Driving Behaviors in Cognitive Agents: Preliminary Results of an Experimental Approach

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Abstract

Understanding driving behavior is critical for enhancing road safety, optimizing insurance, healthcare costs, and informing the development of mobility services and advanced vehicle systems. Driving remains a high-risk daily activity, influenced by a complex interplay of psychological, cognitive, and contextual factors such as stress, impulsivity, risk perception, and environmental conditions. To address this complexity, this research empirically investigated a broad range of psychological and behavioral aspects of driving through a combined methodology involving standardized psychometric surveys and high-fidelity driving simulation. The experimental setup integrates wearable biometric sensors to monitor psycho-physiological responses under varying levels of cognitive load and environmental complexity. Findings will inform the development of cognitively enriched software agents, enabling more realistic agent-based traffic simulations capturing both vehicle dynamics and the psychological dimensions of driving behavior. Preliminary results, mainly aimed to verify the correctness of the experimental design, are presented and discussed to assess the capability of reproducing nuanced driving behaviors within agent-based traffic simulations to enhance their ecological validity, adaptability, and predictive accuracy.

Keywords

Driving Behavior, Driving simulator, Psychological factors, Software agents

1. Introduction

The study of driving behavior carries significant social and economic relevance, particularly in relation to road safety, insurance and healthcare costs, and the integration of shared mobility services [1]. A thorough understanding of driving behaviors – especially those classified as improper or unsafe – is essential to inform regulatory frameworks, enhancing vehicle design and Advanced Driver Assistance Systems (ADAS), and addressing a variety of interrelated transportation challenges.

In recent decades, growing academic attention has been devoted to this domain, employing diverse methodological approaches and analytical techniques [2]. These investigations are inherently complex and resource-intensive, often requiring the collection and integration of heterogeneous data sources that capture both human and technological dimensions [3].

Driving constitutes a routine activity for much of the global population, with average daily driving times exceeding one hour per individual [4]. Nonetheless, it remains a high-risk activity, frequently

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associated with severe injuries, fatalities, and considerable economic costs – many of which can be attributed to adverse emotional states experienced during driving tasks [5].

A wide range of psychological constructs has been identified as influential in shaping driver behavior [6]. These include cognitive abilities (e.g., attention, perception, decision-making), affective dimensions (e.g., stress, anger, anxiety), personality traits, and individual psychological characteristics (e.g., impulsivity, risk perception, emotion regulation, and self-efficacy) [7].

Cognitive abilities directly impact on risk perception. As a result, some drivers exhibit heightened risk sensitivity, prompting more defensive behaviors, while others may underestimate potential hazards and engage in more reckless or aggressive maneuvers [8]. Emotional and psychological stressors have also been shown to modulate driving performance. Drivers experiencing heightened stress or negative emotional states are statistically more prone to exhibit aggressive behaviors, such as excessive speeding, tailgating, or confrontational interactions with other road users [9]. Attitudinal factors, including those related to road safety, risk-taking, and perceptions of other drivers, play a relevant role [10]. Positive safety attitudes are generally associated with decreased engagement in risky behaviors, while higher levels of self-efficacy — defined as an individual's belief in their capacity to execute a specific task – correlate with safer driving practices and greater compliance with traffic regulations [11]. Moreover, certain personality dimensions – such as sensation-seeking and conscientiousness – are associated with divergent driving profiles. However, psychological variables are modulated by contextual factors, including environmental conditions and socio-cultural norms [12].

From a methodological perspective, the study of driving behavior – particularly with respect to aggressiveness – necessitates comprehensive data on a range of interrelated parameters, encompassing driver motivation, environmental features, vehicle dynamics, sensory technologies, and external stimuli. To this end, data acquisition methods typically include psychometric questionnaires, sensor-based monitoring, and driving simulation platforms [13, 14, 15].

The scenario outlined above highlights the intrinsic complexity and critical relevance of driving behaviors. On one hand, these behaviors are influenced by a multitude of psychological, cognitive, and contextual factors; on the other hand, a deeper understanding of such behaviors is crucial for the development of realistic traffic simulation models.

To this end, a consolidated body of literature has explored traffic dynamics through the use of agent-based simulation frameworks, which can operate at varying levels of granularity – namely, microscopic, mesoscopic, and macroscopic [16]. While higher-resolution models offer greater behavioral fidelity, they also demand significant computational resources. However, advancements in computing technologies have progressively mitigated this limitation, making detailed modeling increasingly feasible [17].

The final core objective of this research is to acquire empirically grounded knowledge on driving behaviors to encode this information into cognitive software agents. These enriched agents can be then used to perform realistic agent-based traffic simulations, capturing not only the physical dynamics but also the psychological dimensions of driver behavior.

In what follows, we present and discuss some preliminary empirical findings aimed to verify the correctness of the proposed experimental approach. These results have been obtained by validating a combined methodology involving psychometric surveys and driving scenarios on a high-fidelity driving simulation platform. The platform is enhanced with wearable biometric sensors – such as electrodermal activity (EDA), heart rate, and skin temperature monitors – to capture drivers' psycho-physiological states during various simulated scenarios.

The remainder of the paper is structured as follows: Section 2 reviews relevant literature on aggressive driving and agent-based traffic simulations. Section 3 introduces the psychological instruments and simulation tools employed. Sections 4 presents the collected data and discuss the experimental findings, while Sections 5 discusses finding and limitation of this research. Finally, Section 6 concludes the study and outlines potential directions for future research.

