Driving simulator study of the relationship between motion strategy preference and self-reported driving behavior

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Abstract

Faithful motion restitution in driving simulators normally focuses on track monitoring and maximizing the platform workspace by leaving aside the principal component—the driver. Therefore, in this work we investigated the role of the motion perception model on motion cueing algorithms from a user's viewpoint. We focused on the driving behavior influence regarding motion perception in a driving simulator. Participants drove a driving simulator with two different configurations: (a) using the platform dynamic model and (b) using a supplementary motion perception model. Both strategies were compared and the participants' data were classified according to the strategy they preferred. To this end, we developed a driving behavior questionnaire aiming at evaluating the self-reported driving behavior influence on participants' motion cueing preferences.

The results showed significant differences between the participants who chose different strategies and the scored driving behavior in the hostile and violations factors. In order to support these findings, we compared participants' behaviors and actual motion driving simulator indicators such as speed, jerk, and lateral position. The analysis revealed that motion preferences arise from different reasons linked to the realism or smoothness in motion. Also, strong positive correlations were found between hostile and violation behaviors of the group who preferred the strategy with the supplementary motion perception model, and objective measures such as jerk and speed on different road segments. This indicates that motion perception in driving simulators may depend not only on the type of motion cueing strategy, but may also be influenced by users' self-reported driving behaviors.

Keywords

Motion perception, driving behavior, motion cueing algorithm, driving simulation

1. Introduction

Driving simulators provide flexible, reproducible, and highly repeatable simulation environments. They are used to measure drivers' behaviors, simulate traffic environments, evaluate real-world situations, study driver–human interactions, and validate advanced driver-assistance systems and autonomous driving. One of the main challenges of these platforms is to faithfully reproduce car movements in the simulator when considering workspace limits. To overcome this issue, all the dynamic driving simulators used by car manufacturers and research laboratories implement motion cueing algorithms (MCAs), which aim at better reproducing motion signals from the vehicle model to the simulator while keeping the platform within the actuator's capabilities.

Model predictive control (MPC)[1] is used as a flexible MCA capable of effectively reproducing vehicle movements, manage safety requirements, and maximizing workspace exploitation of driving simulators. Unlike other existing MCAs such as classic, adaptive, or optimal, this technique has shown many advantages in terms of constraints handling[2,3] and workspace use.[4] When using MPC-based MCA, the motion restitution quality depends strongly on the underlying mathematical model, and

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finding the most suitable model is a major task that requires considerable efforts.

The first MPC for MCA applications[5] and some recent MPC versions,[6,7] only included an approximate platform dynamic model in order to prevent exceeding platform limits. Others MPCs[8,9,10,11] choose to additionally integrate the mathematical model of human motion perception into the control loop to minimize the motion sensation error between a real vehicle and the driving simulator. The human motion perception model is based on the mathematical model of the vestibular system since it is the main human organ capable of sensing motion. However, to the authors' knowledge, it has not been shown whether drivers will prefer the simulator's motion with an MCA that integrates or not the vestibular system. Hence, this paper proposes to evaluate two different motion configurations from a user's viewpoint that depend directly on the mathematical model used in the control design. The first configuration takes the platform dynamic model without any human perception model and the second one also uses the vestibular system model proposed by Telban and Cardullo.[12] They will be referred to as A1 and A2, respectively.

Since not all drivers behave in the same way, we believe that normal driving behavior impacts motion perception in a driving simulator. Therefore, we analyze whether the driving behavior is a predictor of the user's preferences in terms of motion perception.

To assess driving behavior, several self-assessment measurements have been used in recent decades, which consist of taking the decisions and actions that drivers take on the road as indicators of their usual driving behavior. Among self-reports are the Driver Behaviour Questionnaire (DBQ),[13] designed to study and classify outlying driving behavior; the Driving Behaviour Inventory (DBI),[14] developed to study the dimensions of driver stress; the Driving Style Questionnaire (DSQ)[15] proposed to assess decision-making styles, the Driver Skill Inventory (DSI),[16] used to compare self-reported driving abilities with general drivers' skills, and the Multidimensional Driving Style Inventory (MDSI),[17] which presents a comprehensive and multidimensional self-report of behavior while driving. We believe that the lack of a common conceptual framework is one of the difficulties to address and understand self-reported driving behavior. In this study, we consider the DBQ and the MDSI as the basis for defining the driving behavior of each participant, since to the best of our knowledge they are the only ones that describe in a general way driving behaviors based only on drivers' behavioral habits.

The DBQ is one of the most used self-reports addressing driving behaviors, but does not consider good behaviors. The original DBQ version[13] and some other modified versions have been used to evaluate different characteristics, such as geographical location,[18–22] age or gender,[23] cultural influence,[24] driving scenario conditions,[25] and have even been used in studies related to driving simulators.[26] The MDSI is newer than the DBQ, but it tries to classify driving behaviors in a much simpler and more understandable way. It was designed from previous self-assessment measurements to create a unique and multidimensional conceptualization of driving styles. Although the measures in the questionnaire are subjective, some authors have shown that they are good indicators of driving behavior.[27–29] Therefore, in this study we evaluate in a psychometric way (internal consistency and reliability), a joint version of both questionnaires in order to address driving behavior in a driving simulator.

In order to analyze objectively the self-reported driving behavior and the MCA mathematical model preference, we use actual measures collected after using the simulator. Research developed by Kaye et al.[27] based on 20 different studies shows that there are similarities and a positive correlation between driver behavior subscales and objective measures. Among numerous existing driver performance indicators, we consider those that have shown to have a significant influence on self-reported driving behavior validation and movement restitution in a driving simulator. Consequently, the average and the standard deviation of speed,[26,30] the average and standard deviation of the lateral position,[28] and the average of jerk[31] are taken as performance indicators of driving simulators.

The main objective of the present study is to provide a deeper understanding of driving behavior and it relationship with the motion perception model preference in a driving simulator. Additionally, objective support is provided by correlating performance measures obtained in driving simulation tests to define in a forward-looking manner the control strategy according to self-reported driving behaviors. In this sense, if the knowledge of drivers' behavior is available, MCAs can be improved and adapted specifically according to drivers' desires, making the simulation more immersive, realistic, and pleasant for each driver.

The rest of the paper proceeds as follows. Section 2 presents the MCA implemented in the driving simulator we used. Section 3 shows the user study including the procedure and all materials employed in this study. Section 4 exposes the research findings, followed by a detailed discussion in Section 5. Conclusions from this work are drawn in Section 6.

