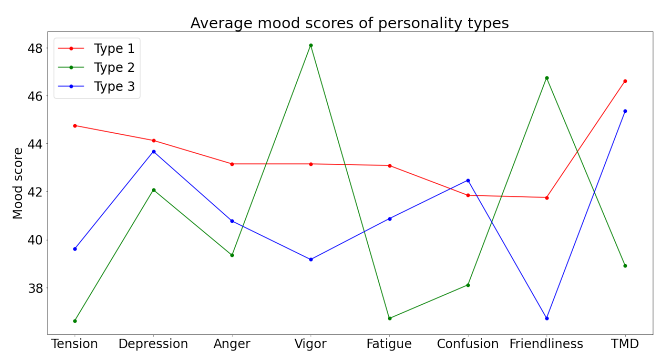


Fig. 7: Average mood states of three personality types

C. Driving Style Recognition

The performance of the proposed fuzzy-logic inference system is presented in Fig.8 and Fig.9, where evaluated features from the different driving styles are compared to illustrate the performance of the fuzzy logic system on driving style separation.

In the city scenario shown in Fig.8, aggressive drivers have a higher maximum acceleration after a stop sign and drive 20 mph faster than the speed limit (25 mph) on average; they usually do not perform a full stop at a stop sign, driving at a minimum speed of 2.84 mph on average. Anxious drivers tend to drive defensively, 1 mph slower than the speed limit on average, and have a low stop sign departure acceleration of 1.59 m/s^2 on average but brake intensely with a deceleration of 3.96 m/s^2 on average. Keen drivers drive 6.79 mph on average faster than speed limit, perform complete stops, and have lower acceleration and deceleration rates than aggressive drivers. Driving defensively, sedate drivers are similar to anxious drivers but focus more on comfort (with the lowest average deceleration of 2.60 m/s^2) and efficiency, which will be better explained in the highway scenario.

Fig.9 illustrates driver performance in the highway scenario. Aggressive drivers drive 25 mph faster than the speed limit (65 mph) on average, tend to tailgate their preceding vehicles with a 0.74s average minimum time headway, and change their lane most frequently. Although keen drivers go over the speed limit, they do not threaten their surrounding vehicles (with 0.94s average minimum time headway). Sedate drivers drive at the speed limit (moving 2 mph faster on average), do not perform hard brakes whilst pressing only 32% brake pedal at most, and seldom change lanes (0.21 times per mile on average).

The distribution of different personality type clusters across different recognized driving styles is presented in Table II. Keen driving was observed to be the most frequent style, accounting for 49.8% of all participants while anxious is the least frequent type with only 2%. Among the three personality types, aggressive driving is more frequent for P-Type 3 at 35.6%. Sedate driving is more frequent for P-Type 1 at 28.8%.

Further, during this longitudinal study, many participants showed more than one driving style under different personality types. As shown in Table III, only 4 of 28 participants insisted on one driving style, 19 drove in two different ways, and 5 showed three driving styles throughout their 8 driving sessions.

TABLE II: Personality Types-Driving Styles Distribution

	Agg.	*Anx.*	*Kee.*	*Sed.*	
*P-Type*1	12 26.6%	1 2.2%	19 42.2%	13 28.8%	22.5%
*P-Type*2	14 25.5%	1 1.8%	29 52.7%	11 20.0%	27.4%
*P-Type*3	36 35.6%	2 1.9%	52 51.5%	11 10.9%	50.3%
	30.9%	2%	49.8%	17.5%	100%

*$Agg.$ - Aggressive, $Anx.$ - Anxious, $Kee.$ - Keen, $Sed.$ - Sedate, P-$Type$ - Personality Type