2. Related Work

This section provides a concise review of the relevant literature concerning the psychological foundations of driving behavior and the tools used for its detection and analysis. Specifically, it synthesizes empirical findings and theoretical contributions that explore both the psychological determinants of driver behavior and the technological tools employed to monitor, simulate and evaluate such behaviors in experimental and applied contexts.

2.1. Psychological Foundations

Driving behavior constitutes a multidimensional construct, and any attempt to develop descriptive or predictive models, implement safety – enhancing technologies, or modifying behavior policies must be grounded in a comprehensive understanding of its underlying determinants – including the psychological and social variables that shape driver attitudes and actions.

Cognitive functions – such as reasoning, judgment, problem-solving, working memory, multitasking, and risk perception – play a fundamental role in driving behavior, enabling individuals to gather, process, and act upon dynamic information from the driving environment [18]. Cognition directly influences risk perception. Drivers with more accurate risk assessment abilities tend to make safer and more deliberate choices [19, 20]. Conversely, individuals with compromised cognitive functions – due to fatigue, sleep deprivation, distractions, or substance use – can increase the likelihood of driving errors and hazardous behaviors [21] for a diminished risk perception, which may lead to underestimate certain behaviors – such as speeding or aggressive maneuvers – and are thus more prone to violations and high-risk driving [22].

Emotional states such as sadness, anger, and anxiety significantly impair driving performance by diverting cognitive resources away from the primary task of driving. These emotions can reduce attention to the road, slow reaction times, and increase the likelihood of engaging in high-risk behaviors, such as speeding or aggressive maneuvers [23]. Anxiety, in particular, has a nuanced impact on driving and in, more severe cases, anxiety may manifest as aggressive or impulsive responses to traffic stressors [24]. *Emotion regulation* is the capacity to modulate and manage own emotional responses. A poor emotion regulation is associated with increased impulsivity and a higher propensity for road rage, aggressive interactions, and risky driving decisions [25]. *Emotional intelligence* (EI) is the ability to perceive, understand, and manage one's own emotions, as well as to interpret and respond to the emotions of others [26]. Drivers with high EI are more capable of maintaining calm, making reasoned decisions, and sustaining attention under pressure [27]; it is correlated with safer and more composed driving behavior.

Personality traits play a fundamental role in shaping driving behavior, often interacting with other variables such as age, experience, individual cognitive profiles, and situational context. For instance, high levels of extroversion have been linked to a greater likelihood of engaging in risky driving behaviors [28]. In contrast, conscientious individuals exhibit more rule-compliant and safety-oriented driving styles [29]. Neuroticism has been associated with erratic and impulsive driving, often under stress or in high-demand conditions [30, 31]; conversely, agreeableness is positively related greater patience, cooperativeness, and lower levels of aggressiveness [30]. Impulsivity has consistently been identified as a significant predictor of risky behaviors [32] and, similarly, sensation-seeking is correlated with greater risk-taking while driving [29, 33]. Finally, individuals with a pronounced risk propensity tend to seek excitement and stimulation, making them more likely to engage in hazardous driving behaviors [34]. These findings underscore the critical role of personality traits in traffic safety research and highlight the importance of incorporating psychological profiling into simulations.

Attitudes and beliefs toward traffic laws and safety regulations influence driving behavior. Positive attitudes are generally associated with greater compliance, such as adherence to speed limits and traffic signals, whereas negative or dismissive beliefs may result in risky actions, including red-light violations or aggressive maneuvers [35]. Personal commitment to road safety also plays a critical role and drivers who hold favorable attitudes toward safe driving practices are more likely to adopt defensive behaviors and exhibit courteous conduct toward other road users. In contrast, individuals with indifferent or negative attitudes toward road safety often engage in behaviors that increase crash risk. Moreover, beliefs about multitasking capabilities are closely associated with distracted driving tendencies [19] leading to severe compromises in attention and situational awareness behind the wheel. Importantly, these attitudes and beliefs are not formed in isolation; they are often shaped by broader social and cultural influences.

2.2. Driving Behaviors Data Collection

The collection of information about driving behaviors is a process involving several disciplines and the methodologies chosen for their analysis, depending on the required level of accuracy. However, more approaches can be also combined in synergistic way to provide a more comprehensive data collection.

The *Driving Behavior Questionnaire* (DBQ) is widely utilized in research due to its simplicity and effectiveness in capturing both statistical and motivational data related to driving behavior. Despite its advantages, the DBQ lacks a direct connection to external variables such as traffic flow conditions, which may also influence driving behavior [36]. The first DBQ [37], referred to as the Manchester Driving Behavior Questionnaire (MDBQ), was a set of 50 questions designed to explore the motivational underpinnings of various driving behaviors –specifically violations, errors, and lapses. Over time, a large number of BDQ have been proposed, although the most part of them substantially is a variant of the original MDBQ.

To acquire empirical data on driving behavior, a range of sensors is employed, typically classified based on their positioning and function into four categories [38, 39, 40], namely:

On-board sensors, typically integrated into vehicles during manufacturing [38], have seen a rapid increase in variety and capability [15]. Their primary function is to monitor vehicle dynamics but recently also track driver states such as sleepiness, alertness, distraction, alcohol levels [41, 42]. High-end professional sensor systems offer superior data accuracy, though lower-cost alternatives – such as smartphone-based platforms – have demonstrated acceptable accuracy in numerous experimental contexts [15, 43].

