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Do adaptive cruise control and lane keeping systems make the longitudinal vehicle control safer? Insights into speeding and time gaps shorter than one second from a naturalistic driving study with SAE Level 2 automation

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ABSTRACT

Advanced driver assistance systems such as adaptive cruise control (ACC) and lane keeping system (LKS) potentially contribute to reducing crash rates and traffic congestion. On-road studies based on early ACC systems operational at medium–high speeds only have shown that the system reduces the proportion of short time gaps when activated. Despite the effects on driver behaviour, most mathematical models assessing the impact of ACC and LKS systems on crash rates and traffic congestion are not based on empirical findings.

This study examines the factors that influence changes in the longitudinal vehicle control when driving with ACC and LKS. The data were collected in a naturalistic driving experiment with full-range ACC and LKS and two different vehicle brands (BMW and Tesla) in the Netherlands. To capture changes that are relevant for traffic safety, speeding and a time gap shorter than one second were investigated. The factors influencing speeding and short time gaps were analysed using statistical tests and logistic regression models with random effects, that allow to control for the impact of different explanatory variables and correlations between repeated 10-s intervals over time.

The findings revealed that, overall, drivers were less likely to speed and they were also less likely to have a time gap shorter than one second in the experimental condition with the ACC and the LKS than in the baseline condition in manual driving. Drivers were likely to speed in the following 10-s interval when the current speed was close to the speed limit, and/or when the next speed limit was lower than the current speed limit, and/or when the acceleration was high. Drivers were likely to have a short time gap in the following 10-s interval when approaching a slower leader, and/or when the current time gap was short and/or when the acceleration was high. Controlled for these main factors, drivers were less likely to speed and to have a short time gap when the ACC and the LKS were active. However, drivers were more likely to speed when

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overruling the ACC by pressing the gas pedal. When the systems were active, one vehicle brand showed a smaller probability of a short time gap than the other brand, suggesting differences in ACC system settings between brands. In addition, the speeding probability increased while the probability of a short time gap decreased over time during the trip after the activation of the systems. Although further studies including a larger sample of participants and a wider range of traffic situations are needed, the results are useful to the design of automated vehicles that prevent speeding and short time gaps, and to the implementation of traffic simulations that evaluate the impact of ACC and LKS on crash rates and traffic congestion according to realistic on-road data.

1. Introduction

Advanced driver assistance systems (ADAS) can potentially reduce crashes and ease traffic congestion. ADAS hold a promise to reduce driver error which is a major contributing factor in road vehicle crashes. The impact of the ADAS currently installed on commercially available vehicles has not been sufficiently investigated yet due to the limited crash data at disposal (Dutch Safety Board, 2019). To forecast the effects on traffic safety in a broad range of traffic circumstances, it is essential to investigate how the ADAS currently available influence driver behaviour based on empirical data. The impact of ADAS such as adaptive cruise control (ACC) and lane keeping systems (LKS) on driver behaviour has been analysed extensively in driving simulator experiments and to a lesser extent in on-road studies. The ACC keeps a target speed and time gap[1] and has therefore a direct impact on the longitudinal control of drivers (Martens and Jenssen, 2012). The LKS system centres the vehicle in the middle of the driving lane and has a direct impact on the lateral control. Notably, usage of these systems in practice can have indirect (negative) impacts on driver behaviour which were not intended by the designers. These non-intended impacts are defined as *behavioural adaptation* (OECD, 1990). Behavioural adaptation can occur both in the short term, immediately after a system is introduced, and in the long term, as drivers become more familiar with the system (Martens and Jenssen, 2012). In this paper, we will use the term *change* in behaviour to cover for both intended and non-intended effects.

Previous on-road experiments have shown that early ACC systems active only at medium–high speeds have a major effect on the longitudinal control of drivers (Alkim et al., 2007; Malta et al., 2012; NHTSA, 2005; Schakel et al., 2017). These findings, however, may be influenced by the circumstances in which the systems are activated (low-medium traffic density and non-critical traffic situations) and the fact that these systems could not be activated at lower speeds. In recent years, full-range ACC that can also operate at low speeds in dense traffic conditions have been installed in commercially available vehicles. This may bring new insights, since these systems might be activated in different circumstances, be used in combination with LKS systems and result in differences in behavioural responses. To date, most on-road studies with ACC and LKS (SAE Level 2 automation) have focused on the analysis of human factors. These factors included workload measures (Banks and Stanton, 2016; Stapel et al., 2019), glance behaviour metrics (Banks et al., 2018; Gaspar and Carney, 2019; Russell et al., 2018; Solís-Marcos et al., 2018), secondary task engagement (Heikoop et al., 2019; Naujoks et al., 2016; Russell et al., 2018), self-reported situational awareness (Endsley, 2017), trust (Russell et al., 2018; Walker et al., 2018; Wilson et al., 2020), and take-over times (Eriksson et al., 2017; Purucker et al., 2018; Russell et al., 2018). With the exception of the naturalistic driving studies[2] by Endsley (2017) and Russell et al. (2018), the other studies were controlled on-road experiments and shed limited light on learning effects with the system over time.

