

Article

Distractive Tasks and the Influence of Driver Attributes

Sónia Soares ¹, Carlos Campos ², João Miguel Leitão ², António Lobo ¹, António Couto ¹
and Sara Ferreira ^{1,*}

¹ Research Centre for Territory, Transports and Environment, Faculty of Engineering of the University of Porto, 4200-465 Porto, Portugal; soniasoares@fe.up.pt (S.S.); lobo@fe.up.pt (A.L.); fcouto@fe.up.pt (A.C.)

² School of Engineering, Polytechnic of Porto, 4249-015 Porto, Portugal; crc@isep.ipp.pt (C.C.); jml@isep.ipp.pt (J.M.L.)

* Correspondence: sara@fe.up.pt

Abstract: Driver distraction is a major problem nowadays, contributing to many deaths, injuries, and economic losses. Despite the effort that has been made to minimize these impacts, considering the technological evolution, distraction at the wheel has tended to increase. Not only tech-related tasks but every task that captures a driver's attention has impacts on road safety. Moreover, driver behavior and characteristics are known to be heterogeneous, leading to a distinct driving performance, which is a challenge in the road safety perspective. This study aimed to capture the effects of drivers' personal aspects and habits on their distraction behavior. Following a within-subjects approach, a convenience sample of 50 drivers was exposed to three unexpected events reproduced in a driving simulator. Drivers' reactions were evaluated through three distinct models: a Lognormal Model to make analyze the visual distraction, a Binary Logit Model to explore the adopted type of reaction, and a Parametric Survival Model to study the reaction times. The research outcomes revealed that drivers' behavior and perceived workload were distinct when they were engaged in specific secondary tasks and for distinct drivers' personal attributes and habits. Age and type of distraction showed statistical significance regarding the visual behavior. Moreover, reaction times were consistently related to gender, BMI, sleep patterns, speed, habits while driving, and type of distraction. The habit of engaging in secondary tasks while driving resulted in a cumulative better performance.

Keywords: road safety; driver behavior; driver attributes; distraction; reaction; eyes-off-road



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1. Introduction

For most people, driving is a common daily activity, which they do in an automatic state, without requiring much attention or consideration. Nonetheless, human error is still the major cause of road crashes worldwide [1]. Drivers are responsible for keeping themselves safe and ensuring the safety of every road user. This sense of responsibility has been forgotten, especially with the evolution of technology, and driver inattention still resulting in several deaths, injured people, and strong economic impacts every year [2].

Despite the fact that extensive research on driving distraction exists, this kind of driver behavior still concerns policy makers, leading to the inclusion of this issue as a main intervention area towards Vision Zero 2021–2030 called “preventing driving whilst distracted” [3]. Moreover, with vehicles' technological evolution, the propensity to engage in secondary tasks is increasing [4,5]. In addition, as fully autonomous vehicles will not be available overnight, the shared control of dynamic driving between human and machine is the main challenge for the advancement of vehicle technology in a context of increasing automation [6,7]; partial and conditional automation levels [8] still require the driver to be prepared to safely regain manual control in every situation, which is proved to be impaired by distraction [9–11].

In this sense, this study was aimed at exploring the influence of distractive tasks on driver behavior using a driver simulator. A within-subjects approach was followed,

in which each participant experienced the same scenario, being asked to engage and disengage from two different secondary tasks at the same points. The selected secondary tasks were to record a video with a smartphone and to look for an object in a backpack. To the best of the authors' knowledge, both kinds of task have not yet been studied in the literature. Looking for an object requiring the use of at least one hand is difficult to regulate and to enforce, despite the obvious risk. On the other hand, more recent behavior has emerged due to frequent handling of mobile phones [12,13] and using social networks such as Facebook, Instagram, and Snapchat [14]. The latter has led to sharing videos while driving and has become very common, especially among younger people. Moreover, a simple internet search can show real cases where a driver was recording a video and an accident occurred. Some of them have resulted in fatalities.

Two distinct non-driving tasks were analyzed and compared in this study guided by the following research questions:

- Does the fact that they are doing a secondary task have an effect on their ability to drive? Is the effect of both tasks similar?
- What are the drivers' attributes and habits that influence the ability to drive while distracted?
- What are the drivers' attributes and habits that influence the perceived workload when performing non-driving tasks? How distinct is the perceived workload between both tasks?

Guided by the research questions, experiments were conducted and novel full research, which includes several and relevant aspects of complex distraction behavior, was developed applying different statistical analyses. To do that, proxy variables were considered to represent distraction, and questionnaires were used to collect data about drivers' attributes, habits, and workload perception. Consequently, this study contributes to distracted driving knowledge, filling in gaps found in the literature and pursuing the orientations of the next decade of Vision Zero. The study's outcomes will also guide future studies, help to improve technologies to warn and help drivers, and sensitize society about a problematic topic that is completely preventable.

This document comprises a background section, showing results from previous studies and reports and explaining some of the decisions of the experimental design. The experimental section, Section 3, describes all the experimental conditions, procedures, and the data acquisition. Section 4 describes each methodological approach and statistical analysis, and Section 5 the respective results of these analyses. In Section 6, the results are discussed, and finally, in Section 7 the final remarks and limitations are provided.

2. Background

Epidemiological research showed that about 5% to 25% of car crashes are caused by driver distraction [3]. These numbers are even more worrying concerning professional truck drivers, where a much higher estimate, around 70%, has been found. Statistics from the National Highway Traffic Safety Administration (NHTSA) [15] revealed that motor vehicle crashes caused 37,133 deaths in the USA in 2017, where 3166, or 8.5 percent of the total fatalities, occurred in distraction-related crashes. It is important to bear in mind that distraction is not only dangerous for the drivers and car passengers, but for every road user, and that 599 of the deaths reported for distraction-related crashes were of non-occupants (pedestrians, cyclists, and others). Crashes do not involve only deaths, but also a large number of people are injured by distracted driving, some of them affected with permanent disabilities. To illustrate this, just in 2015, in the USA, 391,000 people were injured in distraction-affected crashes (16% of the total injuries) [2].

Distraction can be defined as the "diversion of attention away from activities critical for safe driving toward a competing activity, which may result in insufficient or no attention to activities critical for safe driving" [16]. The sources of distraction can be multiple and diverse. There are four typical groups into which they can be divided: visual, auditory, physical/biomechanical, or cognitive [3]. Indeed, a type of distraction usually does not

act in an isolated form. For instance, by receiving and replying to a text message, the four types can be combined: The notification sound induces an auditory distraction; reading and writing involves visual distraction; to write, at least one hand moves out of the steering wheel (biomechanical distraction); and finally, cognitive distraction is required to read and formulate an answer. Moreover, the distraction can also arise from outside the vehicle. Thus, 7% of fatalities caused by distracted drivers originate from people, objects, or events going on outside the car [17]. Distraction is more complex than it seems and, although the sources may be different, all of them can have adverse effects, including a degraded driving performance and increased exposure to risky situations.