2. Motion cueing strategy

The platform we considered here (see Section 3.1) cannot provide long linear accelerations due to the workspace limitations. Hence, in the control design, we use the tilt coordination technique to provide an additional inertial restitution along the inclination axes of the platform. This is made possible by the sensory ambiguity of the otolith

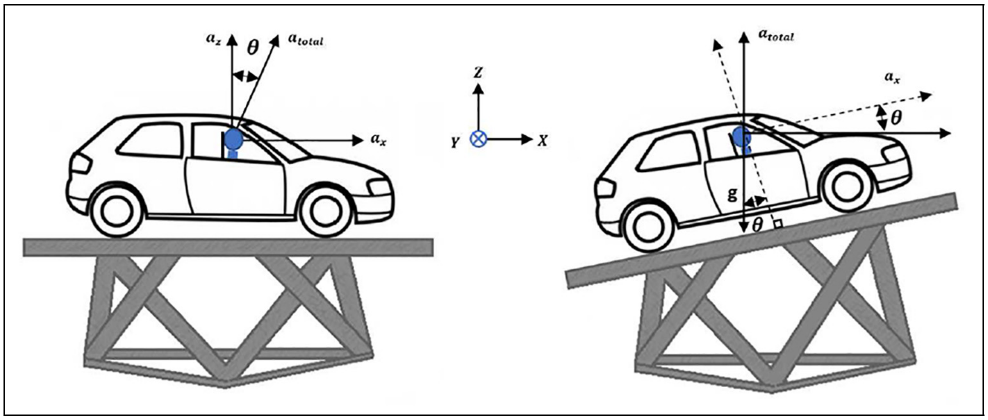

Figure 1. Tilt platform along the longitudinal acceleration.

organs, as they perceive the inclination of the head and horizontal accelerations as linear accelerations. The driver will perceive gravity acceleration g in its vertical plane and an acceleration $g\theta$ in its horizontal plane that intervenes on the perceived specific forces (i.e., the total reaction force acting on a body per unit of mass in m/s^2; equation (1)). This inclination technique allows restituting an acceleration of amplitude $g\theta$, thus providing the perception of a continuous surge acceleration (Figure 1).

$$f_x = a_x - g\sin(\theta) \tag{1}$$

To ensure the proper performance of this technique, it is important to respect the perception thresholds[32] and set the screen on which the driving environment is displayed relative to the platform so that the driver perceives accelerations and not inclinations. If the screen is not fixed, the virtual environment must be modified accordingly.

The MCA implemented in this paper is based on MPC. This strategy allows finding the most optimal longitudinal and rotational accelerations that must be sent to the simulator while respecting the constraints within a prediction window.

2.1. Mathematical model

An approximate mathematical model is used to predict the system's future behavior within a prediction horizon. In this study we consider two main models that will define the optimization statement: the driving simulator dynamic model and the human motion perception model.

2.1.1. Platform model. The simulator dynamic system corresponds to a double integrator (equation (2)) in order to control the platform position p, the linear velocity v, the linear acceleration u_{lin}, the angle θ, the angular speed ω, and the rotational acceleration u_{rot} along the X and Y axes.

$$\begin{aligned} x_{sim}(k+1) &= \overbrace{\begin{bmatrix} 1 & t_s & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & t_s \\ 0 & 0 & 0 & 1 \end{bmatrix}}^{A_{sim}} \overbrace{\begin{bmatrix} p(k) \\ v(k) \\ \theta(k) \\ \omega(k) \end{bmatrix}}^{x_{sim}} \\ &+ \overbrace{\begin{bmatrix} \frac{t_s^2}{2} & 0 \\ t_s & 0 \\ 0 & \frac{t_s^2}{2} \\ 0 & t_s \end{bmatrix}}^{B_{sim}} \overbrace{\begin{bmatrix} u_{lin} \\ u_{rot} \end{bmatrix}}^{u} \\ y_{sim}(k) &= \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} u_{lin} \\ u_{rot} \end{bmatrix} \end{aligned} \tag{2}$$

This model is the one used in the **A1** strategy.

2.1.2. Perception model. The idea is to additionally integrate human motion perception in the control loop to improve simulation realism and immersion. Then, rather than following the acceleration tracking trajectory, the system will track the perceived motion accelerations using a vestibular system model that includes a set of motion sensors for all specific forces.[33] Two main components are involved in motion perception: the otolith organs that respond to linear accelerations, gravitational forces, and head tilt; and the semicircular channels that are sensitive to movements in their specific rotation plane by detecting head rotations or angular accelerations. In the present study, we use the model proposed by Telban and Cardullo.[12]

The model for the semicircular canals is implemented in the control design as a filter for the three rotation angles. The otolith model is represented in a state-space form as

$$
\begin{aligned}
\dot{x}_{oto} &= \overbrace{\begin{bmatrix} -T_{3oto} & 1 & 0 & 0 \\ -T_{4oto} & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \end{bmatrix}}^{A_{oto}} x_{oto} + \overbrace{\begin{bmatrix} T_{1oto} & 0 \\ T_{2oto} & 0 \\ 0 & gT_{1oto} \\ 0 & gT_{2oto} \end{bmatrix}}^{B_{oto}} \begin{bmatrix} u_{lin} \\ u_{rot} \end{bmatrix} \\
y_{oto} &= \overbrace{\begin{bmatrix} 1 & 0 & 0 & 0 \end{bmatrix}}^{C_{oto}} x_{oto}
\end{aligned} \tag{3}
$$

where,

$$
T_1 = \frac{G_{oto}\tau_{aoto}}{\tau_{Loto}\tau_{soto}}, \quad T_2 = \frac{G_{oto}}{\tau_{Loto}\tau_{soto}},
$$
$$
T_3 = \frac{\tau_{Loto} + \tau_{soto}}{\tau_{Loto}\tau_{soto}}, \quad T_4 = \frac{1}{\tau_{Loto}\tau_{soto}}
$$

The different parameters represent the static sensitivity G_{oto}, the long time constant τ_{Loto}, the lead constant τ_{aoto}, and the short time constant τ_{soto}. These constants were obtained through subjective responses collected during different experiments and are detailed by Zacharias.[32]

The system (equation (3)) is merged with the platform system (equation (2)) to impose physical constraints in the optimization phase:

$$
\begin{aligned}
\dot{X}_{force} &= \overbrace{\begin{bmatrix} A_{oto} & 0 \\ 0 & A_{sim} \end{bmatrix}}^{A_{force}} \overbrace{\begin{bmatrix} x_{oto} \\ x_{sim} \end{bmatrix}}^{X_{force}} + \overbrace{\begin{bmatrix} B_{oto} \\ B_{sim} \end{bmatrix}}^{B_{force}} \overbrace{\begin{bmatrix} u_{lin} \\ u_{rot} \end{bmatrix}}^{u} \\
Y_{force} &= \overbrace{\begin{bmatrix} C_{oto} & 0 \end{bmatrix}}^{C_{force}} \begin{bmatrix} x_{oto} \\ x_{sim} \end{bmatrix} + \overbrace{\begin{bmatrix} 0 & 0 \end{bmatrix}}^{D_{force}} \begin{bmatrix} u_{lin} \\ u_{rot} \end{bmatrix}
\end{aligned} \tag{4}
$$

This model is used in the **A2** strategy.

2.2. Motion restitution

Although for the simulator we consider here the system's X–Y available stroke is 5.2 m, the simulator cannot fully restore accelerations in most cases. Then, the input signals have been scaled in order to reproduce as best as possible motion in the simulator. According to Berthoz et al.,[34] the use of lower unit gains between 0.5 and 0.75 provides the best perceived coherence of self-motion. Therefore, in this study we chose a gain of 0.6 for scaling the specific force signal f. The most relevant perception and physical limits implemented in this study are presented in Table 1.

In order to illustrate the tracking performance of strategies A1 and A2, we randomly selected a participant's data obtained from a driving test that lasted approximately 250 seconds. For this purpose, the terrain scenario (see Figure 4) was used. Figure 2 shows the specific force tracking along the X and Y axes for both MCAs.

Table 1. Workspace and perceptive limits considered in the control design.