TABLE III: Participants' Number of Driving Styles

# of driving style	*P-Type*1	*P-Type*2	*P-Type*3	Sum
one	1	1	2	4
two	5	5	9	19
three	1	1	3	5
four	0	0	0	0

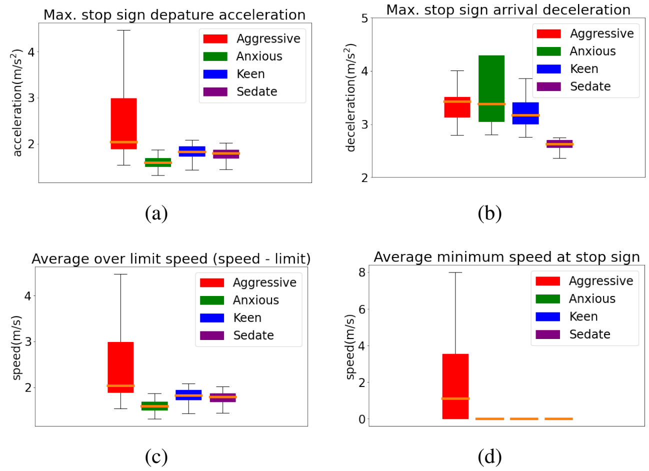


Fig. 8: Features in city driving session: (a) Maximum stop sign departure acceleration; (b) Maximum stop sign approaching deceleration; (c) Average speed over the limit (speed - limit); (d) Average minimum speed at a stop sign.

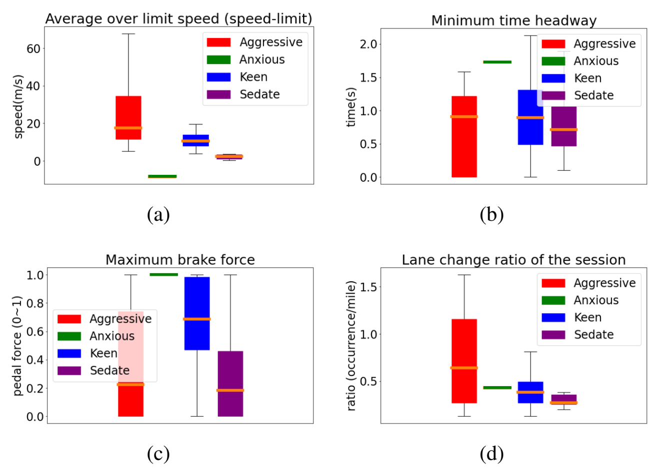


Fig. 9: Features in highway driving session: (a) Average speed over the speed limit; (b) Minimum time headway to slow vehicle; (c) Maximum brake force facing cut-in; (d) Lane change ratio of the session.

D. Prediction Results

To assess the performance of the predictive models, model accuracy and F1-scores were evaluated. These indices are commonly used for unbalanced datasets. The definitions of these indices are defined as (3)(4):

$$Accuracy = \frac{\mathrm{TP}+\mathrm{TN}}{\mathrm{TP}+\mathrm{FP}+\mathrm{TN}+\mathrm{FN}} \tag{3}$$

$$F1\text{-Score} = \frac{2*\frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}}*\frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}}}{\frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}}+\frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}}} \tag{4}$$

where TP is true positive, TN is true negative, FP is false positive, and FN is false-negative (predictions). In this study, macro-average scores [32] for these two indices were chosen to evaluate the model performance on the whole dataset.

The random forest predictions, which utilize different data inputs, were compared in Table IV. For driving style prediction, using only mood states achieved 0.563 Accuracy and a 0.431 F1-score; a slightly higher result of 0.592 Accuracy and a 0.531 F1-score was obtained with personality traits and types. After combining mood states, personality traits, and personality types, the Accuracy and F1-score reached 0.696 and 0.678 respectively. For personality type prediction, although a high correlation was observed as mentioned in Fig. 4, Accuracy was merely 0.356 and the F1-score (0.131) was even worse. Using driving styles and their probabilities (obtained from the fuzzy-logic system) led to increased Accuracy (0.612) and F1-score (0.597); in utilizing driving styles and mood states, the greatest result of 0.705 Accuracy and a 0.669 F1-score was acquired.

TABLE IV: Prediction Result Evaluation

Output	Inputs	F1-score	Accuracy
Driving Style	Mood	0.431	0.563
	Personality	0.531	0.592
	Mood & Personality	0.678	0.696
Personality	Mood	0.131	0.356
	Driving Style	0.597	0.612
	Mood & Driving Style	0.669	0.705

V. Discussion

The goals of this study were to create an integrated dataset for driver profile modeling, to predict driving style using mood states and personality traits, and to predict personality types using driving style and mood. To the best of our knowledge, prior studies have not combined driving style, mood states, personality traits for the prediction of driving style and personality types.

