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► To cite this version:

Morgane Evin, Antonio Hidalgo-Munoz, Adolphe James Béquet, Fabien Moreau, Hélène Tattegrain, et al.. Personality trait prediction by machine learning using physiological data and driving behavior. Machine Learning with Applications, 2022, 9, 10.1016/j.mlwa.2022.100353 . hal-04068899

HAL Id: hal-04068899

<https://hal.science/hal-04068899>

Submitted on 14 Apr 2023

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Personality trait prediction by machine learning using physiological data and driving behavior

Morgane Evin^{a,*}, Antonio Hidalgo-Munoz^b, Adolphe James Béquet^b, Fabien Moreau^b,
Helène Tattegrain^b, Catherine Berthelon^c, Alexandra Fort^b, Christophe Jallais^b

^a Laboratoire de Biomécanique Appliquée, Aix-Marseille Univ, Univ Gustave Eiffel, IFSTTAR, LBA, F-13016 Marseille, France

^b Laboratoire Ergonomie et Sciences Cognitives pour les Transports, TS2-LESCOT Univ Gustave Eiffel, IFSTTAR, Univ Lyon, F-69675, Lyon, France

^c Laboratoire Mécanismes d'Accidents, TS2-LMA, Univ Gustave Eiffel, IFSTTAR, F-13300 Salon de Provence, France

ARTICLE INFO

Keywords:

Driver physiological data
Personality traits
Machine learning
Anxiety
Electrodermal activity

ABSTRACT

This article explores the influence of personality on physiological data while driving in reaction to near crashes and risky situations using Machine Learning (ML). The objective is to improve the driving assistance systems in considering drivers' characteristics.

Methods: Physiological and behavioral data were recorded in sixty-three healthy volunteers during risky urban situations and analyzed using 5 ML algorithms to discriminate the driver's personality according to Big Five Inventory and STAI trait. Seven step process was performed including data pre-processing, Electrodermal Activity (EDA) time windows selection (one by one backward and forward approach comparison with a pseudo-wrapped), personality traits assessment, input algorithms parameters optimization, algorithm comparison and personality trait cluster prediction. ROC Area Under the Curve (AUC) was used to describe improvement.

Results/discussion: The pseudo-wrapped/all possibilities method comparison resulted in 8.3% on average for all personality traits and all algorithms (% of ROC AUC of backward and forward approach). The ROC AUC for the detection of the personality ranged between 0.968 to 0.974 with better detection of Openness, Agreeability and Neuroticism. Use of association between Neuroticism, Extraversion and Conscientiousness previously defined in the literature slightly improve personality detection (maximum ROC AUC of 0.961 to 0.993 for cluster). Results are discussed in terms of contribution to driving aids.

Conclusion: This study is one of the first to use machine learning techniques to detect personality traits using behavioral and physiological measures in a driving context. Additionally, it questions input parameters optimization approach, time windows selection, as well as clustering and association of personality trait for detection improvement.

1. Introduction

Driving is a complex activity and a significant factor of crash occurrence is how the driver behaves. Driver's behavior is related to the driver's personality, physiological and behavioral metrics. In order to decrease crashes, car manufacturers are more and more interested to take all these components into account when developing future driver interfaces. Knowledge of the driver personality could enable an improvement of his/her confidence toward the system. Additionally, the system could be adapted to the driver's characteristics and better fit his/her expectations. The assessment of the driver's personality could improve the adaptation between system functioning and the driver personality. Thus, it could lead to improve both confidence in the system and its effectiveness. Detecting a driver's ability to drive by

estimating his or her emotional state from behavioral and physiological data has been widely studied in recent decades (Gruyer et al., 2017; Sikander & Anwar, 2019). Influence of personality traits on emotional state while driving remains to be investigated.

Usually, variability between drivers is taken into account by questionnaires measuring emotional state, circadian type (Jacobé de Naurois et al., 2019), or personality (Sümer et al., 2005). In the Big Five Inventory (BFI) questionnaire (Satow, 2011a, 2011b), five main personality traits are considered. The Neuroticism measures the tendency to anxiety and potentially respond badly to stress. The Openness indicates the broad-minded characteristic of people and Conscientiousness has to do with self-discipline and persistency. The Agreeableness and Extraversion traits respectively highlight capacities of altruism and

* Corresponding author.

E-mail addresses: morgane.evin@univ-eiffel.fr (M. Evin), arhidalgom@usal.es (A. Hidalgo-Munoz), adolphe.bequet@univ-eiffel.fr (A.J. Béquet), fabien.moreau@univ-eiffel.fr (F. Moreau), helene.tattegrain@univ-eiffel.fr (H. Tattegrain), catherine.berthelon@univ-eiffel.fr (C. Berthelon), alexandra.fort@univ-eiffel.fr (A. Fort), christophe.jallais@univ-eiffel.fr (C. Jallais).