Limits	Displacement	Velocity	Acceleration
X rail	2.6 m	2 m/s	5 m/s^2
Y rail	2.6 m	3 m/s	5 m/s^2
Tilt/roll	5.5°	4°/s	8°/s
Tilt/pitch	5°	4°/s	8°/s

We can observe in Figure 2 that the main difference between the two strategies is that A2 restores more transient accelerations than A1. It is worth clarifying that neither A1 nor A2 manages the tracking trajectory 1:1 due to the limitations of the simulator's workspace (see Table 1).

Another MCA objective is to make the best use of the available platform workspace. When the driving simulator is in the neutral position (X: 0 meter; Y: 0 meter), the available stroke is ± 2.5 m in all directions. In Figure 3 we can see the simulator workspace in terms of position and tilting angles used for each configuration on the 250 s driving test. In terms of rail displacement, strategy A1 exploits more of the working envelop in both X and Y axes. Nevertheless, strategy A2 privileges more the inclination of the platform to restore linear accelerations than does strategy A1.

In terms of simplicity, strategy A2 is more complex than just taking the platform dynamic model as the number of states in the control system is higher; however, both systems can be implemented in real time and, therefore, the computational performance is not discussed in the present study.

It is difficult to decide which of these two strategies is the best in general terms if only a signal analysis is performed. Hence, in the following section we will introduce a driver-in-the-loop experience aiming at analyzing, from both subjective and objective viewpoints, the driver's preference for each of the algorithms.

3. User study

The overall settings and the research approach of the driving simulator study are detailed in this section.

3.1. Apparatus

The experiment was performed on the ULTIMATE driving simulator at Renault, Virtual Reality and Immersive Simulation Center in France. The simulator consists of a real body car integrated to a Hexapod platform and mounted on large X–Y rails that provide a combination of angular and translational motions (see Table 1). This

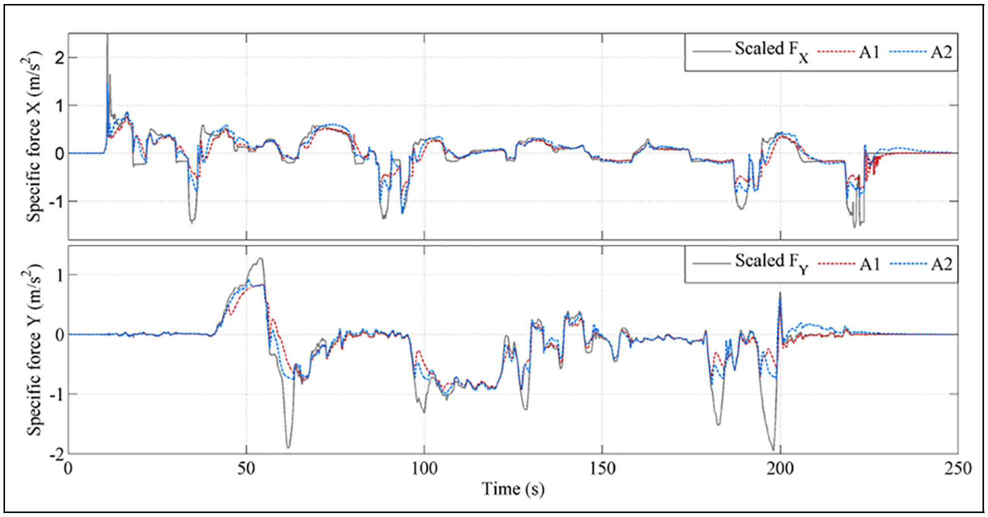

Figure 2. MCA restitution according to the MPC mathematical model: without any perception model (A1) and including a perception model (A2).

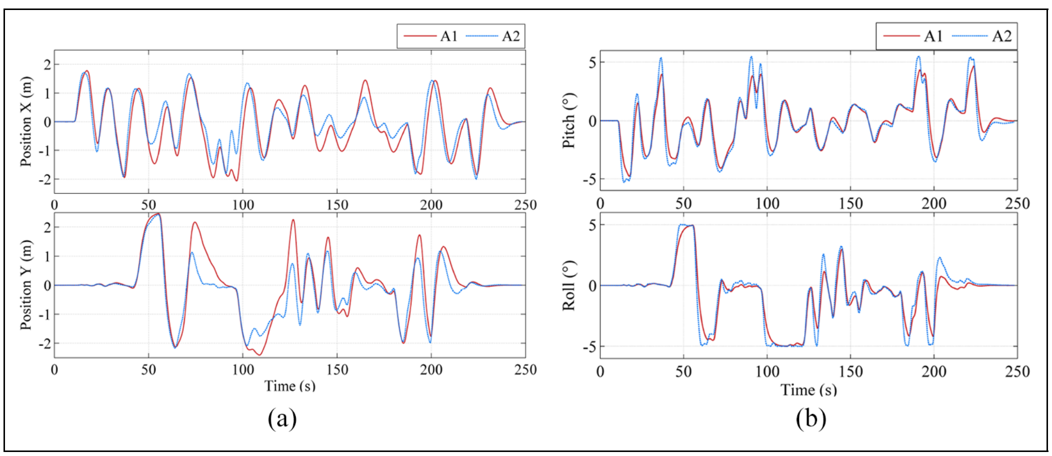

Figure 3. Simulator's workspace during the test. (a) Platform displacement. (b) Hexapod angles.

system integrates a visual scene projected on a spherical screen to provide a 210° field of view. The high-quality projection system and the full-vehicle cabin provide a realistic and immersive environment.

3.2. Participants

Forty-one licensed drivers (8 female, 33 male) with a valid driving license employed by the Renault group completed and returned the driving behavior survey. Given the simulator's availability, 20 participants drove the simulator and signed a consent form (mean age: 36.7 years, SD: 12.1 years). Two of the recruited participants were familiar with the driving simulator, but before the present study they had not driven the simulator with any of the proposed configurations. One participant was unable to finish due to simulator sickness. Five females aged 22–40 years (mean: 27.8, SD: 7.2) and 14 males aged 22–61 years (mean: 39.6, SD: 12.5) were included in the analysis regarding motion perception. The time required for each participant was one hour.

3.3. Experimental setup

The experiment was conducted in several stages. The first phase consisted of filling out the driving behavior questionnaire (see Section 3.4.3) and some information about the subjects themselves, such as age and gender. In the second step, subjects were installed in the simulator and safety instructions were given. Participants were asked to pay attention to the different situations that could affect the movement perception in each track of the scenario (see

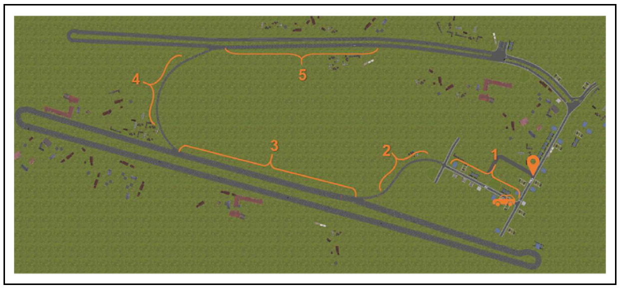

Figure 4. Top view of the terrain used for the driving test.

Figure 5. Screenshot of the drivers' view of the virtual scenario in the first situation.

Figure 4). Participants started with a familiarization driving test that lasted 150–200 s, and then drove the scenario with each of the strategies. The configurations were presented to the subjects in random order to avoid learning effects. Between each drive, participants were requested to complete a motion questionnaire (see Section 3.4.2) to evaluate the perception in the simulator for each MCA, A1 and A2. Each participant took 5–10 min to complete this questionnaire. At the end of the experiment, they were asked to indicate which strategy they preferred.