On-road sensors can be classified as either intrusive or non-intrusive, depending on whether their deployment disrupts normal traffic conditions [44], and as active or passive, based on whether they emit signals (e.g., laser, radar, and wave) or rely on ambient input (e.g., video cameras –generally, more cost-effective and returning high-quality data [45]).

Motion-based sensors infer driver behavior by analyzing the vehicle's motion, modeled as a rigid body responding to driver inputs. These behaviors are detected via either on-board or on-road platforms. However, measurements taken at low speeds (below 10 km/h) are typically excluded due to noise susceptibility and limited relevance [15].

Driver status monitoring systems use physiological and biometric sensors to detect conditions such as distraction [46, 47], fatigue [48], and aggressiveness. The latter requires contextual data involving environmental conditions, vehicle dynamics, and driver-specific characteristics for accurate assessment [49].

2.3. Agent-based Traffic Simulator Platforms

The development of driving simulators dates back to the 1960s [50], but in these last decades technological advancement made them able to emulate real-world in a sophisticated and accurate manner. Driving simulators provide a valuable platform for investigating complex driving behaviors within a controlled, safe, and repeatable environment [51]. Agent-based simulators with programmable behavioral models offer a flexible and powerful approach for analyzing road traffic and driver behavior. They enable each vehicle to be modeled as an autonomous agent with individual characteristics, decision-making capabilities, and specific responses to environmental stimuli. This approach allows realistic simulations – often on large-scale – including a variety of detailed driver profiles to test different scenarios, while significantly reduces costs and risks.

Table 1
Comparison of driving and traffic simulators with behavior customization modes

Simulator	Type	Open Source	Behavioral Customization	Customization Modes
City Car Driving	Driving			Modding
CARLA	Driving			API, scripting, behavior trees
CITIFLOW	Traffic			Neural nets, hybrid control models
FLOW	Traffic			Python rules built on top of SUMO
MATSim	Traffic			Java, score functions, logic rules
SUMO	Traffic			API, logic rules, behavior setting
AIMSUN	Traffic			API, scripting, external modules
VISSIM	Traffic			API, scripting

Several driving traffic simulators are available to reproduce realistic situations that can be largely customized by needs on urban and traffic scenarios, environmental variables, rules, drivers' behaviors, and unexpected events. In Table 2.3, there are some performing driving traffic simulator (e.g., City Car Driving [52], *CARLA* [53], *CityFlow* [54], *Flow* [55], *MATSim* [56], *SUMO* [57], *AIMSUM* [58], and *VISSIM* [59]) that in our opinion came as the most closed to our needs. In the last column customization modalities of embedded agents are reported.

In particular, to verify the experimental approach, the City Car Driving [52] (CCD) simulator has been exploited here, given that a fine customization of drivers' behaviors is not required in this phase – agent customization are admitted in CCD only via modding, being it mainly designed for driver training purposes. After to have validated here our experimental approach, then a highly configurable, open-source driving simulators should be adopted to inject psychological traits in agents. Currently, we are paying attention to the CARLA, MATSim and SUMO simulators – largely used in academic and industrial research for experimental studies in psychology, cognitive sciences, and traffic engineering – for simulating highly realistic, large, dynamic, and customizable scenarios involving high cognitive loads giving the opportunity of encoding in advanced agents profiles real data, psychometric traits, and biometric signals.

3. Methods

This research aims to deepen the understanding of driving behaviors with the objective of integrating these insights into cognitive agent models to improve the behavioral realism of traffic simulations and, in particular, this study is devoted to validate the experimental approach. A mixed-method approach will be employed in the experimental approach, to combine self-report measures with objective performance data obtained from driving simulators. This methodology enables the exploration of the complex interplay between psychological factors and driving behavior within urban environments. In detail, the following research objectives will addressed:

- Examine the relationships between self-reported driving styles, personality traits, difficulties in emotion regulation, empathy, and mindfulness within a sample of drivers.
- Investigate the associations between psychological variables and objective driving performance metrics under conditions of escalating cognitive demand in a simulated driving environment.
- Assess the correspondence between reported driving styles and psycho-physiological responses, as measured by biometric sensors, during simulated driving tasks involving increasingly complex urban scenarios.

By addressing these objectives, the research aims to advance the understanding of the psychological foundations of driving behavior, with the ultimate goal of informing the development of cognitively enriched traffic simulations that reflect individual differences among drivers.