Naturalistic driving studies allow to analyse changes in driver behaviour with a higher level of external validity than driving simulator studies or controlled on-road studies, and to investigate learning effects over the duration of the experiment. Recent naturalistic driving studies with SAE Level 2 automation have shown that road characteristics (Orlovska et al., 2020; Russell et al., 2018), traffic conditions (Orlovska et al., 2020; Russell et al., 2018), weather conditions (Russell et al., 2018) and driver characteristics (Orlovska et al., 2020) have a substantial impact on automation usage. Drivers were more likely to use the systems at low-medium traffic densities, on interstate roads and with clear weather (Russell et al., 2018). In addition, drivers who used the system less frequently activated the system only at higher speeds and during longer trips, while drivers who used the system often activated the system also at low speeds and during short trips (Orlovska et al., 2020). In interviews, drivers reported that the systems were useful to maintain a safe speed and time gap (Novakazi et al., 2020). Further analysis is needed to assess the impact of SAE Level 2 automation on driver behaviour based on empirical data. Section 1.1 discusses changes in the longitudinal control in Level 1 and Level 2 automation based on the analysis of on-road studies in real traffic. Section 1.2 summarizes the research gaps and defines the research objectives.

1.1. Impacts of automation on the longitudinal control

On-road experiments have shown that ACC systems have an impact on the longitudinal control of the vehicle, which is measured by

[1] According to the SAE guidelines (2015), time gap is defined as the time interval for the leading surface of the subject vehicle to reach the trailing surface of the vehicle ahead. Previous studies have often referred to this time interval as time headway.

[2] Although according to Carsten et al. (2013) one could also call these studies Field Operational Tests, we prefer to use the term naturalistic driving studies in line with previous studies (Endsley, 2017; Fridman et al., 2019; Novakazi et al., 2020; Orlovska et al., 2020; Russell et al., 2018).

the driver behaviour characteristics (speed, acceleration, time gap, and relative speed). They found that the mean time gap increased (Alkim et al., 2007; Malta et al., 2012; Schakel et al., 2017), the standard deviation of the time gap decreased (Alkim et al., 2007; Schakel et al., 2017), and the proportion of short time gaps decreased (Alkim et al., 2007; Malta et al., 2012; NHTSA, 2005; Schakel et al., 2017) when the ACC was used compared to manual driving. In contrast, other studies have found that the median time gap was significantly shorter in ACC than in manual driving in non-safety critical driving conditions on motorways and rural roads (Morando et al., 2019). With ACC activated, drivers maintain a larger time gap in stable speed conditions and a shorter time gap when accelerating and decelerating (Schakel et al., 2017). The ACC system did not have an impact on the mean speed (Malta et al., 2012) and on compliance with the speed limits (Alkim et al., 2007). The frequency of harsh braking events decreased (Malta et al., 2012) and the standard deviation of the acceleration decreased in free-flow and saturated traffic (Schakel et al., 2017). A few studies analysed the impact of transitions[3] from ACC longitudinal control to manual control on the driver behaviour characteristics in the 10-s intervals before and after the transition (Pauwelussen and Feenstra, 2010; Varotto et al., 2020). After the ACC system was deactivated by braking or pressing the on–off button, the mean speed decreased significantly in each traffic condition (Varotto et al., 2020) and the mean acceleration decreased (Pauwelussen and Feenstra, 2010; Varotto et al., 2020). In addition, immediately after the deactivation, the mean time gap decreased significantly (Pauwelussen and Feenstra, 2010), the mean distance gap decreased (Varotto et al., 2020), and the proportion of minimum time gaps shorter than one second increased (from 32% to 65% of the events in which ACC was deactivated) (Pauwelussen and Feenstra, 2010). After the ACC was overruled by pressing the gas pedal, the mean acceleration increased significantly (Pauwelussen and Feenstra, 2010; Varotto et al., 2020) and the proportion of short time gaps increased (from 57% to 72% of the events in which ACC was overruled) (Pauwelussen and Feenstra, 2010). These findings show that transitions from ACC to manual control have a significant impact on the longitudinal control of vehicles.

Previous studies with Level 2 automation have dedicated little attention to changes in the longitudinal control, despite the most recent ACC systems might be activated in different situations in combination with LKS and result in different behavioural responses. Naujoks et al. (2016) investigated the impact of Level 1 and Level 2 automation on driver behaviour in a controlled on-road experiment with a Mercedes-Benz E-class on the motorway in different traffic flow conditions. The thirty-two participants in the experiment differed in terms of age and experience with ACC. They found that the maximum longitudinal deceleration was significantly influenced by the speed conditions. The automation level, age and prior experience with ACC did not have a significant impact. Endsley (2017) analysed self-recorded situation awareness probes in a six-month naturalistic driving study with a Tesla Model S. She was the only participant in the study and collected data using questionnaires. She found that knowledge of her speed and speed limit conformance seemed higher with automation than in manual driving, although non-significantly different. Solís-Marcos et al. (2018) analysed driver behaviour with Level 2 automation in a controlled on-road experiment with a Volvo S90 model on the motorway. The twenty-three drivers had a different level of experience with the system. They found that automation level, non-driving task pacing (system-paced vs. self-paced) and experience level did not have an impact on the mean driving speed.