The driving simulator test was conducted using the terrain shown in Figure 4. The sound inside the simulator's cabin depended on the vehicle's engine and remained the same for all maneuvers.

3.4. Materials

3.4.1. Test scenario. During the driving scenario generation, both the terrain and relevant situations were taken into account to evaluate the movement restitution and generate signals with high and low frequencies for longitudinal and rotational accelerations. The terrain was specially designed to generate situations in a city, a highway, merging sections, and long turns. The scenario generation was done with the SCANeR Studio driving simulation software from AV Simulation.

Figure 4 shows the terrain used in the present study. Different road segments named from 1 to 5 were defined to represent specific driving situations. The first segment takes place in the city and the speed is limited to 50 km/h. It reproduces several start-and-stop situations to evaluate linear high-frequency accelerations along X (see Figure 5). The second segment corresponds to a merging section with speed limited to 50 km/h and mostly aims at producing lateral movements. The third segment is a highway limited to 100 km/h and generates linear continuous accelerations along the X axis. The fourth segment is a highway exit limited to 50 km/h to represent constant lateral accelerations. The last one corresponds to an urban road with a 70 km/h speed limit representing a slalom-type condition to reproduce lateral transient accelerations along Y. Traffic signs are present and verbal instructions were provided in the familiarization phase to indicate the respective speed limit for each track. The distance covered by each participant and for each MCA was approximately 2.8 km.

3.4.2. Motion restitution questionnaire. After testing each MCA, participants were asked to score the platform's motion restitution according to certain statements from the study carried out by Berthoz et al.[34] In the questionnaire, four statements had to be scored using a seven-point Likert scale (1: ''strongly disagree''; 7: ''strongly agree''). The statements were: ''I forgot the simulator,'' ''Motion was realistic,'' ''I felt I was driving,'' and ''I drove as usual.''

At the end of the driving test, participants were asked to choose the MCA they preferred, A1 or A2. This choice is essential in the objective analysis as it determines the way the collected data are divided and analyzed.

3.4.3. Driving behavior questionnaires. Self-reported driving behavior questionnaires were implemented to understand whether the subject's preference regarding motion restitution was influenced by real driving behavior or not. For this study, we chose to use two of the most commonly used ones—the DBQ[13] and the MDSI[17]—in order to address driving behavior in a driving simulator. The DBQ is widely used to report and identify individuals' aberrant behaviors such as violations, errors, and lapses. The MDSI categorizes driving behaviors in different styles, not only based on aberrant behaviors. For this reason, in the present study we considered both questionnaires.

Based on the existing questions in the DBQ, a new modified version was produced with 28 items (see Table 2) according to the highest load scores from previous studies.[19,23,25,35,36] Items with high factor loading scores can be used to describe the group of behavior in which they were classified. All 28 items are present in short DBQ versions as in the studies by Lajunen et al.[24] and Reimer et al.[37] and are oriented toward specific populations. These questions include some of the original scales,[13] such as violations, errors, and lapses. However, the factorial structures that define the scales of the DBQ can vary between different driving cultures and nations. Therefore, an exploratory factors analysis was used to define the categories for this modified DBQ (see Section 4.2).

Table 2. Factor model and component loading of the modified DBQ.

Factors and items	Loading	Mean (SD)
Errors $\alpha = 0.79$		
[Q1] Drive away from traffic lights in second gear	0.52	1.55 (0.78)
[Q4] Forget where you left your car in a car park	0.59	2.30 (1.18)
[Q6] Switch on the lights instead of the windscreen wipers	0.79	1.48 (0.93)
[Q21] Nearly hit something due to misjudging my gap in a parking lot	0.51	1.68 (0.69)
[Q24] Get into the wrong lane approaching a roundabout or junction	0.61	1.73 (0.75)
[Q43] Misjudge the speed of an oncoming vehicle when passing	0.66	2.08 (1.07)
Lapses: A $\alpha = 0.76$		
[Q5] Brakes to avoid a collision when vehicle ahead has slowed down	0.49	2.05 (0.81)
[Q8] Forget about the road along which you have just traveled	0.4	2.08 (0.83)
[Q18] Become angered by a certain type of driver and indicate your hostility	0.56	1.53 (0.72)
[Q19] I fail to notice someone at the pedestrian crossing	0.48	1.95 (0.71)
[Q26] Fail to check the rear mirror before pulling out or changing lanes	0.76	1.45 (0.60)
[Q31] Queuing to turn left onto a main road. You pay such close attention to the main stream of traffic that you nearly hit the car in front	0.72	1.78 (0.95)
Lapses: B ($\alpha = 0.7$)		
[Q9] Miss your exit on a motorway and must make a lengthy detour	− 0.58	2.03 (0.83)
[Q25] Misread the signs and exit from a roundabout on the wrong road	− 0.62	2.05 (1.01)
[Q37] Plan my route badly. so that I hit traffic that I could have avoided	− 0.39	2.35 (1.10)
[Q45] Intending to drive to a destination, you find yourself on the road to your usual destination	− 0.43	2.30 (1.24)
Violations: risk A ($\alpha = 0.7$)		
[Q3] Drive close or "flash" the car in front as a signal for that driver to go faster	0.63	2.08 (1.10)
[Q23] Overtake a slow driver on the inside	0.64	2.35 (1.17)
[Q32] Driving too close to the car ahead of you	0.66	2.05 (1.15)
[Q14] Deliberately disregard the speed limits late at night or early in the morning	0.39	2.95 (1.50)
[Q28] Ignore "give way" signs and narrowly avoid colliding with traffic having right of way	0.35	1.35 (0.53)
Violations: risk B ($\alpha = 0.5$)		
[Q12] Drive through traffic lights that have just turned red	0.62	1.25 (0.49)
[Q15] Nearly hit a cyclist who has come up on your inside when turning	0.5	1.23 (0.42)
[Q17] Driving after drinking	0.45	1.53 (0.68)
[Q27] Attempt to overtake a vehicle that you hadn't noticed was signaling its intention to turn left	0.38	1.20 (0.46)
[Q10] Forgetting what gear you are in and checking*		
[Q13] Getting angry with another driver and following him*		
[Q29] Get involved in unofficial races with other drivers*		

α = Chronbach's alpha.
*item removed to compute the expected score and α.

The original MDSI contains 44 items to address four different driving styles: anxious driving, patient and careful driving, careless driving, and angry and hostile driving. In order to reduce the number of questions from the original MDSI form, we selected 27 questions (Table 3) from previous studies.[17,38,39] The 27 items were analyzed in exploratory factor analysis (EFA) to determine their relevance in the factors that address a specific driving behavior. This modification had to be made as the simulator availability and the time per participant to complete all the experiments was one hour. In addition, long questionnaires tend to demotivate subjects in terms of answering seriously and may have a tendency to reproduce systematic answers.[40]

Eight questions were used for both the DBQ and the MDSI questionnaires, which led to a final self-report form with 47 questions.

Subjects indicated the frequency with which they engaged in a specific type of behavior, basing their judgment on their personal driving experience. Each subject was instructed to indicate for each item how often they engaged in such behaviors on a six-point scale, where 1 = never and 6 = nearly all the time.