At present, distraction at the wheel is a multidimensional concern affecting drivers across all age groups. Distraction is responsible for more than 58% of teen crashes, and these crashes represent the number one cause claiming teens' lives in the USA [17]. Young adults have been the largest age group who reported being distracted while driving. Emerging technologies, which are mainly used by teenagers and younger adults, or simply the fact that older people have a higher sense of responsibility, can be a justification for this fact. A report from the NHTSA [18] showed that age groups below 30 years old have the largest percentage of drivers who were distracted and who were using cell phones at the moment when a fatal crash occurred. Notwithstanding, older drivers show to have problematic reactions while responding to sudden critical events, especially when these occur in a complex environment or situation [19]. To illustrate the approach, Karthaus et al. [20] conducted driving simulator experiments and concluded that when facing a complex secondary task, reaction times increased especially in the youngest and oldest groups. The authors explain that these age groups seem to be particularly vulnerable to visual distraction when occurring in parallel to a critical event and comprise conflicting information or responses.

Cell phone usage remains the most common subject of study concerning driving distraction. Currently, almost everyone has a smartphone and its negative effects on driving safety resulted in legislation in many countries around the world. Despite knowing that it is dangerous (and even illegal in some countries) to handle a phone while driving, some studies have shown that many drivers are willing to read, and in many cases respond to text messages while driving [12,13]. However, the problem of texting and engaging in phone conversations was just the beginning of a wide range of distractive activities that a mobile phone can provide. At the first stage, mobile phones were mainly used to have a conversation (hand-held or hands-free) or to text. However, with the rapid technology development, online services, and social networks, using a smartphone is much more than making calls and exchanging text messages. Recent research made by McNabb and Gray [14] studied the impact of four smartphone tasks on driving—text messaging, reading Facebook posts, exchanging photos via Snapchat and viewing updates on Instagram—and found that the distinct uses had distinct effects. Through a simple app, you can do a considerable number of tasks such as reading the news, checking the weather forecast, paying bills, or seeing live videos. Furthermore, users of Instagram, Facebook, Snapchat, or other similar apps have surely noticed that recording videos while driving (directly or posting later) has become a trend. From another point of view, existing studies related to distracted driving mostly addressed driver interaction with technological devices [12–14]. It is common for drivers to perform non-technological tasks (e.g., taking off their coat, eating, drinking, getting out a card for parking, finding money for tolls, looking for something in their wallet), and often even doing these things at high speeds. Therefore, this research asks drivers to record a video and to look for an object in a bag, which are common real-world situations with impacts on safe driving that have not been analyzed in previous studies.

Driving simulators are typical tools to study dangerous states while driving, which is the case of distraction. For ethical reasons, to ensure safety, to allow the control of experimental conditions and for an easier driver monitoring and data collection, this research is supported by simulated driving experiments. In each experiment, both secondary tasks

were introduced. The video had to be recorded using the participant's personal mobile phone, and the object to find in a backpack placed on the passenger's seat was another mobile phone. To evaluate distraction, it is usual to measure its effects on driver behavior and accident risk; Papantoniou et al. [21] identified the following parameters to be used in driver distraction detection and effects: (i) reaction times or stimulus detection, (ii) accident risk, collisions or gap acceptance, (iii) eye movements, (iv) lateral and longitudinal control, and (v) workload or subjective measures.

It is proved that distraction, which decreases drivers' awareness, delays responses to critical situations while driving. Thus, drivers' actions or reaction times under unexpected events are suitable parameters to be analyzed and compared for distinct conditions. For instance, Haque and Washington [22] compared the braking profiles of young drivers for three different situations (hand-held mobile phone conversations, hands-free mobile conversations, and without distraction) and found significant differences among the results. The aggressiveness on braking was higher for distracted drivers, leading to a greater likelihood of rear-end collisions, and for holders of a provisional driving license, which seemed to be more affected by distraction. In the same vein, Choudhary and Velaga [23] studied the reaction times of a hundred drivers for two types of hazardous events and four mobile phone distractive tasks. Results from both events showed that the reaction times increased with the following order: simple conversation, complex conversation, simple texting, and complex texting. Henceforth, there are no doubts that reaction time is a variable with a great potential that has enabled several studies about driver distraction.

In this study, driver reactions to an unexpected event were evaluated for distracted and normal states. Experiments were conducted to analyze the influence of participants' attributes and the distractive activities on their response, which was measured by the deceleration reaction time and type of reaction (deceleration and/or breaking), based on a parametric survival model and a logit model, respectively. To understand the effects of drivers' characteristics, as well as the two distractive activities on the vision field of the driver, the driver was monitored with an eye-tracking system, and the percentage of eyes-off-road was modeled by applying a generalized linear model. Moreover, a subjective questionnaire, the NASA-Task Load Index (NASA-TLX) [24], was introduced to analyze the drivers' feelings regarding each secondary task separately. Overall, the study adds new insights into the distraction research by comparing two unstudied secondary tasks and by providing a comprehensive statistical analysis.

3. Experimental Session

3.1. Participants

The participants in the driving simulator experiments consisted of a convenience sample of 50 drivers with a valid driver's license. In total, 60% were male with a mean age of 35.9 ± 17.1 years. Female participants corresponded to 40% of the sample, with a mean age of 38.5 ± 16.35 years. The age range of the total sample was from 18 to 69 years old (mean of 36.9 ± 16.6). The sample selection included healthy participants without disabilities or other relevant driving impairment conditions. A total of 42% of the sample was wearing eyeglasses or contact lenses; however, it was verified that this did not interfere with the eye tracking calibration and measuring processes. The average body mass index was 24.0 ± 3.9 , showing no cases of abnormal low weight or strong obesity.

The recruitment process was done by e-mailing the students and workers of the University of Porto, and by spreading the initiative orally. There was a concern in achieving a sample with participants from different age groups and evenly divided by gender. It is important to note that this sample is not intended to represent the general population, or a specific group of population, but to provide information and allow comparisons between groups of subjects with different characteristics and habits. Thus, the main effort made to obtain the sample was focused on ensuring a sufficient number of participants, in accordance with what was observed in similar studies [14,25,26].

3.2. Apparatus and Simulation Scenarios

Experiments were conducted between June and August of 2019, in the driving simulator DriS of the Faculty of Engineering at the University of Porto (FEUP). DriS is a full-scale light vehicle fixed-base driving simulator completely developed by the FEUP's members and partners (Figure 1a), which can be modified and customized according to the objectives of different studies. In this study, the vehicle was used in a manual driving mode to create a more demanding situation. Moreover, the FOVIO[®] eye-tracking system was installed inside the driving simulator to record eye features. The device was placed behind the steering wheel, without interfering with the drivers' view.