A recent study proposed a more comprehensive analysis of the impact of automation of the lateral and longitudinal control on driver behaviour. Várhelyi et al. (2020) conducted a controlled on-road experiment (pre-set route) with a prototype vehicle. Complete driver behaviour data in manual driving and automated driving were available for twelve participants. When comparing the speed in the two experimental conditions, they found that the maximum speed and the standard deviation of the speed decreased significantly with automation, while the mean speed did not differ significantly. In addition, the in-vehicle observer registered fewer situations in which the speed at ramps was inappropriate when the system was active. The mean distance gap did not differ significantly between the two conditions. The observer registered situations in which the time gap was shorter than one second seven times less often when the system was active. Finally, conflicts with other vehicles and sudden braking manoeuvres were registered more often when the system was active.

1.2. Research gap and research objective

Previous on-road studies have shown that ACC systems have a significant impact on certain driver behaviour characteristics. Despite the most recent ACC systems could be used in combination with LKS and result in different behavioural responses, most controlled on-road studies with SAE Level 2 automation have dedicated little attention to changes in the longitudinal control and have not found a significant effect of automation. Only Várhelyi et al. (2020) analysed the impact of automation on inappropriate speeds and on short time gaps. This study analysed events annotated by an observer using descriptive statistics and statistical tests. Recent naturalistic driving studies with SAE Level 2 automation (Fridman et al., 2019; Novakazi et al., 2020; Orlovska et al., 2020; Russell et al., 2018) did not analyse changes in the longitudinal control. Naturalistic driving studies allow to investigate safety relevant behaviour with a higher level of external validity than controlled on-road experiments and to capture potential learning effects over the duration of the experiment (e.g., a few months).

The research objective of this study is to reveal the factors that have an impact on the longitudinal control of drivers with SAE Level 2 automation. Speeding and a time gap shorter than one second are investigated to capture changes in the longitudinal control that are relevant for traffic safety. Speeding is defined based on the posted speed limit and the minimum value for speed violations in the Netherlands (Openbaar Ministerie, 2021). Excessive speed and inappropriate speed are considered a contributing factor of 30% of fatal

[3] Based on the definition proposed by Lu et al. (2016), we define transitions of control as transitions that include the reallocation of the longitudinal (or lateral) control task between the driver and the ACC (or the LKS). With these systems, the driver remains always responsible for the monitoring task.

injury crashes (European Commission, 2020). Time gaps shorter than one second represent a traffic violation in certain countries (Vogel, 2003) and are commonly considered safety critical (De Waard and Brookhuis, 1997; Fairclough et al., 1997). The factors investigated are the following: behaviour characteristics of the subject vehicle and of the lead vehicle, traffic density, ACC and LKS system states, treatment period and exposure week, environment characteristics, vehicle brand and driver characteristics. These factors were chosen based on previous studies analysing speeding behaviour (Ahmed and Ghasemzadeh, 2018; Bao et al., 2020; Ghasemzadeh and Ahmed, 2019; Ghasemzadeh et al., 2018; Kong et al., 2020; Richard et al., 2020; Yu et al., 2019) and time gap selection (Ahmed and Ghasemzadeh, 2018; Bao et al., 2020; Varotto et al., 2021a) based on naturalistic driving data in manual driving. Notably, most studies have analysed speeding behaviour and time gap selection at an aggregated level and therefore have shed limited light on the main factors that should be considered to describe the responses of drivers in advanced driver assistance systems and microscopic traffic simulations. For a recent review of the main factors influencing driver behaviour in naturalistic driving studies, the reader is referred to Singh and Kathuria (2021). In the present study, particular attention is dedicated to identifying behavioural changes between the baseline condition in manual driving and the experimental condition with SAE Level 2 automation. In the analysis, the main factors influencing driver responses are explicitly accounted for as they are not controlled for by the experimenters in a naturalistic driving study.

The paper is structured as follows. Section 2 describes the naturalistic driving experiment, the database integration, the data processing and reduction, and the data analysis methods. Section 3 presents the descriptive statistics and the logistic regression models predicting speeding and time gaps shorter than one second. Finally, Section 4 discusses the factors affecting driver responses, recommendations for future research and recommendations for practice.