3.5. *Data extraction*

Data were collected after each drive in the simulator with the intention of objectively analyzing the influence of subjects' driving behaviors and their preference regarding strategies A1 and A2. As explained before, the terrain used for the test scenario was divided into five road segments (see Figure 4). The segments were separated according to the vehicle position in the terrain. The intersections between

Table 3. Factor model and coefficients loading of the modified MDSI.

Factors and items	Loading	Mean (SD)
Anxious driving style $\alpha = 0.84$		
[Q1] Drive away from traffic lights in second gear	0.54	1.55 (0.78)
[Q5] Brakes to avoid a collision when vehicle ahead has slowed down	0.53	2.05 (0.82)
[Q6] Switch on the lights instead of the windscreen wipers	0.66	1.48 (0.93)
[Q7] It worries me when driving in bad weather	0.71	2.13 (1.09)
[Q19] I fail to notice someone at the pedestrian crossing	0.45	1.95 (0.71)
[Q20] Feel uncomfortable while driving	0.62	1.45 (0.86)
[Q21] Nearly hit something due to misjudging my gap in a parking lot	0.65	1.68 (0.69)
[Q36] Driving makes me feel frustrated	0.57	1.85 (1.21)
[Q37] Plan my route badly, so that I hit traffic that I could have avoided	0.42	2.35 (1.09)
[Q43] Misjudge the speed of an oncoming vehicle when passing	0.56	2.08 (1.07)
Careful driving style $\alpha = 0.71$		
[Q11] Feel reassured while driving	0.41	5.13 (1.02)
[Q22] Tend to drive cautiously	0.71	4.75 (1.08)
[Q33] Feel I have control over driving	0.35	5.33 (0.83)
[Q34] On a clear freeway, I usually drive at or a little below the speed limit	0.59	3.85 (1.75)
[Q38] Wait patiently when not having right of way	0.4	5.05 (1.36)
[Q42] Base my behavior on the motto "better safe than sorry"	0.51	4.58 (1.41)
[Q46] Ready to react to unexpected maneuvers by other drivers	0.49	4.85 (1.09)
Hostile driving style $\alpha = 0.78$		
[Q41] Like to take risks while driving	0.72	1.93 (0.99)
[Q47] Enjoy the excitement of dangerous driving	0.83	2.15 (1.21)
Impatient driving style $\alpha = 0.6$		
[Q2] Get impatient during rush hour	0.45	3.28 (1.09)
[Q35] Insert into that lane as soon as possible when the lane next to me starts to move	0.78	2.33 (0.92)
Risky driving style $\alpha = 0.68$		
[Q12] Drive through traffic lights that have just turned red	0.37	1.25 (0.49)
[Q16] Read messages while driving	0.68	1.98 (1.21)
[Q30] Do relaxing activities while driving	0.40	1.97 (1.05)
[Q40] Fix my hair/eat while driving	0.42	1.90 (1.11)
[Q44] Write messages while driving	0.85	1.73 (0.96)
[Q39] In a traffic jam, I think about ways to get through the traffic faster*		

α = Chronbach's alpha.
*item removed to compute the desired loading score and α.

each segment were not taken into account as they were considered as transition sections. We took all subjects' driving data after driving the simulator with A1 and A2 MCAs, then the measures' averages of both strategies were computed for each of the five road segments. The measures (driving-motion indicators) calculated per participant were the average for jerk in m/s^3, speed in km/h, lateral position in meters, and the standard deviations for speed and lateral position. These parameters were selected based on their relevance in reporting driving behaviors in previous studies.[26,28,29,31]

Jerk was calculated as the rate of acceleration change. Only an X or Y jerk value was considered per segment as these depended on the motion restitution signal (e.g., in #1 and #3 road segments, the situations produced mostly X linear accelerations while in the remaining road segments the situations produced Y linear accelerations). The lateral position was provided by the SCANeR Studio simulation software: when the virtual car was in the middle of the lane, the lateral position corresponded to zero, 1.5 m when fully to the right and -1.5 m when fully on the left side. We only took the absolute values to evaluate the average. Regarding this indicator only, the last road section that represents the slalom condition was not considered as the vehicle is constantly changing its lane. In order to be able to compare the simulation data of all participants, we separated them into MCA-preference groups (i.e., the participants who preferred strategy A1 and the participants who preferred strategy A2). We call these group A1 and group A2, respectively. This classification is made to collect the motion indicators by preference group and to verify whether there is a correlation between the groups' data and their self-reported driving behaviors. This decision was also influenced by the disparity between the answers to the different questionnaires. The groups were selected according to the participants' answers regarding the order of preference in the last part of the experiment (see Section 3.4.2).

4. Results

The analysis consisted of several steps mainly divided into objective and subjective analyses. Figure 6 serves as a support to illustrate the way the analyses in this study are

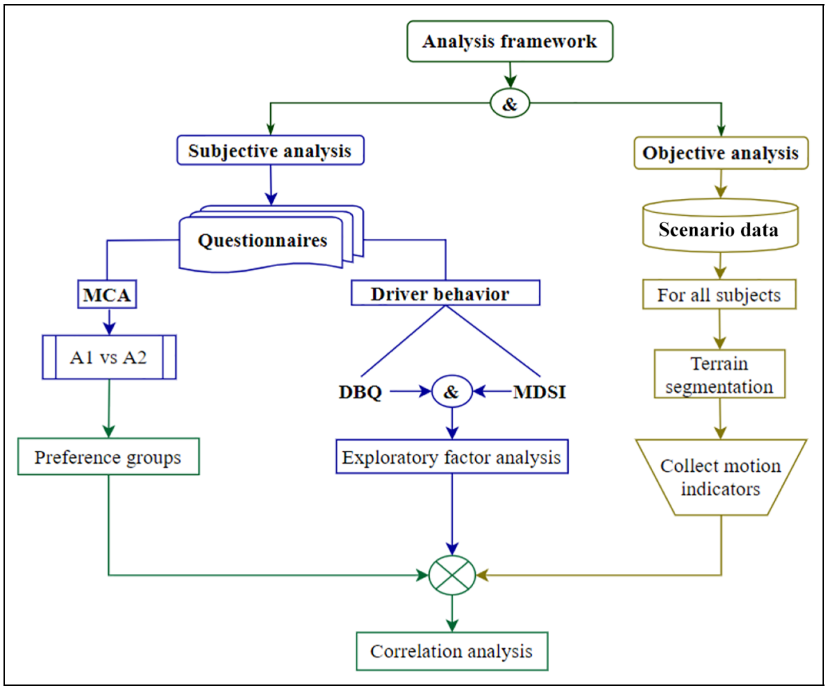

Figure 6. Overview of the analysis framework.