The correlation between personality traits and mood states found that upon separating mood states into those that were positive (Vigor and Friendliness) and negative (Tension, Depression, Anger, Fatigue, Confusion, and TMD), Neuroticism is positively associated with all negative mood states and negatively associated with all positive mood states. This result is consistent with the previous study [33], which related Neuroticism with negative effects, such as anger, anxiety, irritability, emotional instability, etc. Conscientiousness has negative correlations with all negative mood states and positive correlations with all positive mood states, which is similar to the findings in [11] where both Conscientiousness and Neuroticism showed significant correlation with all mood states. Contrary to [11], Extraversion is positively correlated with Confusion in our observations.

Furthermore, personality traits are found to be associated with mood states as shown in Fig. 6 and Fig. 7, illustrated by the comparison between Type 2 and Type 3 persons, whose major differences in personality traits are Neuroticism and Conscientiousness. With lower Neuroticism and higher Conscientiousness, Type 2 individuals have the highest positive and lowest negative mood states while Type 3 persons have the lowest positive mood states.

The influence of mood states and personality traits on driving style is also reflected in Table II; the highest proportion of aggressive drivers is observed in Type 3 personalities, who have the lowest positive mood states. A similar result was presented in [9], indicating that individuals with negative emotions and stress often drove riskily and fast whilst having a low Conscientiousness score. Unlike the big difference between positive and negative mood states seen for Types 2 and 3, each mood state score is neutral for Type 1 individuals and personality traits are close to the mean value (50 in T-score). With balanced mood states and average personality traits, the proportion of sedate drivers for Type 1 is the highest. However, it should be noted that these results do not indicate a strong relationship between personality traits and driving style, in line with [11]. According to Table III, during the four visits, most of the participants from all three personality types demonstrated more than one driving style. This contradicts a past study on the personality-driving style relationship [34], which finds that driving styles tend to be stable.

In this study, the analysis found that mood states were insufficient in the attainment of a good prediction result for personality type, even though strong correlations were found between the two. Additionally, driver behaviors for the three personality types were varied under different mood states, so driving style prediction using just mood states is also insufficient. Further, solely using either driving style or personality traits achieved better accuracy than using only mood states, but both driving style and personality type predictions can be improved significantly by combining the remaining two types of data as the input.

Limitations. While this study identified the possible prediction of personality traits and driving styles using mood states, refining the predictive model can help offer better personalization. As the study is limited to male drivers, a lack of sufficient demographic representation could constrain the predictive power. Besides the sample size issue, mood state assessment relies on a subjective self report, which might not reflect the real mood state of all participants. As we can see, the correlations between agreeableness and all mood states are weak. In some extreme cases, an agreeable person might not report their feelings but may still experience it. As an alternative method, mood states can be objectively assessed by smart devices.

VI. Conclusion

In this paper, a comprehensive framework that considers driver reaction in each predefined event for the identification of driving style was proposed. By synchronizing the driving style data with mood states, and personality traits data, an integrated dataset was developed. Based on the dataset, the correlation between personality traits and mood states was discussed. This found that Neuroticism had the strongest negative correlation with positive mood states while Conscientiousness had the most negative correlation with negative mood states. Three personality types were determined based on clustering, and it was discovered that Type 1 personalities had the most average personality traits and mood states. They also demonstrated more sedate driving than the other types. Meanwhile, Type 2 personalities had the highest positive mood states and completed more keen sessions. Type 3 personalities had the lowest positive mood states and drove more aggressively. A prediction model was trained based on random forest and validated, showing that (1) driving style can be predicted using mood states and personality traits and (2) personality types can be predicted using driving style and mood states.

As one of the first few research projects looking into driving style, mood states, and personality traits combined, improvements can be made alongside its continued development. Future studies would incorporate different demographics to evaluate the predictive model for different population groups. On top of that, it is necessary to examine the proposed models in naturalistic environments to assess their stability and usability. As we have already modeled the general driver profile, a personalized driver profile will be considered in the next step. For this, the Myers-Briggs Type Indicator (MBTI) personality assessment, which requires more data from drivers, can be adopted to define personality types.

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