<https://doi.org/10.1016/j.mlwa.2022.100353>

Received 23 February 2022; Received in revised form 20 May 2022; Accepted 4 June 2022

Available online 11 June 2022

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compliance (Steenhaut et al., 2018) and capacities of experiencing positive emotions in social and work environments (Childs et al., 2014) respectively. The use of a personality questionnaire is difficult in a real driving context, although to discriminate personality trait based on physiological and behavioral data may appear to be an important step in the investigation of the driver's state. It may also improve the subsequent detection of near-crash situations by providing discrepancies between driving demands and the driver's state. The personality traits are linked to the behavior in driving applications, based on the analysis of driving style. It has been shown a relation between high velocity, anger and Neuroticism, low Openness and Agreeableness scores. The carefulness, Conscientiousness and Agreeableness traits have been associated with high Neuroticism and low Agreeableness (Wang et al., 2018). The relationship between the driving situation in older adults and personality traits has been studied. It showed a decrease in the likelihood of capacity to drive with higher Neuroticism and Agreeableness score and a significant likelihood of capacity to drive with the other three traits being high (Gadbois & Dugan, 2015). The driving situations generate different social pressure and time constraints on drivers especially on situations such as left turn and over-taking (Beggiato et al., 2019).

The influence of personality traits on physiological data must also be noted and has notably been studied in other contexts than driving. Steenhaut et al. (2018, 2019) highlighted the link between physiological responses and personality traits. The authors also raised the question of the impact of stimuli arousal and emotional reactivity according to the type of stimuli (films negatively or positively connoted). Cardiac signal, as easily recordable, has been largely associated with personality depending on situations. The cardiac signal responses to stimuli depend on the automatic nervous system (LeBlanc et al., 2004) through cortisol stress reactivity. Higher Neuroticism, lower Openness and Agreeableness scores were correlated with smaller cardiac reactions to stress (systolic and diastolic blood pressure, Heart Rate (HR)) (Bibbey et al., 2013). The HR and HR variability has also been associated with the cognitive workload in aircraft pilots and differentiates between low and high once clustered by personality traits (K-mean clustering) (Hidalgo-Muñoz et al., 2021). Electrodermal Activity (EDA) was used to classify the personality trait of taekwondo athletes before a competition (Binboga et al., 2012). EDA delta score has been defined as the sum of the filtered EDA difference between consecutive signals for the acquired period time or total arousal for the period time. The best correlation was found between EDA and Agreeableness, Emotional stability and Conscientiousness traits using BFI questionnaire in the context of competition. Eye tracking features were associated with Extraversion and Agreeableness (Hoppe et al., 2018). A past experiment consisting in walk and purchase into a campus showed association between eye tracking in everyday situation and personality traits (Hoppe et al., 2018). Saccade movements were influenced in both Extraversion and Agreeableness. Based on driving situation the use of area of interest to define monitoring frequency and monitoring ratio has also been previously used and associated with Openness (Li et al., 2020).

Based on these findings, Machine Learning (ML) has been largely used in diverse applications. The available techniques have been previously classified depending on labeling or not (unsupervised or supervised) and the type of approaches used. The algorithms previously used in driving applications either presented results from the implementation of only a specific method or a comparison between different techniques. More recently, development of autonomous driving architecture has been using machine learning and deep learning techniques (Bachute & Subhedar, 2021). Among such techniques, Support Vector Machine (SVM) (Jacobé de Naurois et al., 2019; Lee et al., 2014; Wang et al., 2015; Yang et al., 2018; Yeo et al., 2009) and Random Forest (RF) (Haleem & Gan, 2013; Lu et al., 2018; McDonald et al., 2014), as well as Neural Networks (NN) (Chong et al., 2013; Liang et al., 2012; Tango et al., 2010) were reported as superior when compared to other approaches. Decision tree (Cichosz & Pawelczak, 2014; Wang & Yang,

2008) and naïve Bayesian (Bakheet & Al-Hamadi, 2021) algorithms are also reported to have been used in driving context especially as easy to interpret for the first and effective for the second.

While specific techniques could be considered to apply machine learning directly on time series mainly in forecasting applications, the use of feature computation as pre-processing enables to question the duration of the relevance of the signal for each of the processed signals. An appropriate selection of the training and validation sets and size of each dataset is crucial to avoid overfitting or bias in the selection of those datasets and guarantee generalization of the results. This question of the selection of features during training and validation of the ML algorithms has been largely discussed. One-by one backward and forward approaches (Evin et al., 2018) can be tested and compared to the pseudo-wrapped approach in order to avoid the possible effect of feature order. Optimization is then performed parameter type by parameters type (EDA, Cardiac, Eye-tracking data and driving behavior). Other approaches could then be considered for further optimization.

This exploratory work aims at (1) assessing the capacity of different ML techniques to classify personality traits under different driving contexts, and (2) assessing the benefit of personality traits clustering based on behavioral and physiological data while evaluating the relative contribution of the different types of bio-signals to improve the accuracy of the algorithm.

2. Methods

2.1. Overview of the methods

The present work was divided into five consecutive steps also reported in Fig. 1:

- A — re-analysis of the influence of the situation type which enables to determine if the knowledge of the situation type is the for the detection of personality traits.
- B — EDA time window selection which enables the better detection of the personality traits.
- C — selection of the EDA final parameters to be used from the previously selected time windows using both forward and backward and all possible approaches.
- D — selection of the other parameters (cardiac and eye-movement parameters) using the same approaches.
- E — final tests in which the personality traits to detect are clustered including algorithms comparisons.