2. Method

2.1. Naturalistic driving experiment

2.1.1. Vehicle and system specification

The experiment was conducted with nine commercially available vehicles from five different brands: four BMW 5 series, two Mercedes-Benz E-Class, one Tesla model S, one Audi A4 Avant and one Volkswagen E-Golf. All vehicles were equipped with full-range ACC and LKS. These vehicles were also used in a previous experiment focusing on vehicle platooning on public roads (Knoop et al., 2019). Based on data completeness considerations, data from four BMW 5 series and one Tesla model S were analysed in the present study. Data from the other vehicles could not be included in the current study because some key signals (e.g., state of the LKS system) were missing. The main characteristics of the ACC and of the LKS systems available in the BMW and Tesla vehicles are described below.

When the ACC was activated by the driver, the system took over speed control and adapted the following distance to the lead vehicle at speeds between 0 and 150 km/h (Tesla) or 180 km/h (BMW). Driver could choose between four (BMW) or seven (Tesla) different target time gaps. When the radar did not detect a lead vehicle, the system functioned as regular cruise control and maintained the target speed set by the driver at speeds above 30 km/h. When the vehicle came to a standstill with the ACC active and remained stationary for <30 s (BMW) or 5 min (Tesla) (e.g., in a traffic jam), the ACC resumed longitudinal control automatically. The ACC could be activated using the buttons on the steering wheel (BMW) or a lever close to the steering wheel (Tesla). The target speed could be regulated manually or directly adjusted to the speed limit detected by the system using the switches (BMW) or the lever (Tesla). The system could be overruled by pressing the gas pedal (active and accelerate) and, when the gas pedal was released, it transferred back to active maintaining the settings previously stored. The system could be deactivated by braking, by pressing the button (BMW) or pushing the lever (Tesla). The system switched off automatically when the vehicle stood still for more than 30 s (BMW) or 5 min (Tesla), when the system-support limits (e.g., maximum deceleration) were achieved in a safety critical situation, and in case of a system failure.

The LKS supported the driver in keeping the vehicle in the centre of the lane and in changing lanes. The LKS could be activated with or without the ACC on (BMW) or only in combination with the ACC (Tesla). The LKS maintained the vehicle in the centre of the lane based on the distance to the lane markings at speeds between 0 and 210 km/h (BMW) or between 30 and 150 km/h (Tesla). The LKS system required the driver to hold the steering wheel. When the lane markings were not detected, the lane keeping could be based on the position of the lead vehicle at speeds between 0 and 70 km/h (BMW) or between 0 and 150 km/h (Tesla). Similarly to the ACC, the LKS could be activated using a button (BMW) or a lever (Tesla). The system supported lane changes when the lane markings were detected and when the speed was between 70 and 180 km/h (BMW) or between 45 and 150 km/h (Tesla) on motorways. In these situations, the system moved the vehicle into the adjacent lane when the driver engaged the turning indicator. The system switched off automatically after providing both visual and auditory warnings when the driver released the hands from the steering wheel for a certain time period (between 10 and 40 s, depending on brand and circumstances), when neither lane markings nor a leader were detected, or when the system-support limits (e.g., maximum steering applicable) were achieved due to sharp curves or narrow lanes. The system transferred back to active as soon as the lane markings and the lead vehicle were detected, and the driver held the steering wheel again.

2.1.2. Data collection systems

During the experiment, the vehicle data and the videos were recorded using an Advantech® TREK-674 computing box. The computing box recorded, among others, the speed, the acceleration, the ACC system state and settings, the LKS system state, the gas and the brake pedals. These vehicle data were recorded from multiple Controller Area Network (CAN) busses. MobilEye® smart cameras were used to detect the presence, distance and relative speed of vehicles in front of the subject vehicle. In addition, the