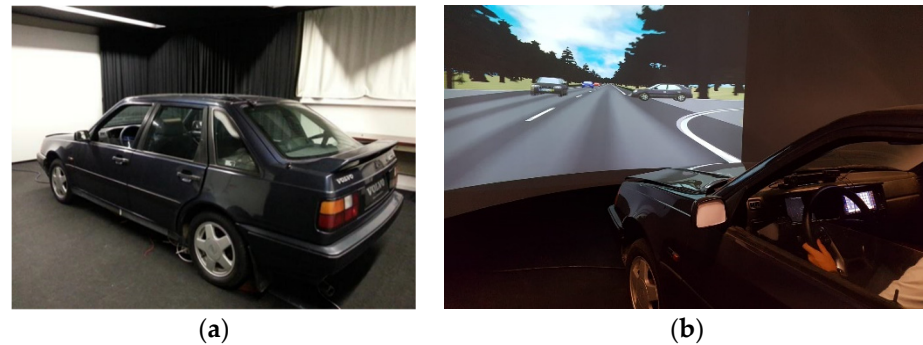


Figure 1. (a) Driving simulator DriS; (b) experimental scenario.

Before starting the experiment, participants performed a training session, driving the simulator until they told the researcher that they felt adapted to the driving and were able to control the vehicle properly (lateral stabilization and appropriate sensation of velocity by connecting the scenario movement to the vehicle panel). The drivers were instructed to drive safely according to the traffic rules, having the most realistic behavior as possible. This session varied from 5 to 10 min, depending on the driver's adaptation to the driving simulator. Participants who suffered from simulator sickness did not proceed to the driving session. After the training, participants were ready to start the experiment.

Then, all the participants drove the same scenario, consisting of a suburban road with moderate traffic. The posted speed limit was set at 60 km/h. The road was a flat (with no variation in the *z*-axis) two-lane highway, featuring 3.75 m wide lanes, large curves, and long straight segments. The simulated traffic circulated in both directions. To guarantee similar conditions for all participants, the traffic speed was set according to the ego vehicle's speed, making it impossible to overtake (free-flow conditions). The route comprised six intersections with secondary roads, with the third, fourth, and sixth intersections featuring a hazard situation. This unexpected event consisted of a fast vehicle approaching from the right that causes the idea that it will not stop, but it was immobilized at the limit of the ego vehicle's lane. The unexpected behavior of the other vehicle, which should yield to the ego vehicle according to the presence of a stop sign, encourages the participant to take action by releasing the acceleration pedal, pressing the brake pedal, or turning the steering wheel. The events were similar in the three intersections to make it possible to evaluate and compare the participants' reactions in three different situations: engaged in each one of the secondary tasks and driving in normal conditions. The other three intersections were free from any interaction, as the virtual vehicles circulating on the secondary roads were stationary or far from the ego vehicle.

The aim of the research was to evaluate the effects of specific and common secondary tasks on driving, rather than spontaneous distraction. The secondary tasks that were the object of this study were to record a video with a smartphone and to look for a mobile phone in a backpack. Each task was introduced twice on straight road segments: under normal driving conditions and in situations corresponding to an unexpected/dangerous event. The tasks were mandatory and started and finished with an oral instruction through the vehicle's sound system. The task engagement and disengagement requests were deployed

250 m before and after an intersection, respectively. Thus, each secondary task occurred over a distance of 500 m centered at the intersections.

The videos were recorded by the participants using their personal mobile phones. This task had a duration of approximately 30 s, depending on the ego vehicle's speed. It was deployed next to two intersections (intersections 2 and 3), whereas in the second one, there was an unexpected event. The participants' personal mobile phones were placed on the passenger seat while not in use. It was observed that all videos were recorded using the right hand, despite the fact that no specific conditions were imposed regarding the accomplishment of this task. Participants were free to film the environment or themselves. In the case of the task of searching for a phone in the backpack, this backpack was prepared by the research team and placed on the floor in front of the passenger seat. The backpack contained several items (e.g., school material, a bottle of water, and a wallet), but there was no mobile phone inside it. In this way, the research team was able to control the duration of the task by guaranteeing that no one could find the object before the point where the task should end, i.e., 250 m after an intersection. This task was engaged two times, without any hazard (intersection 1) and with an unexpected event (intersection 6).

The scheme of the driving session is shown in Figure 2. The sections represented in green are segments formed by curves and straight segments, while the segments around the intersections (in yellow) do not have curves. As can be seen, the first time each non-driving related task is performed, there is no critical event to ensure that, in the second time, with an unexpected event, the distractive task is performed as naturally as possible. The order of the events was chosen to minimize learning effects. Moreover, the type of the approaching vehicles, the road environment, and the traffic flow changed across the events.

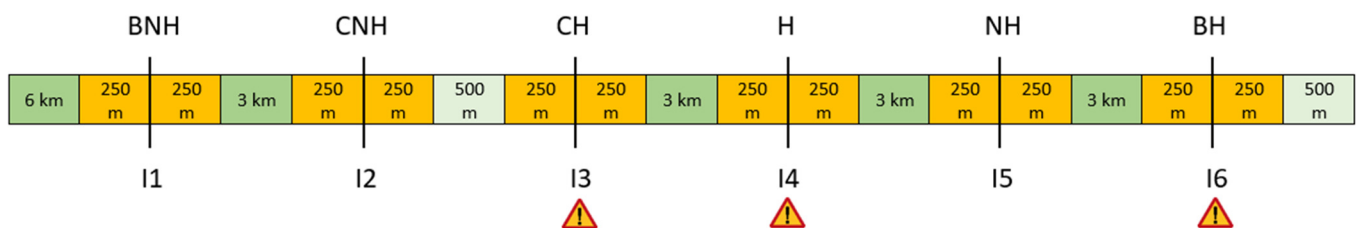


Figure 2. Experimental scheme: B—backpack task; C—mobile phone recording task; I—intersection; H—hazard; NH—no hazard.

3.3. Data Collection

The data analyzed in the present study are provided by three different sources: (1) questionnaires with personal information and habits, and results from the NASA-TLX; (2) driving dynamic parameters; and (3) data extracted from the eye-tracking system.

Before the driving experiment, each participant was asked to fill a questionnaire about generic personal information and driving habits. This questionnaire obtained information about age, gender, body mass index (BMI), and hours of sleep on the night before the experiment. Furthermore, participants were asked to rate (in four levels, from “never” to “frequently”) how often they usually engage in the listed secondary tasks while driving. The rating card shown to the participants is depicted in Figure 3.

This questionnaire was included to understand if there was any relationship between the habits of performing secondary tasks during real-world driving and the driver's behavior in the simulated session. According to Choudhary and Velaga [23], participants who have the habit of performing secondary tasks in the real world should perform slightly better when taking similar tasks in simulated environment. The nine tasks mentioned in Figure 3 were selected according to the typical activities that involve handling a mobile phone, as referred to in Young et al. [27].