2.2. Population and testing protocol

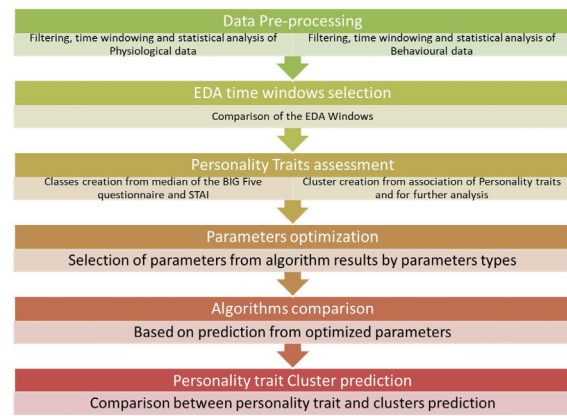
69 healthy volunteers were included in the experiment in which they were asked to drive in a simulated urban environment (see Fig. 1). Six volunteers were excluded from the study as experiencing driving simulator sickness. Final detection was thus performed on 63 healthy volunteers.

The testing protocol consisted of driving simulated situations (simulator as described in Hidalgo-Muñoz et al. (2019): Peugeot 308 cabin equipped with 7-inch screen providing a 270° horizontal and 47° vertical forward field of view). The situations were: a left-turn at a traffic light, an overtaking of trucks stopped in the driving lane and a near-crash situation. The difficulty of each situation was established according to 3 levels: Level 1 without traffic; Level 2 with high traffic and presence of pedestrians, so inducing social pressure and also time pressure by cars honking; and Level 3 with a near-crash with a pedestrian or a car suddenly crossing the street. The level (1, 2 or 3) and situation (left-turn, overtaking car, pedestrian crossing) coding was tested as a pre-analysis of the ML algorithms.

In order to record the physiological signals, during the test each participant was equipped with 5 electrodes from a Biopac MP150 system (BioNomadix system). Such electrodes were located under the last left rib, on the right clavicle and on top of the right hip of the participant



Fig. 1. Driving simulator used in this experiment and step-by-step scheme of the performed work.



for cardiac activity measurements. EDA signals was computed from sensors located on the left-hand index and middle finger (sampling rate of 1 kHz, hardware band-pass filtering 35 Hz). Additionally, each participant wear eye-tracking glasses (Pupil Core glasses from Pupil Labs UG, Berlin, Germany) with post-processing from the pupil Labs software.

2.3. Personality trait, personality cluster detection and personality detection.

The Big five Inventory (BFI) questionnaire was used to classify the drivers into two categories for each personality trait (Openness, Conscientiousness, Neuroticism, Extraversion, Agreeableness) using the median found in the whole population. Such binary classifications were then considered to be the output of the model. Additionally, the State-Trait Anxiety Inventory (STAI) was used to measure anxiety (Spielberger et al., 1970) and classes consisted in the median separation of the STAI.

The clusters were defined as: (1) spectator as low in Extraversion, Neuroticism and Conscientiousness, insecure as low in Extraversion and Conscientiousness and high in Neuroticism and impulsive as high in Extraversion and Neuroticism and low in Conscientiousness (Vollrath & Torgersen, 2002). 8 other clusters were also defined as Neuroticism/Extraversion/Conscientiousness (NCE) clusters (all possibilities of high or low value for those 3 personality traits). Similarly, Neuroticism and Conscientiousness were associated with divided individuals into four groups (Terracciano & Costa, 2004) called RCD (Relaxed, Control, Directed) in this study. Such groups were under-control (high Neuroticism), relaxed (low Conscientiousness), over-control (high Neuroticism and high Conscientiousness) and directed (low in Neuroticism and high in Conscientiousness) as defined in Boyle et al. (2008). These clustering options have proven to be relevant to predict particular risky behaviors (see Vollrath and Torgersen (2002) for details).

2.4. Measures

2.4.1. Physiological measures

Cardiac signal-based features included: the mean of the R to R wave interval length (RR), the standard deviation of the RR intervals (SDNN) and the root mean squared of the successive differences between adjacent RR intervals (RMSSD). Detection of R peaks was automatically performed using HRV Analysis (Pichot et al., 2016) and visually assessed.

The EDA signal consisted in the acquisition of the amplitude of skin conductance level. A decomposition of the skin conductance into tonic and phasic components was carried out by the Ledalab software (v3.4.9) written in MATLAB and available online (www.ledalab.de).

Then an amplitude threshold of $0.02 \mu\text{s}$ (Benedek & Kaernbach, 2010) was set to discriminate relevant phasic responses. Several features were computed from the EDA phasic responses detected: the number of responses (EDA_nb), the mean amplitude of response (EDA_ampMeanScrs), the standard deviation of amplitude of peaks (EDA_SDAmPScrs), the mean latency which correspond to the mean delay between two peaks (EDA_latMean) and the standard deviation of latency as the standard deviation of the delay between two peaks (EDA_SDLat) were computed.