3.1. Driving Behavior Questionnaire

A comprehensive battery of standardized self-report instruments was administered online via Qualtrics to a preliminary sample of 59 young adults (38 females, 21 males), recruited through online advertisements. All participants had a valid driver's license (i.e., were over 18 years old), reported regular driving experience, were fluent in Italian, and were not undergoing treatment for psychiatric or neurological conditions at the time of participation. Informed consent was obtained from all participants prior to enrollment, and no financial compensation was provided. The study protocol received approval from the institutional ethical board. The administered Driving Behavior Questionnaire (DBQ) comprised 165 items covering the following domains:

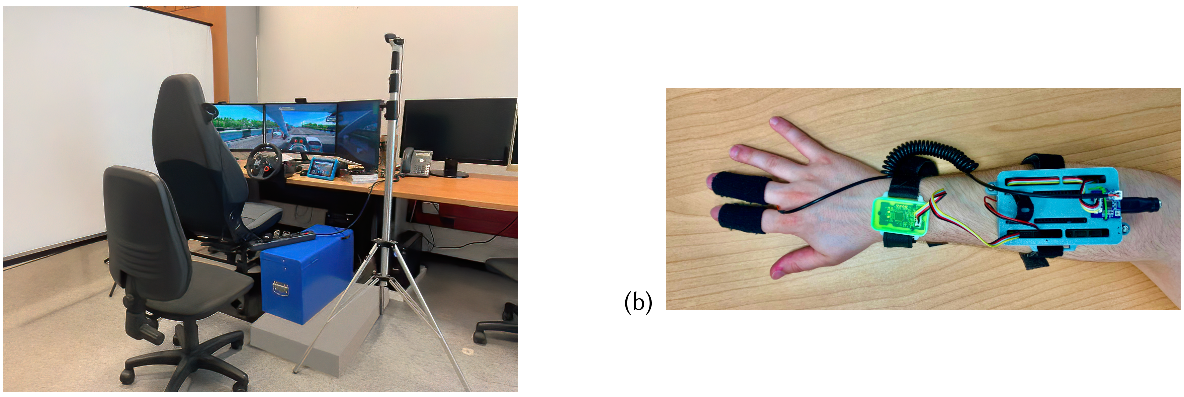
- *Demographics and Driving History*.
- *Driving Styles* — assessed using the Italian validated version of the *Multidimensional Driving Style Inventory* [60, 61], with responses rated on a 6-point Likert scale.
- *Personality Traits* — measured by the *Ten-Item Personality Inventory* [62], using a 7-point Likert scale to evaluate the Big Five personality dimensions.
- *Emotion Regulation Difficulties* — evaluated via the Italian version of the *Difficulties in Emotion Regulation Scale* [63], using a 5-point Likert scale.
- *Empathy* — measured using the *Brief Interpersonal Reactivity Index* [64], structured into four subscales and rated on a 5-point Likert scale.
- *Mindfulness* — assessed through the short form of the *Philadelphia Mindfulness Scale* [65], evaluating awareness and acceptance on a 5-point Likert scale.

3.2. Experimental Driving Simulation Platform

This section presents the integrated hardware and software infrastructure exploited to support the study of Human-Agent Interaction (HAI) in driving scenarios [66]. The platform enables real-time monitoring, data acquisition, and adaptive agent behavior in a controlled yet immersive environment.

3.2.1. Hardware Setup

The simulation station is built to replicate realistic driving conditions and enable naturalistic human-agent interaction (see Figure 3.2.1). It features a high-performance PC with a triple monitor configuration and a Logitech G29 steering wheel with pedals for immersive vehicle control. A tablet positioned beside the wheel simulates in-vehicle infotainment systems, while a real car seat mounted on a customized base enhances comfort during prolonged sessions. Frontal and side views of the participant are recorded using two HD webcams, allowing analysis of gaze direction, facial expressions, and overall behavior.



(a) (b)

Figure 1: Simulation equipment: (a) Driving simulation station; (b) Biometric sensors.

Additionally, a custom wearable device based on the Arduino MKR1000 (see Figure 3.2.1) captures key physiological signals, including the Galvanic Skin Response (GSR) measured with nickel electrodes and converted to conductance using a calibrated resistance model and heart rate acquired via a Groove optical sensor using an I^2C interface [67].

3.2.2. Software Architecture and Simulation Protocol

The experimental platform is based on a modular, agent-oriented software architecture specifically designed to support real-time data integration, adaptive simulation, and multi-modal analysis. The system orchestrates multiple components-sensors, simulation environment, logging tools, and reasoning modules – through a loosely coupled scalable and extensible structure.

- *Driving Simulation Software* - The core of the simulation environment is powered by *City Car Driving – Home Edition* [52] (v1.5.9, 2019), a configurable virtual platform capable of replicating realistic Italian urban traffic conditions. This module allows for the dynamic customization of key environmental variables, including vehicle types, weather conditions, traffic density, and road events. Vehicles are implemented as agents responding to both driver and environmental stimuli in a deterministic way.
- *Protocol Controller* - A dedicated agent manages the experimental driving protocol, configuring the simulation across four progressive sessions with increasing cognitive load and environmental complexity. Parameters such as traffic flow, pedestrian activity, and surrounding driver behaviors are systematically modulated.
- *Data Logging Agent* - Driving behavior and system events data are captured locally via an integrated SQLite backend, enabling downstream process mining and temporal behavior modeling.
- *Communication Broker* - Inter-agent communication is handled asynchronously via an MQTT broker (Eclipse Mosquitto) – including physiological sensors and external monitoring devices-systems – ensuring real-time data exchange.
- *Time-Series Database* - Biometric and contextual data streams (e.g., heart rate, GSR, traffic conditions) are stored in InfluxDB, a time-series database optimized for high-throughput storage and retrieval.
- *Multi-modal Recording Agent* - User interaction and system behavior are captured using OBS Studio, with recordings automatically managed via through the obs-websocket plugin to ensure synchronization with simulation phases.