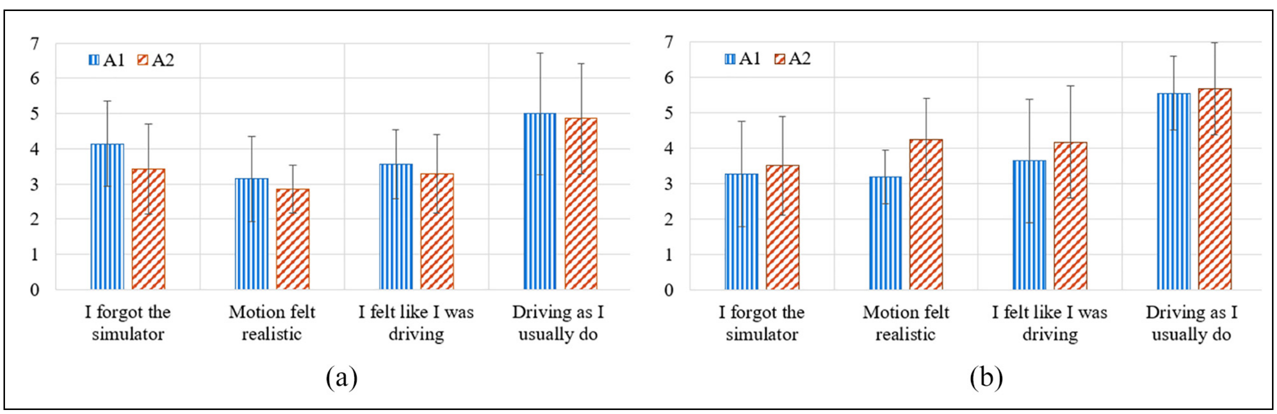

Figure 7. Subjective evaluation of the MCA statements depending on the subjects' preferred strategy. (a) Group A1. (b) Group A2.

presented. The subjective analysis integrated the MCA and the driver behavior forms. Regarding the MCA questionnaire, we evaluated from the participants' viewpoints the differences between strategies A1 and A2. For the driving behavior questionnaire, an analysis was conducted to categorize separately the 28 DBQ items and the 27 MDSI items within specific groups we call factors.

Concerning the objective analysis, we considered the groups based on their MCA preference as presented in the previous section. For each group, correlation tests were carried out between the self-reported driving behavior and the driving-motion indicators.

4.1. MCA preference

Subjective analyses were completed for groups A1 and A2. Seven participants chose the A1 configuration (containing only the vehicles' dynamic model) and 12 participants chose the A2 strategy (which, in addition to the vehicle dynamics, integrates the human perception model).

Since the data for groups A1 and A2 do not follow a normal distribution, nonparametric paired Wilcoxon signed-rank tests with a significance level of 5% were used to compare the differences between the groups. The means and standard deviations for the MCA form scores for each group can be seen in Figure 7. The mean values support the participants' MCA choices (i.e., for the A1 group, the MCA forms statements have been scored better when using strategy A1 than strategy A2 and vice versa).

Regarding only the MCA statement scores that were statistically significantly different, the sign test indicated that group A1 forgot more about the driving simulator when driving the simulator with A1 MCA than with A2 ($Z = 2.731, p = 0.018$). For the participants of group A2, the test found that the statements "I feel like I was driving" ($Z = 2.135, p = 0.032$) and "I drove as usual" ($Z = 2.098, p = 0.036$) were significantly higher when using strategy A2 than using A1 (i.e., their behavior was not influenced by being in a driving simulator rather than a real car). Finally, for the same group, the test indicated that the mean for the motion realism scores with strategy A2 was statistically significantly higher than the mean for the same statement with strategy A1 ($Z = 2.315, p = 0.006$).

In the following sections, these results will be correlated with the data collected from each participant and will be compared with their real driving behavior.

4.2. Driving behavior questionnaire

The 28 DBQ items and the 27 MDSI items used in the present study were submitted to an EFA to reduce the number of variables and clearly identify behavioral factors. In this analysis we used the principal axis factoring method and the varimax rotation to correlate the factors in the final result. The techniques used to determine the number of factors in both forms were the parallel analysis, the Kaiser criterion (i.e., keeping factors with eigenvalues greater than 1), and visual inspection of scree plots. We decided to interpret only the items with an absolute loading value of 0.30 or higher to obtain a good interpretability of factors, considering the size of the population test and the number of questions. This value is supported by the majority of researchers.[41] Neither DBQ nor MDSI items had loading scores inferior to 0.35 (see Tables 2 and 3). Finally, for the consistency of the DBQ and the MDSI, all obtained factors were checked with Cronbach's alpha as an estimate of internal reliability.

MDSI: A first EFA revealed poor results since the loading value of each variable in its respective factor was less than 0.30. In addition, the reliability Cronbach's alpha coefficient was not satisfactory for half of the factors, being less than 0.7. As a result, a second EFA was conducted to group the variables into new factors, this time without question 39 since its loading value was less than 0.3 with its corresponding factor. The second analysis gave a distribution of 26 elements with 5 factors explaining 50% of the total common variance of the modified MDSI. The resulting Tucker's congruence coefficient was 0.84, which corresponds to a fair similarity between the different driving styles or factors. Table 3 summarizes for each driving style the question item, a brief description, the questions' loading values, the α coefficient by style, and the mean and SD for all questions.

DBQ: An initial EFA gave a Tucker coefficient of less than 0.7; therefore, questions with a load below the loading threshold (Q10, Q13, Q29) were deleted and a new analysis was performed. The latter resulted in a distribution of 25 elements with 4 factors explaining 47% of the total common variance of the modified DBQ. The Tucker coefficient obtained was 0.88, which provides a fair similarity between the factors structure.

Following the methodology of Reason et al.,[13] the factors classification depends on the type of behavior and risk category. The different factors were established based on the three main categories found in the literature:[23,25,42] errors, lapses, and violations. In our case, lapses and violations were divided into two subcategories that refer to the risk level: A indicates a higher risk, (i.e., a definite risk to other road users) and B a lower risk (i.e., some possibility of risk to others). The B lapses may correspond to "slips" since they are not intended actions. The internal reliability for the violations for risk B was found to be poor ($\alpha = 0.5$); therefore, we unified the violations into only one factor ($\alpha = 0.68$). All five factors were analyzed. Table 2 shows the means and standard deviations for each of the 25 items of the new version of the DBQ.

In order to investigate whether the type of driving behavior had a relationship with the participants' MCA choice, we compared the self-reported driving behaviors between the groups with Wilcoxon Mann–Whitney U tests. The results of this analysis indicated that group A2 had significantly higher scores in the hostile driving style ($U = 10, p = 0.005$) and in the violations factor ($U = 16, p = 0.046$) than group A1. None of the remaining factors were significantly different between groups A1 and A2.

This result will be correlated with the motion driving indicators in Section 4.3. Figure 8 shows the mean and SD values for the different groups in each driving behavior questionnaire.

To evaluate the relationship between the questionnaires, Pearson correlations were computed between the five driving styles—anxious, careful, hostile, impatient, and risky—and the five DBQ factors—errors, lapses risk A, lapses risk B, violations risk A, and violations risk B. Additional correlations were computed for the violations group (A and B) together, as this factor has greater internal reliability than the separate A and B violations factors. Correlations were computed with the questions' score average (Table 4), and for all participants who answered the DBQ (Section 3.4.3). Strongly positive correlations were observed for two driving styles: the first one is the anxious style with errors and lapses, and the second one is the hostile driving style with violations. The careful style is moderately negatively correlated with errors and lapses