How often do you engage in the next activities while driving?

	Never	Rarely	Sometimes	Frequently
Cell phone conversation hands-free				
Cell phone conversation handheld				
Read text messages/notifications				
Send text messages				
Navigate on social networks				
Post on social networks				
Take pictures				
Make videos				
Play games				

Figure 3. General information questionnaire to capture participants' habits while driving.

In turn, at the end of the experimental session, participants filled out the NASA-TLX questionnaire separately for the two secondary tasks to assess the levels of workload associated with these tasks. The workload can be defined as “a term that represents the cost of accomplishing mission requirements for the human operator” [28]. Having this in mind, and considering that driver attributes influence driving performance [29,30], the effects of secondary task engagement could be different among participants with distinct characteristics and habits. The NASA-TLX allows participants to self-report their behavior when combining the driving activity with other tasks. It consists of six questions or groups of questions representing mental, physical and temporal demands, frustration, effort, and performance. These aspects are rated on a twenty-grade scale that can be converted to a percentage. The questionnaire was used in a simplified form, without the original weighting process and just by analyzing the ratings instead of calculating a single overall workload score. These simplifications are common among the literature [28], enabling to carry out a practical and simple analysis of specific situations in order to better explain the overall results of a study. More information about this questionnaire can be found on the NASA-TLX manual [24].

The DriS collects dynamic driving parameters with an automatic acquisition system. The software records information concerning the ego vehicle's trajectory, speed, steering wheel angle, and accelerator and brake pedal pressure (in percentage). A first analysis of the several simulator parameters was conducted in order to verify those that may be relevant to the study, particularly regarding their variation in the influence area of the critical event intersections. In the end, the lane position and the steering wheel angle, which are related to each other, were excluded from the analysis because only in 10% of the events was there a variation that was considered significant compared with the 6° steering wheel angle used in previous studies [31,32]. In this particular study, driving dynamic parameters are mainly used to analyze participants' reactions when facing an unexpected event. Two types of reactions were identified: deceleration only (in 24% of cases) or breaking right after deceleration (in 76% of cases). Because deceleration was always the first observed reaction, the reaction time was measured as the time starting at a reference point until the driver first responded to the event by releasing the accelerator. It is worth mentioning that some events did not result in a reaction, not even a soft deceleration. However, this only occurred in 6% of cases, which were excluded from the analysis. Following the work done by Charlton [33], we assumed as reference a point located 250 m before each hazard, i.e., before the center of the intersection. Starting from this point, the time until an abrupt pedal accelerator release was calculated and entitled as a reaction time.

The eye-tracking system is a combination of hardware and software that enables the user to collect a large set of variables related to the point-of-gaze, fixations, blinks, pupil diameter, etc. The present study uses eye features to evaluate the time of “eyes-off-road”.

Thus, and assuming that the experimental conditions are not susceptible to inducing sleep-related eyelid closures, the periods during which the eyes are not detected were assumed as blinks or as a consequence of distraction. Since an eye blink is insignificant when compared to the total time with the eyes off the road, the variable “eyes-off-road” was calculated by dividing the number of frames in which the pupil diameter was zero by the total number of frames in a defined interval. Because the secondary tasks start 250 m before an intersection and finish 250 m after the same intersection, the entire 500 m segment was considered as the interval for this specific analysis.

4. Materials and Methods

The analyses applied in this study have several perspectives. Prior to modeling the reactions, a first analysis of the questionnaires, including the NASA-TLX, was carried out, applying correlation tests. Furthermore, a *t*-test or a one-way ANOVA was performed, depending on the number of levels chosen for each independent variable. The results of NASA-TLX and the participants’ personal information allowed establishing some explanatory relationships between variables.

The modeling analyses aim to explore the relationships between drivers’ attributes and habits with three proxy variables of distraction, comparing the two distractive activities and the baseline conditions (no task). The proxy variables are the percentage of time with the eyes off the road, the type of reaction (deceleration and/or breaking), and the reaction time. Statistical models were selected and applied according to the nature of each variable.

4.1. Eyes-off-Road

Regarding the ocular measure, the dependent variable corresponds to the percentage of time with the eyes off the road. It was observed that a large number of observations were corrupted, probably due to flaws in the measuring equipment. Therefore, only 102 out of 150 observations (50 participants observed in 3 tasks) were considered in this analysis.

Since the percentage values were all positive and continuous, a generalized linear model (GLM) with a log link function and gamma distribution was used. In this case, a logarithmic relationship is established:

$$\ln(E(y | x)) = x\beta \text{ or } E(y | x) = \exp(x\beta) = \mu(x; \beta) \quad (1)$$

where $E(y | x)$ is the expected outcome for a set of independent variables x , β is the vector of coefficients, and μ is the mean. In GLM, one specifies a mean and variance function for the observed raw-scale variable y , conditional on x with the general structure:

$$\text{var}(y | x) = \sigma^2 v(x) \quad (2)$$

where, in the case of a gamma structure, $v(y | x) = k(\mu(x))^2$, and $k > 0$; that is, the standard deviation σ is proportional to the mean $\mu(x; \beta)$. The coefficients were estimated using the maximum likelihood estimation method in all models. Considering that three variable measures were collected for each participant, the eyes-off-road values might be correlated at individual levels. To account for the unobserved heterogeneity, a random parameter approach was assumed. The intercept α was tested as random and, in this case, the estimated parameter is represented by $\alpha_i = \alpha + \varphi_i$, where φ_i is a normally distributed term with mean 0 and variance σ^2 . Random parameters are used when the standard deviation of parameter density is statistically significant [34]. However, the standard deviation of the parameter density of the intercept was not statistically significant. This may be due to the fact that several observations were excluded because no value was measured, eventually reducing the unobserved heterogeneity.

4.2. Type of Reaction

Two main reactions were assumed by the participant when facing a critical event: deceleration or braking right after deceleration. In order to analyze the type of reaction,

which can take two forms, a binary model was developed to study the factors leading to the participant's decision. Most of the participants resorted to the use of the brake pedal (76%); thus, this category was taken as a reference (category 0). Consequently, the binary variable assumes the value $Y = 1$ if the participants only decelerate and $Y = 0$ if they also use the brake pedal. The probabilities associated with the model category, which are gathered in a vector x to define the decision between the categories, are represented as follows:

$$\begin{aligned}\text{Prob}(Y = 1|x) &= F(x, \beta) \\ \text{Prob}(Y = 0|x) &= 1 - F(x, \beta)\end{aligned}\quad (3)$$

where Y represents the category of the dependent variable (1 if only decelerates or 0 otherwise), x is the vector of independent variables, and β is the vector of parameters to be estimated. β reflects the impact on the probability of changes in x . A logistic distribution (logit model) was chosen for $F(x, \beta)$ because it produced a small improvement in the goodness-of-fit measures. The logit model is expressed as follows:

$$\text{Prob}(Y = 1|x) = \frac{e^{\beta x}}{1 + e^{\beta x}} = \Lambda(\beta x)\quad (4)$$

where the function $\Lambda(\cdot)$ is a commonly used notation for the standard logistic distribution function. Additionally, as in the previous model, a random parameter approach was assumed to capture the heterogeneity across observations. The intercept was tested as random with a normal distribution, and in this case, it was revealed to be statistically significant.