The simulation protocol consisted of four sequential driving sessions, each one progressively designed to induce higher levels of stress and cognitive demand. Their optimal setup required the execution of some preliminary tests to the aim. Therefore, as a result of this setting activity:

- *Session 1* - Traffic density = 10%, driver behavior = cautious, pedestrian presence = 20%;
- *Session 2* - Traffic density = 20%, driver behavior = cautious, pedestrian presence = 20%;
- *Session 3* - Traffic density = 30%, driver behavior = aggressive, pedestrian presence = 40%;
- *Session 4* - Traffic density = 30%, driver behavior = aggressive, pedestrian presence = 60%.

To simulate emotionally salient and unpredictable driving conditions, each session introduced progressively complex challenges, such as abrupt braking by lead vehicles, sudden lane changes, unauthorized pedestrian crossings, and collisions. These controlled manipulations were designed to systematically elicit cognitive and emotional responses while maintaining ecological validity.

4. Experiments

In this section, we present the preliminary statistically-based results of our experimental study carried out to validate a combined methodology exploring the relationships between psychological variables, self-reported driving styles, and physiological responses during simulated driving tasks. The analysis is structured into three main parts: first, we examine correlations between psychological measures and driving styles. Next, we analyze physiological activation through GSR data under varying driving conditions. Finally, we interpret these findings in the context of emotional regulation, personality traits, and task difficulty. Data analyses were conducted on a total sample of 59 participants who completed the questionnaire designed to examine associations between driving styles (MDSI), personality traits (I-TIPI-R), empathy (B-IRI), mindfulness (PHLMS), and emotion regulation (IT-DERS18). Out of the 59 participants, 30 constituted a subsample of volunteers who took part in the second phase of the experiment, which involved a driving simulation and the recording of physiological data during the practical task. Descriptive features of these samples are reported in Table 2 and Table 3.

Table 2
Demographic Characteristics of the Questionnaire Sample ($N = 59$)

Variable	Category	n	%
Gender	Male	40	67.8
	Female	19	32.2
Age Group	18-25 years	29	49.2
	26-35 years	28	47.5
	36-45 years	2	3.3
Education level	Bachelor's degree or higher	42	71.2
	Upper secondary education	17	28.8
Occupational Status	Full-time student	20	33.9
	Full-time worker	22	37.3
	Student and worker	16	27.1
	Other	1	1.7
Professional Drivers	yes	5	8.6
	No	54	91.4
Years Since Driving License (B)	Mean (SD)	6.7(4.27)	

Table 3
Demographic Characteristics of the Driving Simulator Sample ($N = 30$)

Variable	Category	n	%
Gender	Male	19	63.3
	Female	11	36.7
Age Group	18-25 years	14	46.7
	26-35 years	15	50.0
	36-45 years	1	3.3
Education level	Bachelor's degree or higher	17	56.7
	Upper secondary education	8	26.7
	Postgraduate specialization	5	16.6
Occupational Status	Full-time student	9	30.0
	Full-time worker	12	40.0
	Student-worker (work predominant)	4	13.3
	Student-worker (study predominant)	5	16.7

For this subsample, analyses were carried out to explore the associations between drivers' physiological indices during the simulation and the psychological constructs assessed via questionnaire. Additionally, to investigate whether certain psychosocial variables could predict skin conductance responses, regression analyses were conducted using GSR measurements during the driving sessions as the dependent variable, and the psychosocial constructs of empathy, emotion regulation, and mindfulness as independent variables. The selection of predictors was based on the results of bivariate analyses and theoretical considerations. Descriptive analysis revealed that the most frequently endorsed driving styles among participants were anxious, risky, and dissociative, consistent with findings from prior research in young adult populations. Regarding personality traits, participants scored highest on agreeableness and openness, and lowest on emotional stability (Table 4).

Table 4
Descriptive statistics of the driving styles and the psychological variables.

Driving styles (MDSI)	Mean	Standard Dev	Minimum	Maximum
Dissociative	1.9	0.55	1.0	3.6
Anxious	3.2	0.52	2.2	4.3
Risky	1.8	0.83	1.0	4.5
Angry	2.2	0.88	1.0	5.0
High velocity	2.6	0.67	1.3	4.2
Distress reduction	2.6	0.82	1.0	4.0
Patient	4.3	0.66	2.0	5.5
Careful	3.5	0.51	2.7	5.0
Personality trait (I-TIPI-R)	**Mean**	**Standard Dev**	**Minimum**	**Maximum**
Extraversion	4.3	0.69	2.0	7.0
Agreeableness	4.3	0.88	2.5	6.0
Conscientiousness	4.5	0.82	3.0	7.0
Neuroticism	4.3	0.80	3.0	6.5
Opennesstoexperience	4.9	0.67	3.5	6.0
Empathy (B-IRI)	**Mean**	**Standard Dev**	**Minimum**	**Maximum**
EmpathicConcern	4.0	0.57	2.8	5.0
PersonalDistress	2.5	0.72	1.0	4.5
PerspectiveTaking	3.9	0.77	1.5	5.0
FantasyScale	3.3	0.92	1.0	5.0
Mindfulness (PHLMS)	**Mean**	**Standard Dev**	**Minimum**	**Maximum**
Awareness	18.7	2.98	11.0	25.0
Acceptance	14.7	3.44	7.0	21.0
Emotion dysregulation (IT-DERS18)	**Mean**	**Standard Dev**	**Minimum**	**Maximum**
Awareness	11.5	2.28	5.0	15.0
Clarity	6.0	2.63	3.0	12.0
GoalOriented	9.1	3.56	3.0	15.0
Impulse	5.2	2.89	3.0	15.0
NonAcceptance	6.2	3.01	3.0	14.0
Strategies	6.7	2.88	3.0	15.0
Total	44.7	10.5	27.0	77.0