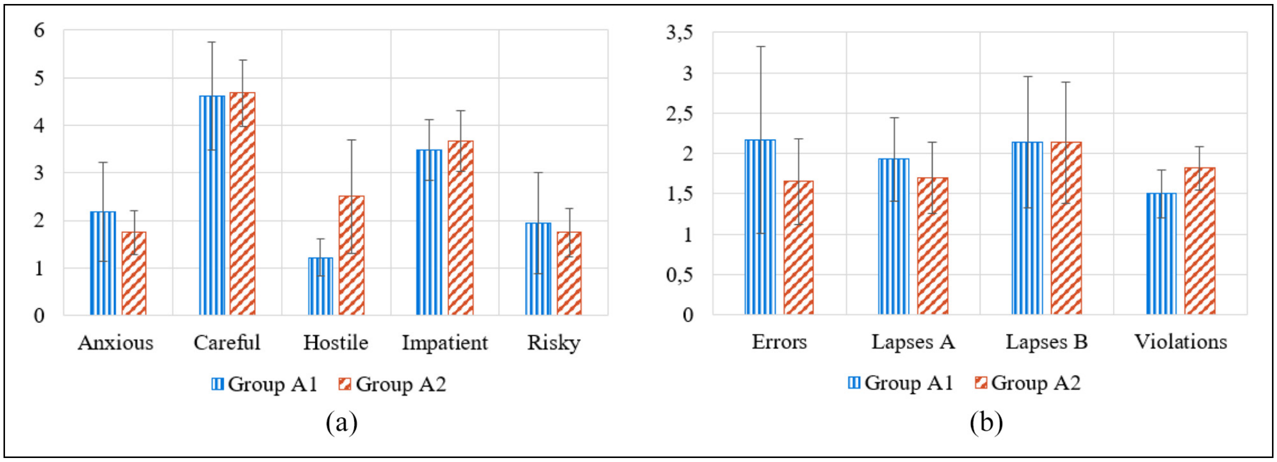

Figure 8. Groups A1 and A2 means and standard deviations for the factors in the MDSI and DBQ forms. (a) MDSI scores. (b) DBQ scores.

Table 4. Correlations of DBQ and MDSI driving behaviors.

Styles	Errors	Lapses A	Lapses B	Violations A	Violations B	Violations (AB)
Anxious	**0.87 (< 0.001)**	**0.58 (< 0.001)**	**0.473 (0.003)**	– 0.089 (0.594)	0.033 (0.844)	– 0.064 (0.700)
Careful	**– 0.329 (0.043)**	**– 0.396 (0.013)**	0.109 (0.513)	– 0.203 (0.221)	0.110 (0.512)	– 0.134 (0.421)
Hostile	– 0.005 (0.981)	0.143 (0.391)	0.000 (0.998)	**0.55 (< 0.001)**	**0.345 (0.034)**	**0.60 (< 0.001)**
Impatient	0.114 (0.490)	– 0.096 (0.565)	– 0.080 (0.631)	0.258 (0.118)	0.043 (0.118)	0.237 (0.151)
Risky	– 0.056 (0.742)	0.074 (0.656)	0.000 (0.997)	0.171 (0.304)	0.239 (0.305)	0.235 (0.155)

Table entries are correlation coefficients (*r*) with *p* values in parentheses. Statistically significant values are in bold.

with important risks. We can observe also that the impatient and risky styles are not correlated with DBQ factors.

4.3. Relationship between self-reported and actual driving behavior

From the previous results we can show that the only difference between groups A1 and A2 regarding driving behavior was found for the MDSI hostile style and for the DBQ violations factor. Pearson correlations indicate that there was a significantly positive association between both factors ($r = 0.597, p < 0.01$). In order to understand objectively this result, and using the methodology explained in Section 3.5, we computed the minimum, maximum, average, and standard deviation values for all driving-motion indicators (speed, jerk, and lateral position) in each road segment. These indicators are listed in Table 5 and are correlated with the hostile style and the violations factors.

Table 6 provides an overview of Pearson correlations between the driving behavior scores for both factors and motion indicators for groups A1 and A2. Correlations were made for each road segment since the situations in each segment were generated to reproduce different types of motion, as explained in Section 3.4.1.

For group A1, none of the measures presented had a significant correlation with the hostile style, and only the SD of the lateral position presented a significantly and strongly negative correlation with the violations factor ($r = -0.805, p = 0.029$). This result was expected since the first road segment only lasts 300 m and presents

Table 5. Mean, standard deviation, minimum, and maximum scores for motion indicators.

	Min.	Max.	Mean	SD
Road section 1				
Jerk X	– 224.23	198.65	0.09	0.02
Speed	0.00	66.65	25.46	3.01
Lateral position	0.00	0.56	0.14	0.07
Road section 2				
Jerk Y	– 9.95	15.91	– 0.08	0.10
Speed	30.11	79.20	51.73	5.63
Lateral position	0.00	1.65	0.41	0.13
Road section 3				
Jerk X	– 17.86	16.35	– 0.04	0.04
Speed	34.35	120.20	81.00	7.00
Lateral position	0.00	1.15	0.27	0.14
Road section 4				
Jerk Y	– 9.25	17.92	0.03	0.03
Speed	41.63	97.39	61.66	9.39
Lateral position	0.00	1.75	0.41	0.24
Road section 5				
Jerk Y	– 19.12	54.81	0.01	0.03
Speed	1.17	112.33	74.77	8.86

Table 6. Correlation for groups A1 and A2 between performance indicators and factors that present a statistically significant difference in the driving behavior questionnaire: hostile style and violations.

	Hostile – group A1	Violations – group A1	Hostile – group A2	Violations – group A2
Road section 1				
Mean jerk X	– 0.242 (0.600)	– 0.230 (0.620)	***0.648 (0.031)***	0.534 (0.090)
Mean speed	– 0.093 (0.843)	– 0.096 (0.837)	0.215 (0.525)	– 0.026 (0.939)
SD speed	– 0.537 (0.214)	– 0.572 (0.180)	0.132 (0.698)	0.398 (0.225)
Mean lateral position	– 0.340 (0.456)	– 0.739 (0.058)	– 0.102 (0.764)	– 0.409 (0.212)
SD lateral position	– 0.352 (0.438)	***– 0.805 (0.029)***	– 0.162 (0.635)	– 0.332 (0.319)
Road section 2				
Mean jerk Y	0.615 (0.142)	0.578 (0.174)	– 0.08 (0.816)	– 0.477 (0.138)
Mean speed	– 0.573 (0.179)	– 0.598 (0.156)	***0.618 (0.043)***	0.550 (0.080)
SD speed	– 0.061 (0.896)	– 0.492 (0.262)	0.195 (0.566)	0.191 (0.573)
Mean lateral position	0.338 (0.458)	0.372 (0.411)	0.209 (0.538)	– 0.506 (0.113)
SD lateral position	0.220 (0.636)	0.480 (0.276)	0.235 (0.486)	– 0.592 (0.055)
Road section 3				
Mean jerk X	0.180 (0.699)	0.140 (0.764)	0.497 (0.120)	– 0.154 (0.651)
Mean speed	– 0.370 (0.414)	– 0.140 (0.765)	0.596 (0.053)	0.567 (0.069)
SD speed	– 0.222 (0.632)	– 0.311 (0.497)	0.101 (0.768)	0.244 (0.470)
Mean lateral position	0.275 (0.550)	0.144 (0.758)	– 0.395 (0.230)	– 0.115 (0.736)
SD lateral position	0.244 (0.598)	– 0.003 (0.994)	– 0.175 (0.607)	– 0.22 (0.516)
Road section 4				
Mean jerk Y	0.094 (0.841)	0.337 (0.460)	0.466 (0.149)	0.202 (0.551)
Mean speed	– 0.272 (0.555)	– 0.154 (0.741)	***0.743 (0.009)***	***0.669 (0.024)***
SD speed	– 0.086 (0.854)	– 0.606 (0.149)	0.483 (0.132)	0.345 (0.298)
Mean lateral position	– 0.295 (0.521)	0.649 (0.115)	0.413 (0.207)	– 0.168 (0.620)
SD lateral position	– 0.100 (0.832)	0.648 (0.116)	0.315 (0.345)	– 0.246 (0.466)
Road section 5				
Mean jerk Y	– 0.355 (0.435)	– 0.387 (0.391)	0.121 (0.722)	– 0.379 (0.251)
Mean speed	– 0.493 (0.261)	– 0.491 (0.263)	0.548 (0.081)	0.360 (0.277)
SD speed	0.573 (0.179)	0.659 (0.107)	0.415 (0.204)	***0.631 (0.037)***