2.4.2. Eye movement measures

The eye-tracking data (collected at 200 Hz with the Pupil Core system from Pupil Labs) consisted in four features associated with fixations. All visual gaze located in a 0.5° visual angle during 66 ms was considered as a fixation. Such implementation of fixation detection on Pupil Labs software is a dispersion-based method.

The number of fixations, the total duration of the fixations (NB_Fix), the mean duration of the fixations and the standard deviation of the duration of the fixation were computed. Occurrence of the total duration of the fixations and mean duration of the fixation in the final results had then be computed as a preliminary step before final optimization.

For biosignal, outliers were withdrawn using a threshold of mean value ± 3 standard deviations.

2.4.3. Behavioral measures

Behavioral data consist of three parameters averaged on 0–120 s time windows: Standard Deviation of the Lateral Position of the vehicle (SDLP), Standard Deviation of the Wheel Angle (SDWA) and Steering Reversal Rate (SRR). This SRR is defined as the number of times per minute that the direction of steering wheel is changed by an angle from 0.5 to 10° .

Finally, the time windows adapted to average the physiological and behavioral data vary according to the types of data considered. Mostly, two minutes after each situation could be acceptable for cardiac, behavioral and eyes tracking situations even though 0–30 s time windows was previously suggested for cardiac (De Rivecourt et al., 2008; Smith et al., 2013).

Thus, every signal was averaged on a 0–120 s time windows for the basic set of features, but electrodermal activity time windows averaging was questioned. Further analyses of several averaging of the EDA signal on different time windows were performed in order to determine the best windows to be used in terms of algorithm performance and the 0–60 s time windows were preferred as the first approach.

2.5. Statistical analysis and machine learning algorithms

Machine learning techniques used here were described and implemented in Weka (University of Waikato, [Hall et al. \(2009\)](#) and [Witten et al. \(2011\)](#)) and the one by one backward and forward approach was previously described ([Evin et al., 2018](#)).

Decision tree (C45) enables simple representation which make interpretation easier. C is the confidence threshold for pruning and M is the minimum number per leaf ($C = 0.25$, $M = 2$ in this work).

Naïve Bayes (NB) algorithm is implemented according with [John and Langley \(2013\)](#). No parameters are required for such run.

Random Forest (RF) implementation is the Breiman's random forest algorithm ([Breiman, 2001](#)). P is the percentage of the training set size taken for each bag, K is the number of attributes to randomly investigate, M is the minimum number of instances per leaf, V is the minimum numeric class variance proportion and S is the seed for random number generator. Such parameters were taken as follow: $P = 100$, $K = 0$, $M = 1$, $V = 0.001$, $S = 1$.

Support Vector Machine (SVM) in Weka is an implementation of sequential minimal optimization which have two different implementations in Weka depending if it is used through Weka or Rweka, the first one is the E1071 SVM implementation ([Keerthi et al., 2001](#)) while the second is John C. Platt's sequential minimal optimization ([Platt, 1998](#)). The second will be used in this work. C is the complexity constant, L, the tolerance parameter, P, the epsilon for round-off error, N, the normalization Boolean (if normalized or not), V, the number of folds for the internal validation and W the random number seed. Such parameters were taken as follow: $C = 1$, $L = 0.001$, $P = 1E-12$, $C = 1.0$, $L = 0.001$, $P = 1.0E-12$, $N = 0$, $V = 10$, $W = 1234$.

The Neural Networks (NN) classifier is based on a multilayer perceptron in Weka using backpropagation to learn a multi-layer perceptron to a class instance with sigmoid nodes. L is the learning rate for the backpropagation algorithm, M is the momentum rate, N is the number of epochs to train through and E is the number of consecutive increases of error allowed for validation. The number of layers is fixed to the sum of attribute and class, divided by two. One node is considered by layer. These were taken as follows: $L = 0.3$, $M = 0.2$, $N = 500$, $E = 20$.

The backward and forward one-by-one approach, which will be used later on, is a comparison of algorithms results when adding one by one parameter as input and removing one by one parameter. All possibility or a pseudo-wrapped approach is an approach in which all possibilities of input parameters are tested. The two approaches will be compared to measure the difference in terms of algorithms results. Both implementations are performed with R statistics language.

3. Results

Population was described using the BFI and STAI. The following characteristics of the population was found: 4 ± 1.55 for Openness, 4.47 ± 1.29 for Agreeability, 3.24 ± 1.35 for Extraversion, 1.25 ± 0.25 for Neuroticism; 4.1 ± 1.36 for Conscientiousness and 2 ± 0.28 for STAI traits.

Algorithms run separately on a i5 -8265U CPU @1.60 GHz ran in less than 3 s

3.1. Pre analysis of the influence of situation type

[Table 1](#) shows the Openness detection as an example. It highlights that the knowledge of the situation (type and levels) does not benefit to the results of any algorithm. The ROC AUC results improved when removing the situation feature (percentage defined as ROC AUC difference between with and without situation feature divided by ROC AUC without situation feature). Such results were similar for all personality traits (Neuroticism: up to 15%, Agreeability: up to 20%, Extraversion: up to 8%, Conscientiousness: up to 19% and STAI trait: up to 12%). Thus, the rest of the study was carried out without the situation features.