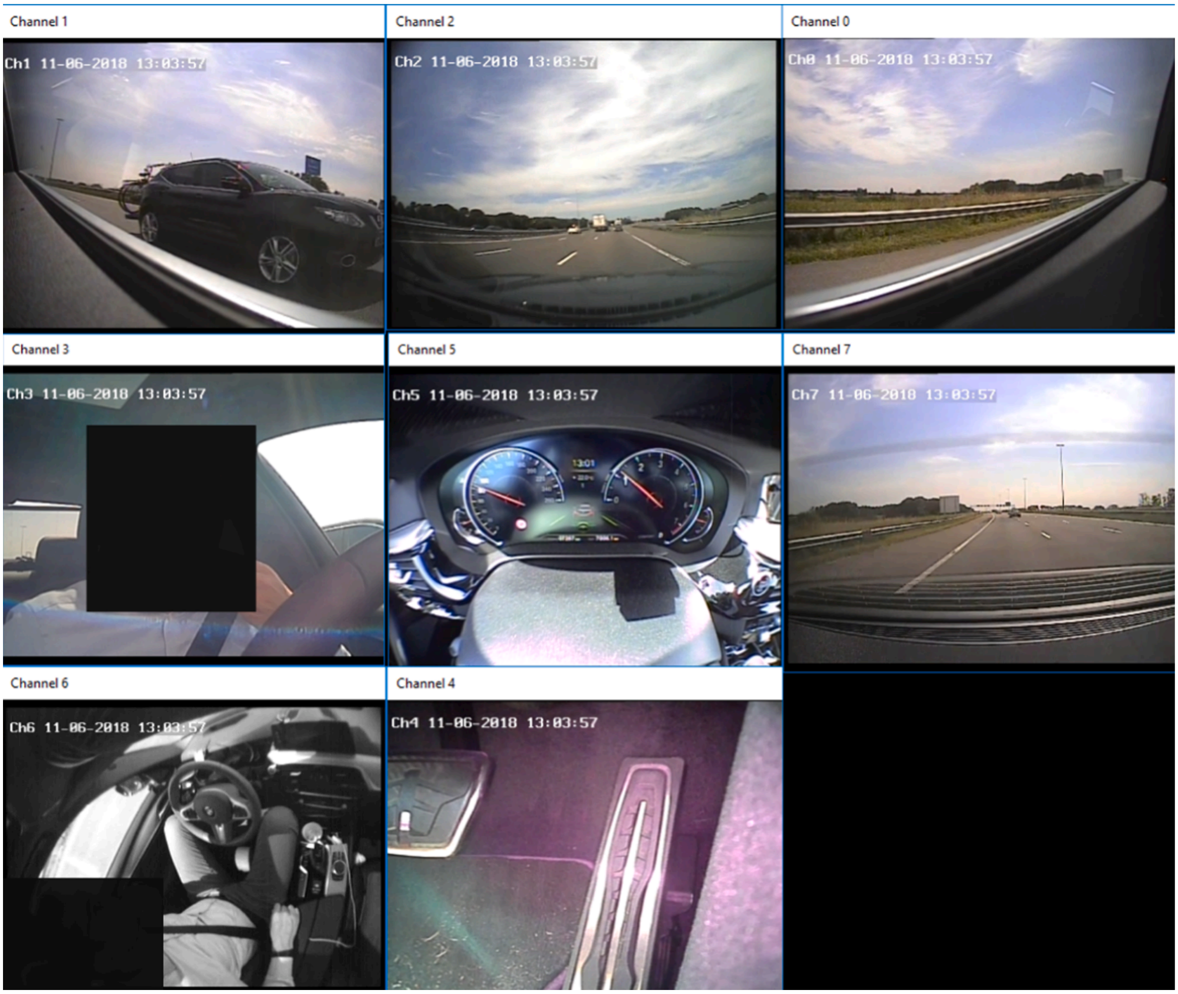

Fig. 1. Eight camera views available in the database when the ACC and the LKS were active: traffic situation on the left side, forward traffic situation, traffic situation on the right side, driver face, dashboard, backward traffic situation, driver body, and driver feet. The face of the driver has been obscured to protect his privacy.

MobilEye® smart cameras detected the distance of the subject vehicle to the lane markings, the type of lane marking (e.g., solid), and the confidence level of these measurements (four-point scale). A GPS receiver was used to obtain the location of the vehicle expressed in coordinates at the frequency of 1 Hz. Eight video cameras were used to record the surrounding traffic situation, the driver and the dashboard (Fig. 1). All data were recorded on flash drives in the data logger. All equipment was designed to operate fully automatic, without requiring user actions. Starting the vehicle triggered the logging system to boot and start recording data. Stopping the engine for five minutes or longer triggered an automatic shut-down procedure.

2.1.3. Participants

To be eligible for participation, candidates needed to have at least five years of driving experience, a minimum annual mileage of 20,000 km, and an age between 35 and 60 years old. In the current study, data from ten participants were used. Three participants drove a leased Tesla vehicle and seven drove a leased BMW vehicle. The mean age was 48.3 years (SD = 5.7 years), the mean driving experience was 28.6 years (SD = 6.2 years), and the mean annual mileage was 39,200 km (SD = 11,700 km). The mean kilometres driven during the experiment for each participant was 12,442 km (SD = 4936 km) and the mean duration was 107 days (SD = 23 days).

2.1.4. Experimental design and data collection

Candidate participants were briefed in writing about the background of the project, the systems involved, the procedures, their rights and obligations, and the nature of the analyses (i.e., usage of and interaction with ADAS). The data logging equipment, including video, was also explained. All participants signed an informed consent form before being admitted to the experiment. The data handling and processing followed the GDPR regulations. The project was approved by the TNO ethical committee that oversees all studies involving human participants.