4.3. Reaction Time

The reaction time (expressed in seconds) was modeled as the duration variable using parametric survival analysis [22,23]. In the survival analysis, the duration variable is the time elapsed until an event occurs, and it is a continuous random variable T with a continuous probability distribution $f(t)$, where t is a realization of T . The cumulative probability is:

$$F(t) = \int_0^t f(s)ds = \text{Prob}(T \leq t)\quad (5)$$

The probability that the duration variable (i.e., the reaction time) is at least of length t is given by the survival function:

$$S(t) = 1 - F(t) = \text{Prob}(T \geq t)\quad (6)$$

which leads to the conditional hazard rate function:

$$h(t) = \frac{f(t)}{[1 - F(t)]}\quad (7)$$

In order to include the effects of the independent variables, the parametric survival analysis was applied considering the accelerated failure time (AFT) model, as previously used by Haque and Washington [22] and Choudhary and Velaga [23]. In this model, the effects of the independent variables rescale the duration variable directly in the baseline survival function. Following the previous studies of [22,23], the Weibull distribution was selected because it can handle monotonic increasing and decreasing hazard rates. In this kind of analysis, the hazard rate is expected to be monotonously increasing, i.e., the probability of having a reaction increases over time. The hazard function $\lambda(t)$ is as follows [35]:

$$\lambda p(\lambda t)^{p-1}\quad (8)$$

where λ and p are two parameters known as the location and scale parameter, respectively. The survival function $S(t)$ is as follows [35]:

$$S(t) = \exp(-\lambda t^p)\quad (9)$$

To incorporate Weibull distribution in the AFT model, the regression equation for T is given by:

$$\log T = \beta_0 + \beta X + \sigma \varepsilon \quad (10)$$

where σ is assumed to follow some extreme value function such that T leads to the Weibull distribution. In this model, the independence is assumed between observations. However, considering that three repeated measures of reaction time were collected for each participant, the reaction time values might be correlated at individual levels. To account for the unobserved heterogeneity $f(v_i)$, a gamma distribution with mean 1 and a variance $\theta = 1/k$ was assumed for v [35].

These three mentioned models were developed using the econometric software Limdep 9.0 (Econometric Software, Inc., Plainview, NY, USA).

4.4. Data Description

The dependent variables in the three models are summarized in Table 1.

Table 1. Description of the dependent variables.

Model	Dependent Variable	
	Variable	Statistical Description
Lognormal model (GLM)	Eyes-off-road	Mean = 0.34 Standard deviation = 0.27 Minimum = 0.01 Maximum = 1 (Number of observations = 102)
Binary logit model	Reaction type (0/1)	Braking reaction (category 0): 76% Deceleration reaction (category 1): 24% (Number of observations = 141)
Parametric survival model (Weibull with heterogeneity)	Reaction time (s)	Mean = 5.5 s Standard deviation = 2.2 s Minimum = 2.4 s Maximum = 10.8 s (Number of observations = 141)

Regarding the independent variables, and in addition to the dummy variables that identify the type of distractive task (baseline, video, or backpack), the variables included in the three models can be divided into three main groups: participant characteristics, dynamic driving parameters, and habits of secondary task engagement. Table 2 describes the independent variables included in the models that were shown to be statistically significant in at least one model. The instant speed is measured at the moment when the accelerator pedal is released. Some variables were categorized to simplify the interpretation of results. Nevertheless, when the created categories did not show statistical significance in the models, revealing that these groups do not represent the sample, the continuous variable was used. Age groups were divided according to Anund et al. [36]. Regarding the BMI, participants were classified as “less than normal” (BMI < 20), “normal” (BMI between 20 and 25), or “above normal” (BMI > 25). This classification is common in medical research [37]. Moreover, a 7 h sleeping time was defined as a threshold to distinguish between “insufficient” and “sufficient” sleeping, according to Tefft [38]. Finally, drivers’ habits, collected according to Figure 3, were merged into two groups “never/rarely” and “sometimes/frequently”, since there was not enough representability by using the four levels. The sample characterization by groups, and according to the responses to the general information questionnaire, is shown in Table 2.

Table 2. Description of independent variables.

Variable Type	Continuous Variables	Mean	Std. Dev.	
Dynamic driving	Instant speed (km/h)	71.7	12.7	
Participant characteristics	Age	36.9	16.6	
	BMI	24.01	3.90	
	Hours slept	6.96	1.39	
Variable Type	Categorical Variables	Groups	Number of Participants	
Participant characteristics	Age	Young (≤ 25 years old)	17	
		Adults (26 to 54 years old))	21	
		Older (≥ 55 years old)	12	
	Gender	Male	30	
		Female	20	
	BMI	Less than normal	9	
		Normal	24	
		Above normal	17	
	Hours slept	Sufficient (≥ 7 h)	31	
		Insufficient (< 7 h)	19	
	Habits	Hands-free phone conversation	Never/rarely	22
			Sometimes/frequently	28
Hand-held phone conversation		Never/rarely	35	
		Sometimes/frequently	15	
Read text messages/notifications		Never/rarely	30	
		Sometimes/frequently	20	
Send text messages		Never/rarely	41	
		Sometimes/frequently	9	
Navigate social networks		Never/rarely	46	
		Sometimes/frequently	4	
Post on social networks		Never/rarely	49	
		Sometimes/frequently	1	
Take pictures	Never/rarely	46		
	Sometimes/frequently	4		
Record videos	Never/rarely	47		
	Sometimes/ frequently	3		
Play a game	Never/rarely	49		
	Sometimes/frequently	1		

5. Results

In this section, the results from the statistical analyses are provided. For the ANOVA, it was assumed that the NASA-TLX results would be affected by the driver-related parameters. Thus, drivers' personal aspects and habits, presented as categorical variables in Table 2, were introduced as independent variables. After confirming that all data assumed a normal distribution, a one-way ANOVA was applied for the categorical variables with more than two levels, while the binary variables were analyzed through a *t*-test. The results

are summarized in Table 3. The variables characterized in Table 2 that are not included in Table 3 did not reveal statistical significance in the analysis.

Table 3. Results of the ANOVA for the independent variables related with NASA-TLX.