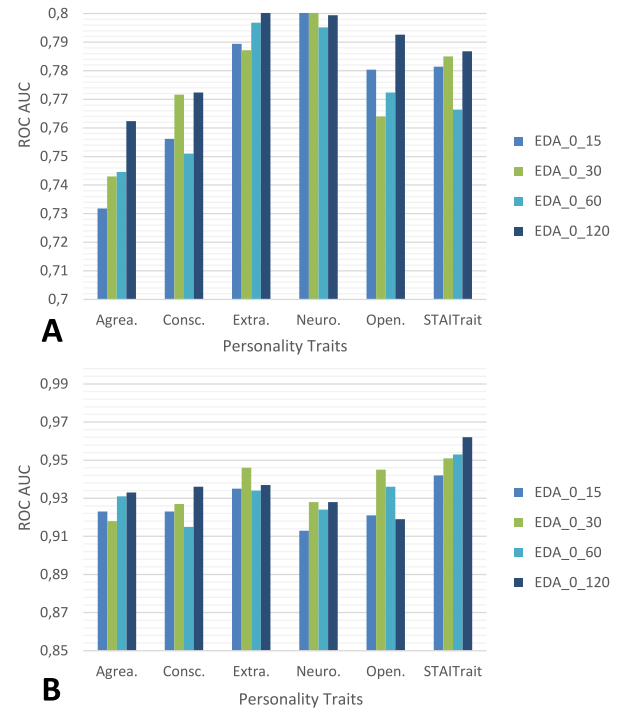


Fig. 2. EDA time windows investigation (A) average for all algorithms (RF, J48, SVM, NN, NB) (B) maximum value by personality trait.

3.2. EDA time windows optimization

Based on the literature, no consensus on EDA time windows analysis have been reached and EDA measurement protocols differed ([Chen & Chen, 2017](#)). The four time-windows (0–15, 0–30, 0–60 and 0–120 s) have been tested here in terms of contribution to better personality detection. When averaging on all algorithms by time windows and using all the EDA features without optimization, ROC AUC averaged on all algorithms was found higher for the 0120 s than for other time windows for all personality trait except Neuroticism ([Fig. 2A](#)).

When focusing on maximum value, the 0–120 s EDA time window remained the most selected while the 0–30 s EDA time window presented higher ROC AUC for Extraversion, Neuroticism and Openness ([Fig. 2B](#)). Finally, in the rest of the work, the time windows considered for EDA feature computation are presented in [Table 2](#).

While 0–30 s time window is the EDA time window the best results (43% for 0–30 s vs. 13.3% for 0–15 s, 20.3% for 0–60 s, 23.3% for 0–120 s), it should be noticed that most of the results are mixed and depend on the used algorithm.

In the one by one forward and backward approach, the most used EDA feature alone is the EDA_ampMeanSrcs while EDA_nbSrcs is mostly discarded. J48 and RF appeared to follow a pattern with similar EDA features for every personality trait.

3.3. Comparison of EDA feature selection type

Results of the one by one backward and forward approach and an all possibility approach (pseudo wrapped method) is presented in [Table 3](#). Depending on the detected personality trait, the ROC AUC changes on average on all personality traits and all ML techniques by 8.3% (ROC AUC difference between backward and forward approach and all possibility approach divided by ROC AUC backward and forward approach results).

Table 1

Tests of the algorithms with situation features and level for Openness;%: corresponding of improvement or worsening of the ROC AUC between All: all features with situation and level; Witho.: without situation and level, TP r: True positive rate, FP r: False positive rate, Prec: precision, ROC AUC: Receiver operating characteristic area.

Openness		TP r	FP r	Prec	Recall	F-measure	MCC	ROC AUC	PRC area	(%)
RF	All	0.69	0.308	0.692	0.69	0.69	0.382	0.761	0.769	-1.8
	without	0.687	0.309	0.691	0.687	0.686	0.378	0.775	0.785	
J48	All	0.599	0.401	0.6	0.599	0.6	0.198	0.604	0.568	-13
	without	0.62	0.377	0.623	0.62	0.62	0.243	0.682	0.665	
NB	All	0.608	0.382	0.621	0.608	0.604	0.232	0.635	0.617	-1.6
	without.	0.614	0.375	0.629	0.614	0.609	0.246	0.645	0.628	
SVM	All	0.566	0.433	0.568	0.566	0.566	0.133	0.567	0.539	1.7
	without.	0.557	0.444	0.557	0.557	0.557	0.113	0.557	0.532	
NN	All	0.545	0.458	0.544	0.545	0.545	0.087	0.577	0.576	-23
	without	0.66	0.343	0.659	0.66	0.659	0.317	0.713	0.698	

Table 2

EDA time windows selection according to algorithm and personality traits.

Personality Traits/Algo.	RF	J48	NN	NB	SVM	Main
STAITrait	0–120	0–15	0–30	0–30	0–60	0–30
Openness	0–30	0–30	0–120	0–120	0–60	0–30/120
Neuroticisl	0–30	0–30	0–15	0–30	0–30	0–30
Extraversion	0–60	0–30	0–60	0–120	0–15	0–60
Conscientiousness	0–30	0–30	0–60	0–30	0–120	0–30
Agreeableness	0–120	0–60	0–15	0–120	0–30	0–120
Main	0–30	0–30	0–15/60	0–30/120	0–30/60	

Table 3

Comparison of EDA feature selection approaches by personality trait and depending of algorithm (Algo): one by one backward and forward approach and wrapped method approach for the best three algorithms. Imp: improvement.