4.1. Correlations between Driving Styles and Psychological Variables

Analyses were conducted to examine the relationships between the previously described constructs and various driving styles, namely: “dissociative”, “anxious”, “risky”, “angry”, “high-speed”, “stress-reducing”, “patient”, and “attentive”. Preliminary assessments indicated that the variables did not meet the assumption of normal distribution. Consequently, a non-parametric data analysis approach was adopted. This framework utilized non-parametric correlation coefficients to quantify the strength and direction of associations between variables, offering a robust alternative when parametric assumptions are violated.

Specifically, Kendall’s tau (τ) correlation coefficient was computed for each pair of variables; it is a non-parametric measure of association that evaluates the strength and direction of the relationship between two variables by comparing the number of concordant and discordant pairs across all possible observation pairs. Unlike Pearson’s correlation coefficient, which assumes normally distributed data and assesses linear relationships, Kendall’s tau does not require the normality assumption and is robust to outliers. This makes it particularly suitable for analyzing ordinal data or datasets that deviate from normality, ensuring a more reliable assessment of associations under these conditions. Kendall’s tau correlations showed that (Table 5):

- Risky, Angry, and High velocity driving style was significantly negatively correlated with the perspective-taking subscale of empathy (τ = -0.273/-0.212/-0.208, p $<$ .05);
- Dissociative, Anxious, and Angry was positively correlated with DERS total score (τ = 0.214/-0.287/-0.200, p $<$ .05), while Risky style was correlated with the impulse subscale of IT-DERS18 (τ = 0.253, p $<$ .05), indicating greater emotional dysregulation;

- Anxious driving style was significantly positively correlated with the agreeableness subscale of personality traits (τ = 0.269, p $<$ .05).

4.1.1. MANCOVA and Follow-up ANCOVA Analysis on GSR Physiological Indices

A repeated Multivariate Analysis of Covariance (MANCOVA) [68] measures was conducted to investigate the effect of incrementally challenging driving conditions on physiological responses measured through Galvanic Skin Response (GSR). The four dependent variables were GSR-derived indices: number of peaks, peak amplitude, EDA_Tonic_SD, and EDA_Sympathetic. The number of peaks refers to the count of rapid changes in skin conductance, also known as phasic events, within a specific time interval. This metric indicates the frequency of immediate physiological responses to stimuli, reflecting the individual's level of arousal or reactivity. Conversely, the amplitude of these peaks quantifies the intensity of each phasic response; higher amplitudes denote greater physiological activation in response to a given stimulus. Utilizing these two parameters, two indices were computed: the average number of peaks and the average peak amplitude for each driving session. These indices comprehensively assess the frequency and intensity of the participants' autonomic responses during the driving tasks (Table 6).

The within-subjects factor consisted of the three driving sessions (Sessions 1, 2, and 3), each one characterized by increasing difficulty levels (see Section 3). The six driving styles measured by the Multidimensional Driving Style Inventory (MDSI) were included as covariates to account for individual differences that could affect physiological activation. The analysis revealed a significant multivariate effect of the driving session on the combined physiological variables: F(8, 14) = 3.705, p = .016, Wilks' Λ = .321, partial η^2 = .679. This indicates that the increasing difficulty of the driving task significantly influenced physiological responses, even after controlling for individual driving styles. Moreover, significant interactions were found between the driving session and specific driving styles, particularly:

- Dissociative driving style: F(8, 14) = 2.99, p = .035, Wilks' Λ = .369, partial η^2 = .631;

Table 5
Correlation coefficient (Kendall τ) among driving styles and psychological variables.

	Driving styles (MDSI)							
	Dissociative	Anxious	Risky	Angry	High velocity	Distress reduction	Patient	Careful
Personality trait (TIPI-R)								
Extraversion	0.006	0.109	-0.108	0.140	0.160	-0.127	0.063	0.137
Agreeableness	-0.45	0.269**	0.033	0.162	0.114	0.087	-0.123	-0.019
Conscientiousness	0.127	0.094	0.097	0.039	-0.032	-0.0.89	0.144	0.056
Neuroticism	0.093	0.070	0.020	-0.002	0.0.58	-0.131	0.021	0.039
Opennesstoexperience	-0.151	0.124	-0.117	0.038	0.080	0.012	0.148	0.048
Empathy (B-IRI)								
EmpathicConcern	0.302**	0.129	-0.119	-0.026	-0.072	0.168	-0.003	0.043
PersonalDistress	0.253**	0.213*	0.060	-0.052	0.160	-0.047	0.013	0.020
PerspectiveTaking	0.212*	0.063	-0.273**	-0.212*	0.160*	0.141	0.060	-0.031
FantasyScale	0.220*	0.269**	-0.105	0.023	0.160	0.118	-0.005	-0.046
Mindfulness (PHLMS)								
Awareness	-0.088	-0.165	0.017	-0.178	-0.011	0.173	-0.136	0.035
Acceptance	-0.094	-0.155	0.036	-0.041	-0.029	-0.027	-0.039	-0.016
Emotion dysregulation (IT-DERS18)								
Awareness	0.063	-0.062	0.073	-0.104	-0.007	0.109	-0.174	0.067
Clarity	0.144	0.219	0.065	0.126	-0.068	-0.102	0.139	-0.014
GoalOriented	0.271**	0.290**	0.106	0.184	0.002	0.038	0.166	0.024
Impulse	0.050	0.114	0.253	0.387**	0.180	-0.036	-0.141	-0.167
NonAcceptance	0.021	0.134	0.064	0.043	-0.005	0.081	-0.097	-0.131
Strategies	0.177	0.173	0.018	0.088	-0.048	-0.007	0.025	0.009
Total	0.214	0.287**	0.129	0.200*	0.032	0.011	0.002	-0.058