Independent Variable	Main Conclusions	Results
Age	Older participants rated higher scores of mental and physical demands and frustration for both secondary tasks Young adults rated a much higher physical demand on the backpack task than on the video task (M = 49.87, SD = 29.99 and M = 22.90, SD = 21.46, respectively)	Age × mental demand × backpack F(2, 47) = 3.424; $p \leq 0.05$ Age × mental demand × video F(2, 47) = 15.214; $p \leq 0.05$ Age × physical demand × backpack F(2, 47) = 6.801; $p \leq 0.05$ Age × physical demand × video F(2, 47) = 23.79; $p \leq 0.05$ Age × frustration × backpack F(2, 46) = 3.507; $p \leq 0.05$ Age × frustration × video F(2, 46) = 11.272; $p \leq 0.05$
Gender	Men showed a higher temporal demand for both tasks (M = 64.42, SD = 23.88 for men, and M = 42.75, SD = 28.83 for women) The temporal demand, for both genders, had higher scores for the backpack task	Gender × temporal demand × backpack T(48) = 2.892; $p \leq 0.05$ Gender × temporal demand × video T(48) = 2.591; $p \leq 0.05$
Hands-free phone conversation Hand-held phone conversation Read text messages/notifications Send text messages Navigate social networks	Mental and/or physical demands resulted in significant differences among the groups for those who answered with higher or lower frequencies In all cases, those who reported never engaging in these tasks while driving also reported higher levels of demand For all the results, the demand levels attributed to the backpack task were higher than those attributed to the video task	Hands-free phone conversation × mental demand × backpack F(3, 46) = 3.886; $p \leq 0.05$ Hands-free phone conversation × physical demand × backpack F(3, 46) = 5.305; $p \leq 0.05$ Hands-free phone conversation × physical demand × video F(3, 46) = 3.118; $p \leq 0.05$ Hand-held phone conversation × mental demand × backpack F(3, 46) = 3.099; $p \leq 0.05$ Hand-held phone conversation × physical demand × video F(3, 46) = 3.108; $p \leq 0.05$ Read text messages/notifications × physical demand × backpack F(3, 46) = 4.504; $p \leq 0.05$ Read text messages/notifications × physical demand × video F(3, 46) = 9.597; $p \leq 0.05$ Send text messages × mental demand × backpack F(3, 46) = 3.138; $p \leq 0.05$ Send text messages × physical demand × backpack F(3, 46) = 3.477; $p \leq 0.05$ Send text messages × physical demand × video F(3, 46) = 8.698; $p \leq 0.05$ Navigate social networks × mental demand × backpack F(3, 46) = 3.689; $p \leq 0.05$ Navigate social networks × mental demand × video F(3, 46) = 3.411; $p \leq 0.05$

Table 4 presents the estimation of the Lognormal Model for the “eyes-off-road” variable. As can be concluded in Table 4, only the age and the type of distraction showed statistical significance. The results demonstrate that young adults drive more time without looking at the road than the other age groups. In turn, the group formed by participants over 55 years old show low values for the variable “eyes-off-road” than the adults between 26 and 54 years old. Furthermore, both secondary tasks induced a strong deviation of the look into the distractive activity. Thus, the percentage of time not looking at the road

increased when drivers were distracted, especially when they were searching for the mobile phone in the backpack.

Table 4. Results of the Lognormal Model for “eyes-off-road”.

Percentage of “Eyes-off-Road”	Coefficient	Standard Error	Prob. $ z > Z$
Intercept	0.3515	0.0671	0.0000
26 to 54 years old	−0.1559	0.0713	0.0289
55 years old or more	−0.2533	0.0719	0.0004
Video	0.1064	0.0579	0.0659
Backpack	0.3625	0.1091	0.0009
Sigma (variance for lognormal distribution)	1.1055	0.1171	0.0000

Notes: Log likelihood = −132.1333; AIC = 276.3; AIC/N = 2.708; the variables that were not statistically significant at the 90% level were removed from the analysis.

Table 5 represents the parameter estimations of the Binary Logit Model for the variable “type of reaction” (only deceleration or deceleration and braking).

Table 5. Results of the Binary Logit Model with random effects for the type of reaction.

Reaction Type	Coefficient	Standard Error	Prob. $ z > Z$
Instant speed	−0.1095	0.0389	0.0048
Video	3.1865	1.1051	0.0039
Backpack	−0.4942	0.8550	0.5633
26 to 54 years old	−2.5681	0.9277	0.0056
55 years old or more	−6.3225	1.8332	0.0006
Take pictures: sometimes/frequently	3.8497	1.3102	0.0033
Intercept (mean)	4.89310	2.47319	0.0479
Intercept (standard deviation)	6.9062	1.75413	0.0001

Notes: Log likelihood = −64.9936; McFadden Pseudo R-squared = 0.0091; AIC = 146.0; AIC/N = 1.035; the variables that were not statistically significant at the 90% level were removed from the analysis, except the backpack category because it is the focus of the study and the common variable between the three models.

The results from the application of the Binary Logit Model show significant differences among the tendency to adopt each reaction type, where braking represents 0 and decelerating represents 1. For the instant speed, the negative signal of the coefficient shows that, when the vehicle has a higher speed at the moment of reacting, the tendency to brake is higher. When analyzing the type of reaction regarding the distractive task, it can be noticed that the video task leads to an increased probability of deceleration while the backpack task tends to induce a braking reaction. Furthermore, age groups had relevant effects on this tendency; the older group is more prone to brake than the younger and middle-aged groups. Finally, participants who reported having the habit of taking pictures while driving had a higher tendency of only deaccelerating instead of decelerating and braking.

Finally, the parameter estimations of the Parametric Survival Model (Weibull distribution with heterogeneity) regarding the reaction times are presented in Table 6.

Table 6. Results of the Parametric Survival Model for the reaction time.

Reaction Time	Coefficient	Standard Error	Prob. $ z > Z$
Intercept	2.0355	0.0603	0.0000
Men	−0.0334	0.0169	0.0475
BMI *	0.0069	0.0017	0.0000
Hours of sleep *	−0.0358	0.0166	0.0311
Video	−0.4006	0.0169	0.0000
Backpack	0.4828	0.0160	0.0000
Instant speed	−0.0076	0.0005	0.0000
Navigate social networks: sometimes/frequently	−0.0618	0.0236	0.0087
Theta **	1.1914	0.3532	0.0007
p **	24.8938	3.6441	n/a

Notes: Log likelihood = −161.8003; AIC = −303.6; AIC/N = −2.153; * continuous variable; the variables that were not statistically significant at the 90% level were removed from the analysis; ** ancillary parameters for survival.