Table entries are Pearson correlation coefficients (r) with p values in parentheses. Statistically significant values are in bold.

several start-and-stop maneuvers with a maximal speed limit of 50 km/h. Regarding group A2, Pearson correlations showed several strong relations between the factors and the measures. Comparing the hostile style, the mean of jerk along X for road segment 1 ($r = 0.648$, $p = 0.031$) and the mean speed on road segments 2 ($r = 0.618$, $p = 0.043$) and 4 ($r = 0.743$, $p = 0.009$) presented a strongly positive correlation. Regarding violations, two measures correlated strongly positively with this factor: mean speed on road segment 4 ($r = 0.669$, $p = 0.024$) and SD of speed on road segment 5 ($r = 0.631$, $p = 0.037$). This result supports that there is a difference according to the self-reported driving behaviors between groups A1 and A2.

5. Discussion

The aim of this study was to analyze, from a driver's viewpoint, the MCA mathematical model's influence and its relationship with driving behavior in a driving simulator. Two different models were compared: A1, which included only the simulator dynamics, and A2, which complemented A1 with a human motion perception model. Such a study can generally be obtained by using only a subjective approach. However, in the current study we performed a deeper analysis with respect to the reasons that led participants to choose the strategy that suits them best. Hence, we examined objectively the self-reported driving behaviors and the real data indicators obtained after driving the simulator with both strategies.

Comparing subjectively the A1 and A2 strategies, the results showed that the preference between both strategies can arise for different reasons. In fact, the group that preferred strategy A1 scored higher for the statement "I forgot the simulator," while group A2 scored higher for the remaining statements such as "I felt I was driving" and "I drove as usual and motion felt realistic." This result can be explained by seeing how strategy A1 restores movement (see Figure 2)—that is, transient accelerations are smoother than those produced by strategy A2, thus producing a comfortable but slightly unrealistic motion effect.

Looking at driving behavior's influence on participants' MCA choice, we evaluated a modified version of the MDSI and DBQ forms. Items from the original scales of the DBQ and MDSI revealed a structure of five components each. For the DBQ, the factors are interpreted as errors, lapses of risk A, lapses of risk B, and violations. This structure confirms the original classification[13] and supports the distinction between each factor as observed in other studies.[19,23] For the MDSI, the structure reveals five styles interpreted as: anxious, careful, hostile, impatient, and risky. These were in line with those reported in the literature,[28,38,39] except for the distress-reduction style as it was composed of many items that were not considered in this study.

The results showed two main findings: first, both forms have several factors with strongly positive correlations, such as the hostile style with violations and the anxious style with errors and lapses. The careful style presented moderately negative correlations with errors and lapses A. This finding reflects the importance of creating a unified form to facilitate and generalize driving behavior understanding. The second finding indicated that only the violations and hostile factors can be considered as potential indicators for MCA design—that is, the participants who preferred driving the simulator with strategy A2 scored higher in both factors than participants of group A1.

As we aimed to support previous outcomes, we examined objectively the relationship between both self-reported factors (i.e., hostile driving and violations) and different driving indicators such as jerk, speed, and lateral position. We used the participants' data after driving the simulator with strategies A1 and A2. The objective analysis was performed for both groups; group A1 included participants who preferred strategy A1 and group A2 included the remaining participants. Regarding group A1, no relationship was found between the factors and the driving simulator measures. However, for group A2 the indicators had several correlations with these factors. In the hostile style, jerk in the first section of road was strongly positively correlated. This means that drivers who scored higher on the hostile driving style scale had higher average jerk when facing situations with high-frequency accelerations such as starting and braking scenarios. The same group had higher average speed in road segments that represented merging and exit sections on the highway. Regarding violations behavior, group A2 had a strong correlation with mean speed and SD of speed in road segments characterized by high and low frequencies of lateral acceleration. This result is in line with the studies by Zhao[25] and Helman and Reed,[26] in which a significantly positive correlation exists between average speed and the violation factor. This factor is correlated positively with a more aggressive driving style. Unlike the results found by Hooft van Huysduynen et al.,[28] the role of mean and SD of the lateral position as relevant indicators for assessing driving behavior was not confirmed in this study.

These results provide additional evidence that drivers' MDSI or DBQ scores are a useful and reliable tool to identify people's behavior while driving, as also observed in previous studies.[25,27,29,43] Furthermore, these results support that a joint version of violations and hostile behavior also could be used to assess the MCA characteristics in specific driving scenarios that require more important motions, such as the slalom situation or a braking scenario. Drivers with this self-reported driving behavior will prefer that linear and lateral accelerations be faithfully restored by the simulator.

5.1. Limitations

There are two major limitations in this study that could be addressed in future research. First, given the availability of the simulator, this study had a low number of participants. The moderate size and low representation of the subjects may limit the generalization of our findings. This fact may be responsible for the internal reliability values in some driving behavior factors and contribute to lower correlations regarding objective measures. In addition, the small sample size did not make it possible to analyze others factors that may affect the motion preference and the self-declared driving behavior such as the gender and age of the participants. Nevertheless, this study provides a promising basis for adapting and validating the type of model to be used, taking into account driver behavior. Thus, replication of our results in a larger confirmatory study is needed.

Second, proper adaptation of the self-reported forms is needed before using the presented DBQ for general motion control design. However, the current study supports the importance of using driver-in-the-loop feedback when designing MCAs.

6. Conclusions

Despite the small sample size, the present study suggests important insights that can improve movement perception in a driving simulator:

- The model implemented in MPC-based MCA plays an important role in users' motion perception. The results show that subjects were able to differentiate between using only the model dynamics and additionally integrating the vestibular system model.
- Driver-in-the-loop feedback must be considered in the motion control design to improve MCAs as it is difficult to evaluate motion perception if only theoretical data and signal analysis are taken into account. The knowledge of each subject's driving behavior can provide more realistic, pleasant, and immersive simulations.
- Self-reports can be a valuable tool to study and improve motion perception in driving simulators. They can provide reliable information about the reasons that motivate drivers to choose a specific MCA.
- The results show that it would be ideal to unify and further improve both the DBQ and the MDSI questionnaires to facilitate research in real road driving behavior.

- The results give complementary support for the use of driving simulators in studies related to driving behavior in a controllable, virtual, and safe environment.
- From a practical viewpoint, only a hostile style and violations behavior serve as a predictor to know whether or not to implement a motion perception model into the control design in MPC.

Additionally, this study reveals that the knowledge of users' driving behavior can be exploited in driver profiling for MCAs in specific situations and for specific groups of drivers. Future research would increase the number of subjects and incorporate more elements in the DBQ to address the types of behaviors that reflect greater correlation with the choice of control strategy, especially those related to hostile style and violations behaviors. A validated subject's psychological fidelity form will be an important part of further experiments in order to thoroughly understand the impact of the perception model on the control algorithms.

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Declaration of conflicting interests

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