	Algo	Approaches			Imp. (%)
		EDA param	ROC AUC 1by1	ROC AUC All	
Openness	J48	0_30	0.945	0.971	-2.8
	NN	0_120	0.828	0.936	-13.0
	NB	0_120	0.698	0.828	-18.6
Neuroticism	J48	0_15	0.861	0.963	-11.8
	NN	0_30	0.883	0.882	0.1
	NB	0_30	0.764	0.836	-9.4
Extraversion	J48	0_60	0.965	0.977	-1.2
	NN	0_60	0.862	0.954	-10.7
	NB	0_120	0.745	0.862	-15.7
Conscientiousness	J48	0_30	0.952	0.966	-1.5
	NN	0_60	0.847	0.948	-11.9
	NB	0_30	0.715	0.847	-18.5
Agreeableness	J48	0_60	0.866	0.972	-12.2
	NN	0_15	0.864	0.882	-2.1
	NB	0_30	0.59	0.84	-42.4

3.4. Optimization of feature by personality traits

Based on previous results, the optimization of feature selection by the one by one backward and forward approach has been furtherly used. First, a feature selection for behavioral and eye tracking data was performed and then for eye tracking data. The results presented in Table 4 summarize the best prediction based on ROC AUC for each personality trait with the optimized selection of features. Only first three best algorithms were reported. Best results were found for the Openness personality trait followed by the Agreeableness and Neuroticism. All best ROC AUC results when comparing algorithms were found for RF, followed by J48 and NN. J48 presented ROC AUC reduced by 3.1% when compared to RF and NN implemented as MP were found to be 14.5% lower than RF result in average. STAI trait resulted in better results than personality traits based on ROC AUC with RF.

Eye-tracking features presented the highest percentage of total features after optimization (29.2% in average vs. EDA: 27.9, ECG: 24.9 and behavioral: 18% - Fig. 3). However, the most used feature for RF

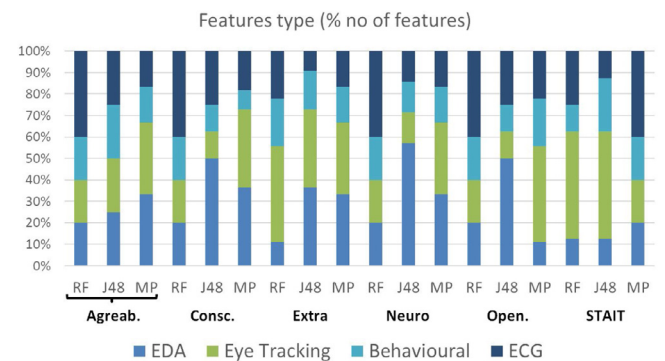


Fig. 3. Percentage of features used on the total number of features by feature types. Agree: Agreeableness, Consc.: Conscientiousness, Extra: Extraversion, Neuro.: Neuroticism, Open.: Openness.

is ECG features, although a lower number constituted the initial set EDA for J48 and Eye tracking features for MP. Number of features for each type (EDA, EDA, eye-tracking, behavioral) is depicted in Fig. 4. MP implementation required the use of more features than both RF and J48 (Fig. 4). Depending on the algorithms the number of used features changes. The trends between the average number of features per personality trait should be considered carefully: Extraversion used 10.7 features in average while Conscientiousness and Neuroticism used 8 and others traits 7 features.

EDA — 10 algorithms used only one feature, EDA_ampMeanSrc is the most used along of the EDA features. Of note, Conscientiousness, Extraversion and Neuroticism are the personality traits for which more EDA features are used.

ECG — 14 algorithms over 18 used two ECG features rather than one. RR is the most used feature from ECG parameter while RMSSD is largely removed and SDNN is preferably used alone.

In behavioral data, 11 over 18 algorithms used only one feature, mostly SDWA feature.

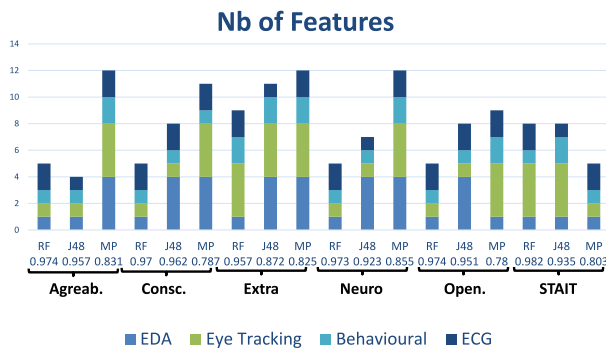
Finally, eye tracking features were used either one by one either as a group, total duration of fixation was the mainly used feature while mean duration of fixation was the most removed when using a group of features.

Table 4

Algorithms results for each personality trait — three best algorithms based on ROC AUC and with EDA, ECG/Behavioral and Eye Tracking features after optimization.