The results show significant differences for several aspects directly related to the driver, driving dynamics, and driving conditions. In this case, there were significant differences for the independent variables associated with gender, BMI, hours of sleep, and the habit of browsing social networks while driving. As can be seen from the results, women showed longer reaction times than men. Likewise, participants with a higher BMI tended to react slower. An unexpected outcome was the hours of sleep the night before the driving, with the participants who slept more hours registering longer reaction times. The habit of navigating social networks while driving was associated with participants with shorter reaction times. Regarding instant speed, results showed that higher speeds led to quicker responses. Finally, the two secondary tasks were reflected in distinct reactions compared to the baseline. When the participant was looking for a mobile phone in the backpack, the reaction times increased. Curiously, and in contrast with the authors' expectations, the task of recording a video with a smartphone induced a faster reaction than in the baseline (no distraction). The results exposed in this section are better explored in the "Discussion" section for all the analyses.

6. Discussion

Some of the obtained results were in line with previous studies, which were focused on other types of distractive tasks, and were consistent with the authors' expectations. Even so, some less expected results were obtained. Thus, in the next subsections, the results are discussed for the parameters' estimations obtained for the "eyes-off-road" variable, the reaction type, and the reaction times. Furthermore, results from the ANOVA are explored and associated with the overall outcomes.

6.1. Results from the Lognormal Model

For the analysis of the "eyes-off-road" variable used as a proxy for visual distraction, the group aged between 18 and 25 had a higher percentage of time without looking into the driving scenario, especially when comparing it with the participants with 55 years old or more. Younger people may feel more capable of reacting effectively; however, their behavior may be less safe as they spend much more time without looking at the road. This is reasonable because younger individuals tend to be more confident about their driving skills, evaluating themselves as having lower levels of workload when engaged in the secondary tasks. These results lead to the idea that the age effect is complex and can have diverse impacts on driving.

Furthermore, analyses were done regarding the type of distraction compared with the baseline situation (absence of task). As expected, both secondary tasks resulted in higher percentages of time without looking at the road. However, the video recording task is related to a lower percentage of time without looking at the road when compared to the backpack task. This fact may contribute to the lower reaction times associated with the

video task. It is important to have in mind that any secondary task will almost certainly decrease the time spent looking at the road, since the sources of distraction are usually combined and almost always include visual distraction. This induces an increased risk, and it only takes 3 s of distraction for a crash to occur [17]. It should be noted that, according to the overall analysis, the backpack task showed to have more impact on drivers' reactions.

6.2. Results from the Binary Logit Model

The application of the binary model to the type of reaction allowed understanding the way a driver reacts through a qualitative explanation/output. Thus, it was possible to identify the tendency of the driver to adopt a specific type of reaction, according to some personal aspects and driving conditions.

The dynamic driving parameter "instant speed" showed statistical significance, with a higher instant speed at the time of the first reaction tending to induce the driver to brake. This result has a logical justification because the higher the speed, the lower the time to judge and react. Thus, the driver may assume that braking is more effective to avoid a potential crash. Note that drivers' aggressiveness was not addressed in this research, which does not invalidate that aggressive braking is more common at higher speeds and might increase the likelihood of rear-end collisions [22].

The type of reaction was also affected by the nature of the task being performed by the driver at the moment. The results showed that the video task leads to more cases of deceleration, while the backpack task tends to induce a braking reaction. The latter is associated with a higher perceived risk and with a stronger reaction. These results are in line with the outcomes from the survival analysis and the reported workload from the NASA-TLX.

Moreover, age is an important factor that, most of the time, has a strong influence on driving behavior. This correlation was expected to be negative, which means that there is a higher tendency for the older people to brake and for the younger to decelerate only. Usually, aging produces psychophysiological changes that reduce drivers' ability, including the impairment of visual and auditory perception, and the deterioration of cognitive and motor abilities [39]. Furthermore, results from the NASA-TLX showed that the older group rated the frustration and the mental and physical demands higher for both secondary tasks. Ulak et al. [40] reported that "studies have verified that aging drivers are not very prone to taking risks in the traffic, and they tend to be less aggressive than younger drivers", which can be seen as a compensating behavior for the lack of agility. Thus, braking may result from a risk compensation attempt that reflects more caution, prevention, and sense of responsibility of the older group.

Finally, the habits while driving were correlated with the type of reaction, with significant differences being found for participants who had the habit of taking pictures while driving, which showed less tendency to brake. This denotes this type of drivers may be overconfident around their multitasking capabilities, having judged that the event was not hazardous enough to activate the brakes.

6.3. Results from the Parametric Survival Model

This analysis consisted of identifying the influence of drivers' personal characteristics, driving dynamics, and driving conditions on the measured reaction times, considering the release of the accelerator pedal as the first reaction.

The first aspects to discuss are those related to the drivers' characteristics. A recent study was carried out to assess the influence of gender on driving performance and concluded that the risk felt in both genders was similar. However, despite this similarity, behavior during braking was different and women started braking later, exerting greater pressure on the pedal, which can be explained by a poor assessment of the time and space available for braking [41]. Although in the present study, the pedal pressure was not evaluated, the reaction times are aligned in both studies. Nevertheless, the responses to the NASA-TLX can justify this. The question "How hurried or rushed was the pace of the

task?" had statistical significance concerning gender; men rated the temporal demand as higher than women, and this sense of urgency may lead men to adopt quicker reactions.

Regarding the BMI, the model results showed a positive correlation, which means that the time needed to react had higher values as the BMI increased. These results can be justified by some medical literature. Studies have shown that reaction times are associated with health and general cognitive abilities, with some authors using BMI as an indicator of obesity to study its influence on the time-to-react [42,43]. To illustrate this approach, Skurvydas et al. [42] studied the relationship between simple reaction time and BMI and concluded that the responses to a stimulus (moving a joystick as soon as possible when detecting a star appearing in the center of a monitor) was significantly slower for participants with higher BMI.

Unexpectedly, by correlating the hours of sleep with the reaction times, the results revealed that insufficient sleep reduced the reaction time. This outcome was in contrast with the authors' expectations since insufficient sleep or sleep deprivation is usually associated with impaired driving performance, and higher drowsiness states are associated with higher braking response times [30]. However, it should be noted that no information was collected regarding, for instance, the ingestion of medication or the emotional state, aspects that might interfere with sleep quality. The collected information about sleep quantity does not necessarily represent sleep quality [44], which highlights the lack of full information to interpret this specific parameter.