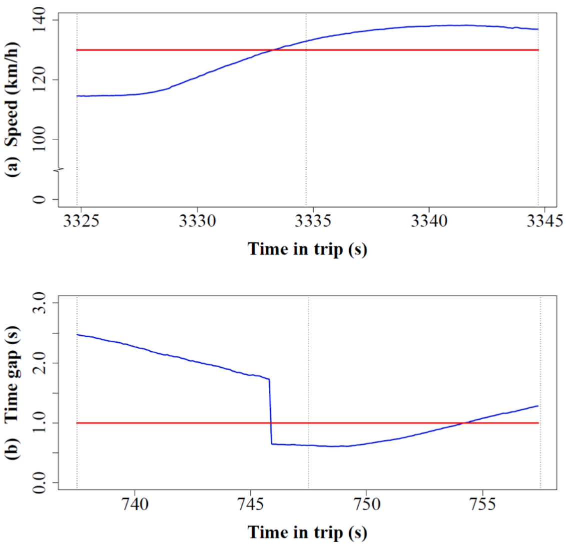

Fig. 2. Examples of (a) speeding and (b) a time gap shorter than one second when the ACC and the LKS were active. Solid blue lines indicate the speed in (a) and the time gap in (b). Solid red lines denote the speed limit in (a) and a time gap equal to one second in (b). Black dotted lines indicate the beginning and the end of the 10-s intervals. The minimum and the maximum of the axis scales are selected based on the values observed in the data.

All participants completed a one-month baseline condition and a two-month experimental condition. In the baseline condition, participants were instructed to drive manually and not to use the ACC and LKS. In the experimental condition, participants were instructed to use both systems whenever they considered appropriate. At the beginning of the experimental condition, participants received extensive instruction and in-car demonstrations of the functioning of the ACC and LKS available in the instrumented vehicle. During the experiment, participants agreed to exclusively use the instrumented vehicle – which was at their complete disposal – and not use their own vehicle. Fuel costs were paid by the participants, while insurance costs and taxes were funded by the project.

The data were collected in the Netherlands between January 2018 and February 2019. Questionnaires were administered before and after participating in the experiment. The questionnaires administered before the experiment included driver age, years of driving experience, annual mileage, experience with ADAS, expectations towards automation, and acceptance of automation. The acceptance questionnaire consisted of nine five-point rating-scale items, denoting the usefulness of and the satisfactions with the systems (Van Der Laan et al., 1997). The questionnaire administered after the experiment included experiences with and acceptance of the systems available during the experiment.

2.2. Data processing

All measurements collected from different vehicles were harmonised in terms of definitions, parsed into a common database, and synchronised to one common clock signal with a 10 Hz frequency (Appendix A, A1. Database integration and synchronization). The variables collected during the experiment were further elaborated to derive the variables relevant to the current study (Appendix A, A2. Variable definition). The relevant variables included the driver behaviour characteristic (speed and acceleration of the subject vehicle, time gap, relative speed, type of lead vehicle, driving lane), the road and traffic characteristics (lane width and curvature, posted speed limits, number of lanes, traffic density level), the states of the ACC and the LKS systems, the environmental characteristics (exposure week, time of the day, day of the week, season of the year, light conditions), the characteristics of the driver (age, years of driving experience and annual mileage) and of the vehicle (brand). Notably, six different systems states were recognised: ACC and LKS inactive, ACC active and LKS inactive, ACC active accelerate (i.e., overruled by pressing the gas pedal) and LKS inactive, ACC inactive and LKS active, ACC active accelerate and LKS active, and ACC active and LKS active. Valid observations were identified based on the systems available and the map data (Appendix A, A3. Data selection and reduction). We only selected motorway segments with a posted speed limit equal to or higher than 100 km/h in which the lane, the system state, the target speed and the target time gap did not change for a duration longer than 20 s. The segments were divided into non-overlapping 10-s intervals. The mean and the standard deviation of the variables were calculated for each valid 10-s interval.

2.3. Data analysis methods

2.3.1. Descriptive analysis and statistics

Speeding was defined based on the regulations for legal speed violations in the Netherlands (Openbaar Ministerie, 2021) and the mean speed of the subject vehicle during the 10-s interval. The mean speed was corrected applying a 3% measurement error. Drivers were defined to be speeding (binary variable) if the corrected speed was more than 1 km/h above the posted speed limit when the speed limit was 130 km/h, or more than 4 km/h above the speed limit when the speed limit was lower than 130 km/h. In these circumstances, drivers would be fined for speed violations. Based on this definition, Fig. 2 (a) presents an event in which the driver was speeding when the ACC and the LKS were active. Time gaps shorter than one second were defined only when a direct leader was present all the time. Drivers were defined to have a time gap shorter than one second (binary variable) when the mean time gap during the 10-s interval was shorter than one second. Time gaps shorter than one second represent a traffic violation in certain countries (Vogel, 2003) and are commonly considered safety critical (De Waard and Brookhuis, 1997; Fairclough et al., 1997). Fig. 2 (b) presents an event in which the driver had a time gap shorter than one second when the ACC and the LKS were active.