	Algo	TP rate	FP rate	Accuracy	Recall	F-measure	MCC	ROC area	PRC area
Agreeableness	RF	<i>0.919</i>	<i>0.09</i>	<i>0.923</i>	<i>0.919</i>	<i>0.918</i>	<i>0.84</i>	<i>0.973</i>	<i>0.974</i>
	J48	0.931	0.071	0.931	0.931	0.931	0.86	0.963	0.957
	MP	0.795	0.209	0.795	0.795	0.795	0.59	0.853	0.831
Conscientiousness	RF	0.895	0.147	0.9	0.895	0.892	0.78	0.968	0.97
	J48	0.934	0.065	0.935	0.934	0.934	0.86	0.965	0.962
	MP	0.753	0.28	0.751	0.753	0.752	0.48	0.797	0.787
Extraversion	RF	0.898	0.102	0.9	0.898	0.898	0.8	0.959	0.957
	J48	0.828	0.172	0.828	0.828	0.828	0.66	0.884	0.872
	MP	0.768	0.233	0.769	0.768	0.768	0.54	0.833	0.825
Neuroticism	RF	<i>0.895</i>	<i>0.106</i>	<i>0.895</i>	<i>0.895</i>	<i>0.895</i>	<i>0.79</i>	<i>0.972</i>	<i>0.973</i>
	J48	0.88	0.12	0.88	0.88	0.88	0.76	0.932	0.923
	MP	0.795	0.205	0.795	0.795	0.795	0.59	0.862	0.855
Openness	RF	<i>0.898</i>	<i>0.102</i>	<i>0.898</i>	<i>0.898</i>	<i>0.898</i>	<i>0.79</i>	<i>0.974</i>	<i>0.974</i>
	J48	0.889	0.113	0.889	0.889	0.889	0.78	0.953	0.951
	MP	0.732	0.267	0.734	0.732	0.732	0.46	0.799	0.78
STAIT Trait	RF	0.928	0.079	0.928	0.928	0.928	0.85	0.982	0.982
	J48	0.877	0.145	0.876	0.877	0.876	0.74	0.94	0.935
	MP	0.774	0.239	0.777	0.774	0.775	0.53	0.825	0.803

a. Italic three highest results.

**Fig. 4.** Barplot for number of features for each algorithm and each personality trait.

3.5. Personality cluster detection

Similar steps with EDA time windows selection and feature selection by signal type (ECG, behavioral and Eye-tracking) were performed. Neuroticism/Extraversion/Conscientiousness approach consists in 8 clusters according to the three personality traits: Neuroticism, Conscientiousness and Extraversion by disregarding the rest and RCD in 4 clusters (by combining Neuroticism and Conscientiousness). In addition, binary classifications to detect particular personality profiles were performed: Spectator, Insecure and Impulsive.

When compared to average performance for the prediction of personality traits (0.969) one by one, improvement of the prediction performance when using cluster even when using binary cluster is little 2%.

The 0–15 EDA time window was the mostly used when considering best results of all algorithms followed by 0–30, 0–60 and 0–120 s time windows. Except for RCD in which only 0–15 and 0–30 s time windows were used, no trend appeared for other clusters.

Table 5 present the best three algorithms per type of clusters. RF presented higher ROC AUC results in all case followed by J48. SVM implemented as SMO ranked twice higher than MP for NCE and RCD. Specific profiles detection (binary clusters based on spectator, impulsive and insecure trait) presented slightly higher prediction (0.989) when compared to NCE (0.978) and RCD (0.961).

For EDA feature, EDA_nb and EDA_ampMeanScrs are the two mainly removed features but also the most used alone. In behavioral data, SDWA is the mostly used features, and in ECG data, RR is the mostly used. For eye tracking feature the SD duration of fixation is the most used feature.

4. Discussion

This article tested the possibility of using physiological and behavioral data to classify personality traits. The highest accuracy was found for Agreeableness, Neuroticism and Openness. It also showed the necessity of testing time windows for EDA post-processing which depends on the personality traits and raised the question of the optimization process. The best results were found for RF and J48, as expected from the literature. However, the low performance of SVM was surprising since used only for the cluster detection with relatively good results similar to NN. Of note, the improvement of detection when providing type of situations and levels of the implemented situations could be explained by the redundancy of similar driving behavior demands and consequent physiological associated responses.

The cases for which the lowest numbers of features were found for the classification of Agreeableness, Neuroticism and Openness.

Although Neuroticism was previously associated to physiological data, Openness and Agreeableness were also shown here to be able to be detected from behavioral and physiological data.

The results from the different measures show that:

EDA-, RF and J48 algorithms used only one EDA feature. S-Trait Anxiety Inventory (STAI) detection used only one EDA feature which could be explained by previous findings in which no association between STAI and EDA were found in Binboga et al. (2012).

ECG-Different relationships between cardiac signals and Neuroticism, Openness and Agreeableness were previously reported (Bibbey et al., 2013) and, similar results were found here. In our findings, the use of ECG features was constant along all algorithm and personality trait.

BEHAVIOR – SDWA has been found as the most discriminant feature selected by the algorithms. SDWA has been previously found significantly different between mean attentive and mean distracted time period in driving context based on a gaze based real time distraction detection algorithm (Kircher & Ahlstrom, 2010).