* $p < 0.05$
** $p < 0.001$

Table 6
Mean and standard deviation of GSR index during the three driving sessions.

	Mean	Standard Dev	N
s1_SCR_Peaks_N	5.63	2.97	30.0
s2_SCR_Peaks_N	4.87	2.86	30.0
s3_SCR_Peaks_N	4.63	2.51	30.0
s1_SCR_Peaks_Amplitude_Mean	0.32	0.33	30.0
s2_SCR_Peaks_Amplitude_Mean	0.45	0.69	30.0
s3_SCR_Peaks_Amplitude_Mean	0.61	0.64	30.0
s1_EDA_Tonic_SD	0.93	0.10	30.0
s2_EDA_Tonic_SD	0.92	0.12	30.0
s3_EDA_Tonic_SD	0.93	0.15	30.0
s1_EDA_Sympathetic	0.05	0.17	30.0
s2_EDA_Sympathetic	0.04	0.21	30.0
s3_EDA_Sympathetic	0.02	0.10	30.0

- Risky driving style: F(8, 14) = 3.937, p = .012, Wilks' Λ = .308, partial η^2 = .692;
- High-speed driving style: F(8, 14) = 3.183, p = .028, Wilks' Λ = .355, partial η^2 = .645.

These data show that the GSR peak frequency varied as a function of the interaction between driving style and task difficulty level. Moreover, these findings, univariate Follow-up Analysis of Covariance (ANCOVA) [69] were conducted. Considering only the driving session as the independent variable, a significant effect was found for the number of peaks, F(2, 42) = 5.274, p = .009, partial η^2 = .201, confirming that task difficulty significantly influenced the frequency of physiological responses. No significant effects were found for the other GSR indices. Planned contrasts further examined differences in the number of peaks across driving sessions. These analyses revealed a significantly lower number of peaks in Session 3 vs. Session 2, and in Session 1 vs. Session 2, suggesting a physiological activation pattern that peaks during intermediate challenge levels and decreases thereafter, potentially due to adaptation or response saturation (Table 7).

5. Discussion

The present study is aimed to explore the psychological and physiological correlates of driving behavior in a sample of young adult drivers using a simulator-based assessment. The findings validated – with some limitations – the adopted experimental design for providing empirical support for the relevance of emotional and personality-related constructs in predicting both self-reported driving styles and real-time physiological arousal, useful for implementing realistic driving behaviors of cognitive agents in driving simulators.

5.1. Psychological variables and Driving Styles

One of the key findings was the negative correlation between empathy, particularly perspective-taking, and risky driving behavior (mainly risky, angry, and high-velocity driving styles). This suggests that individuals with lower capacity to consider others' viewpoints may be more inclined to be engaged in reckless or aggressive behavior behind the wheel. This is consistent with previous researches linking deficits in empathy to reduced prosocial behavior and increased impulsivity in high-stress contexts. Similarly, emotional dysregulation emerged as a strong predictor of maladaptive driving

Table 7
Test of within-subjects contrast for the driving session variable.

Tests of Within-Subjects Contrasts		df	F	Sig	Partial Eta Squared η^2
SCR_PeaksN	Session 1 vs. Session 2	1	4.678	0.042	0.182
	Session 2 vs. Session 3	1	16.420	0.001	0.439

styles, including risky, angry, and high-speed driving. Participants who reported greater difficulties in managing their emotional responses tended to display styles characterized by poor judgment, aggression, or impulsivity. These findings align with emotion regulation theory, which posits that individuals with low regulation capacity are more reactive in stressful or uncertain environments, such as dense urban driving conditions.

Regarding the relationships between personality traits and driving styles, the only significant correlation identified was a positive association between anxious driving style and the personality trait of agreeableness. As one of the Big Five personality dimensions [70], agreeableness encompasses qualities such as kindness, empathy, and cooperativeness. Individuals high in agreeableness tend to be more concerned about the well-being of others and are motivated to maintain harmonious interpersonal relationships.

The positive and significant association between anxious driving and agreeableness may suggest that these psychological characteristics interact among them to produce a driving profile in which anxiety is expressed as an increased caution and attentiveness toward other road users. Drivers exhibiting this combination may be more sensitive to social and relational dynamics, translating their interpersonal concerns into a style of driving that emphasizes safety, respect, and avoidance of potential conflict or misunderstanding in traffic environments. However, contrary to previous findings (e.g., [71]), this study did not find clear evidence linking maladaptive driving styles with maladaptive personality traits. Several factors, including methodological and experimental design differences, could explain the discrepancy between these results and prior literature.