We selected only 10-s intervals in which drivers were currently driving within the speed limit (or had a current time gap longer than one second) and we analysed whether drivers were speeding (or had a time gap shorter than one second) in the following 10-s interval. Using descriptive statistics and statistical tests, we compared the conditions in the 10-s interval before drivers were speeding (or had a time gap shorter than one second) to the conditions in the 10-s interval before drivers remained within the limits (or had a time gap longer than one second). This interval of time was chosen considering the time needed by drivers to adjust their speed when they decide to do so, and the time needed to observe the speed variation based on the mean speed. Using this time interval, previous studies have found significant variations in the mean driver behaviour characteristics (Pauwelussen and Feenstra, 2010; Varotto et al., 2020). Based on these findings, driver assistance systems may forecast in advance whether drivers are likely to speed or have a time gap shorter than one second. In this study, we define as safety relevant behaviour the conditions in the 10-s before drivers were either speeding or had a time gap shorter than one second. For each numerical explanatory variable, we calculated the mean and the standard deviation during safety relevant behaviour and during non-safety relevant behaviour. The two-sample Kolmogorov-Smirnov test was used to test differences between the variable distributions in the two groups (safety relevant behaviour vs. non-safety relevant behaviour). For each categorical variable, we calculated the number of 10-s intervals available in each group and in each category. The Pearson's Chi-squared test of independence was used to test the relation between the different groups when five or more 10-s intervals were available in each group. When some groups had a small number of 10-s intervals and the variable had more than two categories, the groups with a small number of 10-s intervals were merged to other groups that had a similar meaning (e.g., dusk and dark light conditions). These bivariate tests allowed us to identify significant relationships between each explanatory variable and the safety relevant behaviour observed.

2.3.2. Logistic regression model

The factors preceding either speeding or a time gap shorter than one second (safety relevant behaviour) were examined in logistic regression models (Zuur et al., 2009). These models permit to investigate the effect of several explanatory variables on driver behaviour capturing explicitly correlations between 10-s intervals over time in the same trip (Farah et al., 2019; Ghasemzadeh and Ahmed, 2019) and by the individual driver (Farah et al., 2019; Ghasemzadeh and Ahmed, 2019; Paschalidis et al., 2018; Varotto et al., 2017, 2018). These models are very useful to analyse data collected in naturalistic driving experiments, where the impact of several factors is not controlled by the experimenters and it is difficult to identify comparable traffic situations which can be used as baseline (Carsten et al., 2013). The definition of speeding and a time gap shorter than one second are explained in Section 2.3.1. The latent regression functions for safety relevant behaviour (SR) and non-safety relevant behaviour (NSR) for driver n at time t are presented in equations (1) and (2):

$$\mathrm{SR}_n(t) = \alpha^{SR} + \boldsymbol{\beta}^{\mathbf{SR}} \bullet \mathbf{X}_{\mathbf{n}}^{\mathbf{SR}}(\mathbf{t}) + \zeta^{SR} \bullet \delta_n^{SR} + \varepsilon_n^{SR}(t) \tag{1}$$

$$\mathrm{NSR}_n(t) = 0 + \varepsilon_n^{NSR}(t) \tag{2}$$

where α^{SR} is the constant, $\boldsymbol{\beta}^{\mathbf{SR}}$ is the vector of parameters associated with the explanatory variables $\mathbf{X}_{\mathbf{n}}^{\mathbf{SR}}(\mathbf{t})$, ζ^{SR} is the parameter associated with the trip-specific error term $\delta_n^{SR} \sim N(0,1)$, and $\varepsilon^{SR}(t)$ and $\varepsilon^{NSR}(t)$ are i.i.d. (independent and identically distributed) extreme value error terms. Equation (1) can include explanatory variables as the driver behaviour characteristics of the subject vehicle and of the lead vehicle, the level of traffic density, the states of the ACC and the LKS systems, the treatment period and exposure week, the characteristics of the environment, the vehicle brand and the driver characteristics. The definitions of the explanatory variables influencing safety relevant behaviour are explained in Appendix A. The probability of observing safety relevant behaviour is given in equation (3):

$$P\left(Y_n(t) = 1 \middle| \delta_n^{SR}\right) = \frac{\exp\left(\alpha^{SR} + \boldsymbol{\beta}^{\mathbf{SR}} \bullet \mathbf{X}_{\mathbf{n}}^{\mathbf{SR}}(\mathbf{t}) + \zeta^{SR} \bullet \delta_n^{SR}\right)}{1 + \exp\left(\alpha^{SR} + \boldsymbol{\beta}^{\mathbf{SR}} \bullet \mathbf{X}_{\mathbf{n}}^{\mathbf{SR}}(\mathbf{t}) + \zeta^{SR} \bullet \delta_n^{SR}\right)} \tag{3}$$

The parameters α, β, ζ were estimated using the R package 'glmmTMB' (Brooks et al., 2017). This package permits to select a specific structure of the variance and covariance components, and to estimate the model using either restricted maximum likelihood (REML) or maximum likelihood (ML) approach. Using REML approach, it is possible to control for the loss in degrees of freedom determined by the fixed effect estimation and to estimate the variance and covariance components without any biases (Harville, 1977). The estimated marginal probability of safety relevant behaviour was determined using the R package 'ggeffects' (Lüdecke, 2018). To calculate the estimated marginal probability including confidence and prediction intervals, one explanatory variable was altered while all the other variables were maintained fixed. The uncertainty about the estimates of the fixed effects was captured by the confidence intervals, while the uncertainty about the estimates of both fixed and random effects was captured by the prediction intervals.