The analysis of habits while driving showed that both the task of recording a video and the habit of navigating social networks were significantly correlated with shorter reaction times. Multitasking habits may lead to an increased ability to perform secondary tasks while driving, especially for the video recording that implies using the driver's own smartphone. This result is in line with the ones previously obtained for the type of reaction, i.e., smartphone handling habits and the video recording are associated with decelerations only. Furthermore, this confirms the outcomes obtained by Haque and Washington [22], who found that drivers who reported using a mobile phone while driving frequently exhibited faster slowing times (i.e., approximately 12% smaller) in comparison with moderate frequent users. More recently, Choudhary and Velaga [23] also showed that participants who had the habit of receiving calls while driving had 19% smaller reaction times than participants who rarely use the mobile phone while driving. In the context of conditionally automated driving, Gold et al. [45] confirmed the benefits of at least certain tasks to improve drivers' performance during manual recovery by increasing the minimum time-to-collision in relation to the absence of secondary task. A possible explanation for the negative correlation between the video task and the reaction times can be an increasing caution when drivers know that they are in danger, implicit as a compensatory behavior [46,47]. Moreover, the habits were correlated with the drivers' reported workload levels. Mostly mental and physical demands were distinct between drivers who usually execute other tasks while driving and those who not. All responses resulted in lower levels of demand for those who more frequently engage in secondary tasks, revealing an adaptation and learning on how to deal with hazardous situations [48]. This cannot be understood as a motivation to increase the engagement in non-driving related tasks, but on the contrary, as an alert to the risks of diverting the attention from the road, especially when the driver is not familiar with the task.

In turn, searching for an object while driving is a common and almost daily task that drivers do not expect to be dangerous. However, looking for a mobile phone in the backpack was the task with the greater impairment of driving, and even the younger group rated a much higher physical demand on the backpack task than on the video task. In accordance, this task induced a strong increase in reaction times in comparison to the video recording and the no task (baseline) situations. Regarding the driver workload perception, results from the ANOVA showed that both genders rated higher temporal demands for the backpack task, which represents an increasing rush and possibly an increasing conflict

with the driving abilities. Moreover, the results from the NASA-TLX showed that this task induced higher levels of workload regardless of age, gender, and habits.

Shorter reaction times were associated with participants with higher instant speeds. Again, risk compensation should play a role in this outcome, with drivers reacting more quickly to reduce speed [46,47] and, consequently, stopping distance, in case the event is revealed to be critical and requires an emergency stop.

7. Limitations and Closing Remarks

This study shows that the impacts of distraction on driving, measured by the reaction times and nature, are considerable but complex and depend on drivers' physiological aspects, habits, and the type of engaged distraction. Statistical analyses were applied using diverse models, and it was observed that reaction times, which have been assumed as a safety proxy, were consistently related to gender, BMI, sleep patterns, speed, habits while driving, and type of distraction. No statistical significance was observed for the impacts of distinct age groups on reaction times. However, age was found to affect the decision of the driver on how to react, i.e., to decelerate only or to apply the brakes. In this case, the results showed that the older group is more prone to brake, eventually assuming a safer action due to some increased difficulties in evaluating the critical event. The hours of sleep in the night before resulted in an unexpected outcome, indicating that sleeping seven or more hours leads to higher reaction times. For this variable, a limitation can be pointed out, since the hours of sleep could not be representative of the sleep quality [44], and no other variables related to medication and emotional states were collected to characterize sleep quality. Furthermore, being a woman, having a higher BMI, and adopting lower speeds increased the time necessary to react after perceiving the danger. At higher speeds, drivers have a stronger tendency to brake, as expected, to guarantee a safe distance to the critical event.

Recording a video was shown to be less dangerous distractive task when compared with searching for an object in a backpack. In the case of reaction times, the values associated with video recording are even lower than the baseline situation of no task. Indeed, this task was found to be related with a higher probability of a deceleration only reaction. Moreover, compared to the backpack task, recording a video implies a low percentage of eyes-off-road. These results contradict the authors' expectations, since most research states that all types of phone-related tasks increase reaction times [49,50]. Nevertheless, a recent study analyzed the braking reaction times and headway time for text-based and image-based phone-related tasks, and the results showed no significance on the measured variables for the image-based tasks [14]. This suggests that interacting with image-based smartphone apps has different effects on driving performance than text-based apps; therefore, the results for this specific task should be interpreted with caution. The characteristics of the critical event may have influenced drivers' reactions and, although some differences have been added to the scenario, the three events were still similar, which may have led to a behavioral adaptation when the event was repeated [48]. On the other hand, this particular task may be underestimated compared to a real situation, because drivers were not worried about the quality of the video and may not dedicate as much effort to this task as they would do in a real situation.

Despite the previous findings, this distractive behavior may lead to unpredictable and unadjusted reactions in face of some critical or unexpected events, as has been increasingly confirmed by posts on social networks. By contrast, searching for a mobile phone in the backpack had greater impacts on all the dependent variables analyzed for all the models applied, proving to be a high-risk task. Thus, further research is needed on this topic, and efforts have to be made to minimize the effects of these tasks, whose dangerousness is often neglected by drivers. Legislation may not be a reliable countermeasure per se; however, increasing the consciousness of the drivers may result in increased caution when performing these tasks and/or preventing them from occurring.

Participants' characteristics and habits while driving were also studied, and the results showed that they have strong impacts on drivers' agility when performing the secondary tasks during the simulations. Even so, engaging in non-familiar tasks resulted in a greater impairment of driving performance, and consequently, a higher risk for road safety. The task workload perception was in line with the modeling results that have determined that the backpack task is more dangerous. In this sense, participants rated this task as much more demanding than the video recording task.

The aforementioned findings, especially the unexpected ones, should be better explored in future research. The presented results are representative of a small sample of 50 drivers and should therefore be interpreted with caution. The limitation of the sample size is a common issue in this kind of studies but could be mitigated by conducting new experiments, preferably also increasing the heterogeneity of the participants. Additionally, distinct methods and measures for drivers' reactions should be investigated to complement existing findings. Finally, driver behavior in a driving simulator may be different from real driving; thus, naturalistic studies can complement driving simulation whenever possible.

Overall, this study explored several variables to represent driver distraction by applying robust models to provide a novel and comprehensive characterization of this phenomenon. Additionally, several driver attributes were considered, showing that the complex process of drivers' reactions is influenced by them. Such a detailed analysis is not so common in studies focusing on driver distraction. Furthermore, the selected tasks were not studied before and, perhaps, have been underestimated by researchers.

This study shows that, although the use of technology devices at the wheel is widely acknowledged as a major safety risk and strongly punished under the legal framework of most countries [3], handling and searching for everyday objects can be even more hazardous despite the difficulties in enforcing avoidance of this unsafe behavior. Looking for an object can lead to serious problems and interfere with the attention of drivers, compromising their ability to react quickly and effectively. This may be particularly relevant in view of the deployment of semi-autonomous vehicles in which the human driver is still responsible for monitoring driving activity and manually intervening in the face of critical situations. In conclusion, this research provides relevant contributions to understand the risks of secondary task engagement at the wheel by analyzing drivers' behavior, workload, and perceptions and ultimately to raise awareness about the need for the development of new and effective driver monitoring/warning systems tailored to different driver profiles.

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