It is important to note that researches involving personality traits frequently yields nuanced findings, and inconsistencies in results across studies are not uncommon. More research is needed to clarify the nature and strength of the relationships between personality characteristics and maladaptive driving behaviors, primarily through studies using diversified samples and multimethod assessments.

5.2. Physiological Activation, Driving Styles, and Simulation Difficulty

A repeated-measures MANCOVA was conducted to examine the relationship between skin conductance indices, driving styles, and driving simulation sessions. The goal was to assess how different simulated driving sessions, each characterized by increasing difficulty levels, affected GSR-derived physiological indices while accounting for individual differences in driving style.

The results revealed that, when controlling for individual driving styles, simulated driving sessions significantly affected the overall physiological response. Significant interactions emerged between the driving session factor and three specific driving styles: dissociative, risky, and high- speed. These findings suggest that such styles modulate physiological reactivity differently, depending on the difficulty of the driving task. However, among the GSR indices only the “number of peaks” index [72] was significantly affected by the driving session. Pairwise comparisons revealed that the frequency of GSR peaks was significantly lower in the Session 1 vs. Session 2, and lower in Session 2 vs. Session 3, the most demanding condition. No significant effects were observed for the other GSR indices. Interestingly, the decrease in galvanic skin response peaks with increasing task difficulty contradicts the assumption that more challenging conditions elicit higher stress and greater physiological arousal. A possible reason is that, despite the increased difficulty, participants may have developed greater confidence and familiarity with the simulator, thus resulting in habituation. In the initial sessions, participants may have shown stronger physiological responses due to novelty or uncertainty; however, as task complexity increased, adaptive mechanisms may have reduced arousal even as the demands grew.

Another hypothesis relates to cognitive focusing: with greater difficulty, participants may have become more cognitively engaged and focused on the task, dampening automatic emotional responses. Under such conditions, the brain may allocate more resources to problem-solving and action planning, which could suppress unnecessary sympathetic activity, as measured by GSR peak frequency. Moreover, the experimental design was conceptualized at increasing difficult, but it may not have imposed sufficient stress or cognitive engagement to elicit stronger physiological responses. Thus, a process of progressive familiarization may have prevailed over a true challenge response, resulting in reduced physiological activation. This underscores the importance of re-evaluating task difficulty and experimental parameters in future studies to calibrate the intended stressor effect better.

5.3. Limitations

Despite the promising results, this preliminary study has several limitations. First, the sample was relatively small and consisted mainly of university students, limiting the generalization to broader populations. However, from the perspective of validating the experimental approach, the composition of the sample is essentially irrelevant at this stage of the research. Second, using a driving simulator—although ecologically valid—does not fully replicate real-world driving conditions, which may influence behavior. Third, the self-report nature of psychological measures may introduce biases such as social desirability or inaccurate self-assessment. Future research should include larger, more diverse samples with a longitudinal design to assess changes over time. The integration of additional physiological and behavioral data, such as heart rate variability or eye tracking, could enrich the understanding of emotional driving processes. Moreover, it will be needed to test whether enhancing emotional regulation and mindfulness can causally improve driving behavior and reduce accident risk. Finally, validated the experimental design, future research should also adopt a different driving simulation software able to support the required high-degree of customization.

6. Conclusions

This study highlights the need for a comprehensive, interdisciplinary approach to understand human driving behavior. The multifactorial nature of driving behavior – encompassing cognitive, emotional, personality-related, and contextual dimensions – demands sophisticated methodologies capable of capturing its inherent complexity. By combining psychometric data, high-fidelity driving simulation, and biometric monitoring, models of human behavior, not only facilitate a deeper understanding of individual differences in driving styles, but also provide the necessary foundation for modeling these behaviors within cognitive software agents.

Agents, endowed with realistic, detailed psychological profiles, represent a powerful tool for enhancing the behavioral fidelity and predictive power of agent-based traffic simulations, moving beyond purely physical models to incorporate psychological realism, better reflecting the variability and unpredictability inherent in real-world traffic systems. This advancement has the potential to significantly improve the design of smart transportation systems, contribute to the development of more adaptive Advanced Driver Assistance Systems (ADAS), and support the formulation of evidence-based road safety policies. Besides, behavioral heterogeneity among agents can, in turn, produce emergent traffic patterns that more closely mirror actual urban dynamics, providing deeper insights into system-level outcomes such as congestion, accident probability, and responsiveness to policy interventions.

The integration of psycho-physiological states further augments the behavioral realism of agents, enabling the simulation of dynamic fluctuations in driver performance under varying cognitive loads and emotional conditions. This level of modeling will be useful not only for studying current human-driven traffic systems but also for anticipating interactions between human drivers and autonomous vehicles in mixed traffic environments.

Our preliminary findings demonstrate the feasibility and value of the proposed approach, and the design of simulations, establishing a foundation for the systematic translation of psychological constructs into programmable agent parameters. Future work will focus on consolidating and expanding the empirical dataset, refining cognitive agent models, validating both the customization capabilities of the driving simulation software and the simulation outcomes to bridge the gap between psychological theory and traffic engineering practice.

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Declaration on Generative AI

The authors have not employed any Generative AI tools.

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