EYE- In our results, the use of eye tracking features in Openness detection is limited to one feature (total fixation duration) with RF.

Our work, however, proved that the association between personality traits through clustering is limited in terms of results, but could provide a new perspective in drivers' personality. The NCE 8 clusters were indeed already used to study the association with health risks and association between Neuroticism, Conscientiousness and Extraversion and risky health behaviors are contradictory (Vollrath & Torgersen, 2002). Such study reported that individuals defined as impulsive and insecure are more particularly inclined to engage in risky health behaviors and better results in prediction with NCE cluster when compared to

Table 5

Cluster detection results for the 3 first algorithms. RCD — Relaxed, control, directed cluster, Spect: Spectator; Imp: Impulsive; Ins: Insecure.

	Algo	TP rate	FP rate	Accuracy	Recall	F-measure	MCC	ROC area	PRC area
Neuroticism, Extraversion, Conscientiousness	RF	0.816	0.037	0.854	0.816	0.818	0.798	0.978	0.925
	J48	0.801	0.03	0.802	0.801	0.8	0.769	0.924	0.794
	SMO	0.611	0.076	0.661	0.611	0.604	0.557	0.866	0.521
Relaxed, Control, Directed	RF	0.813	0.08	0.839	0.813	0.812	0.754	0.961	0.916
	J48	0.801	0.074	0.802	0.801	0.801	0.729	0.939	0.867
	SMO	0.69	0.126	0.705	0.69	0.687	0.579	0.802	0.587
Spectator	RF	0.943	0.486	0.946	0.943	0.933	0.655	0.993	0.994
	J48	0.967	0.231	0.966	0.967	0.965	0.813	0.923	0.966
	MP	0.937	0.436	0.932	0.937	0.93	0.618	0.805	0.921
Impulsive	RF	0.931	0.752	0.936	0.931	0.908	0.407	0.987	0.992
	J48	0.982	0.164	0.982	0.982	0.981	0.878	0.969	0.987
	MP	0.937	0.492	0.929	0.937	0.931	0.532	0.74	0.911
Insecure	RF	0.904	0.648	0.913	0.904	0.878	0.48	0.987	0.991
	J48	0.955	0.165	0.954	0.955	0.955	0.798	0.889	0.941
	MP	0.88	0.552	0.864	0.88	0.869	0.389	0.784	0.877

Extraversion, Neuroticism and Conscientiousness alone are promising. In any case, they need to be further investigated in the context of driving and maybe on focusing on approach on risky situation. As expected, binary cluster on spectator, impulsive and insecure cluster from the NCE cluster presented better predictions than the prediction of the 8 clusters.

EDA time windows investigation could be further interpreted when considering both personality trait and cluster detection. Indeed, by the definition of the cluster as an association of personality trait, clusters have been reported to detail reaction rather than personality itself. Thus, spectator, impulsive and insecure could have been using respectively longer EDA time windows and it was not the case in the results. However, the results did not show that the EDA signal was the best to differentiate between reactivity. The association between reactivity and biometrics is complex and does not only reflect personality, since, for example, studies on emotional reactivity, alcohol or sleepiness has also largely shown their effects on these biometrics (Béquet et al., 2020).

5. Conclusion

This work presented the potential of physiological and behavioral measurement analysis to classify driver's individual differences. The first findings were presented in term of capacity to detect personality trait, the possibility for personality trait clustering as well as the optimization process to consider. It suggests a potential to estimate a driver psychological profile based on machine learning (ML) models. To the best of our knowledge, this is the first study to present a complete ML analysis of personality trait using physiological and behavioral data from a driving simulator experiment. Additionally, literature reported applications in which physiological and behavioral measurements could improve the car occupant wellbeing (Koohestani et al., 2019).

This study presents some limitations as performed in an artificial environment. One drawback of artificial environment experiment is also the specificity of the tasks and situations to be tested. Additionally, the tested population is relatively limited and could introduce bias in the reported results despite the gender and age consideration inclusion. Such limitations could be addressed by performing ecological measurements, however such measurements still present technical challenges such as sensor communication and the quantity of data to transfer. Of note the work on omnipresent sensing system on unsupervised techniques should be noticed (Saeed et al., 2021).

Further studies, in real environment are in fact needed desirable to characterize more precisely the relationship between personality traits and driver state based on physiological and behavioral data in the context of driving. In term of machine learning methodology, search method for model parameter optimization could have been considered and should be investigated in further work.

CRedit authorship contribution statement

Morgane Evin: Methodology, Writing – original draft. **Antonio Hidalgo-Munoz:** Conceptualization, Methodology. **Adolphe James Béquet:** Data collection, Data curation. **Fabien Moreau:** Data collection, Methodology, Software. **Helène Tattegrain:** Supervision. **Catherine Berthelon:** Conceptualization, Draft preparation, Supervision. **Alexandra Fort:** Writing – review & editing. **Christophe Jallais:** Writing – review & editing, Visualization, Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

The authors thank Marleen De Weser and Gabriel Othmezzouri from Toyota Motor Europe as well as Toyota Motor Europe for the funding of the experimentation.

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