In this study, safety relevant behaviour was influenced by the mean driver behaviour characteristics and environment characteristics observed in the 10-s interval preceding the observed behaviour. The explanatory variables presented in the final model specification were selected based on their interpretation and statistical significance (p-value < 0.05). We centred numerical explanatory variables in the means. We statistically tested the effect of each variable by comparing different model specifications using likelihood ratio tests and ML estimation approach. The variables that showed a significant relationship with the safety relevant behaviour based on the descriptive statistics were tested first. We separately added variables which were highly correlated (e.g., driver age and years of driving experience) to the model and each time inspected the correlation matrix of the estimated parameters. Using this procedure, possible instances of multicollinearity between variables were identified. Indicators of multicollinearity considered in this study were large changes in the estimated parameters when a new variable was included in the model or a significant improvement in goodness of fit when the parameters of several variables were non-significant. Variables that had an analogous meaning and did not have a significantly different impact on safety relevant behaviour were combined into a new variable, while variables that did not have a significant impact were excluded. Certain explanatory variables were available only for part of the 10-s intervals (e.g., the level of traffic density was measured only in proximity to loop detectors). In these situations, a binary variable was added in equation (1) in addition to the variable of origin to denote the missing values (dummy variable adjustment method). We compared different variance and covariance components using likelihood ratio tests and REML estimation approach. The final models do not include error terms related to the individual drivers (driver-specific error term) and to the ACC and the LKS states (system state-specific error term) because they did not lead to significant improvements in goodness of fit.

3. Results

3.1. Descriptive analysis and statistics

Based on the procedure presented in Section 2.2, we identified 7,175 valid 10-s intervals. A lead vehicle was detected all the time in 78.4% of the intervals (5,622 10-s intervals). When a lead vehicle was detected, drivers were speeding 19.3% of the time (1,085 10-s intervals) and had a time gap shorter than one second in 33.6% of the intervals (1,887 10-s intervals).[4] To analyse the main factors influencing speeding behaviour, we selected 4,537 10-s intervals in which drivers were not speeding and a lead vehicle was detected. These intervals happened in 465 distinct trips by 10 drivers. For each driver, the number of trips was between 6 and 84 (median = 46.5) and the number of 10-s intervals was between 17 and 1207 (median = 347). Speeding was observed immediately after 200 of these 10-s intervals (4.4%). For each driver, speeding was observed between 1 and 66 times (median = 14.5) in a number of trips between 1 and 37 (median = 10.50). To investigate the main determinants of time gaps shorter than one second, we selected 3,731 10-s intervals in which the time gap was longer than one second. These 10-s intervals occurred in 445 distinct trips by 10 drivers. For each driver, the number of trips was between 3 and 80 (median = 41) and the number of 10-s intervals was between 12 and 993 (median = 219.5). A time gap shorter than one second was observed immediately after 370 of these 10-s intervals (9.9%). For each driver, a short time gap was observed between 1 and 71 times (median = 28.5) in a number of trips between 1 and 41 (median = 19.5).

To understand the situations in which drivers started to speed or to maintain a time gap shorter than one second, we compared the distributions of the variables when drivers were speeding, were not speeding, had a short time gap and did not have a short time headway. The mean, the standard deviation and the test statistics of the two-sample Kolmogorov-Smirnov tests on the similarity of the distributions between the two groups for each numerical explanatory variable were analysed (Appendix B, Table B1). In this section, we discuss only the results that were significant based on the Kolmogorov-Smirnov tests, which indicated significant relationships between each individual explanatory variable and the safety relevant behaviour observed. Comparing the means, we noticed that drivers were speeding more often when the speed and the acceleration were high, when the time gap was small, and when the lead vehicle was faster. In addition, drivers were speeding more often when the time passed after the activation of the ACC and the LKS was long, when the lane curvature was large, and when the age and the years of driving experience were low. The distributions of these variables differed significantly between conditions in which drivers were speeding and conditions in which they were not speeding.

[4] We also explored the deceleration and the time to collision as indicators of safety relevant behaviour, but the number of safety relevant events identified was too limited to conduct a statistical analysis. We analysed events in which the deceleration was higher than 4 m/s^2, a threshold which was used in a previous naturalistic driving study (Malta et al., 2012), for a minimum duration of 0.2 s during the 10-s interval. In addition, we analysed events in which the time to collision was lower than 3 s, a threshold used in previous studies (Vogel, 2003), for a minimum duration of 0.2 s during the 10-s interval. During the 7,175 valid 10-s intervals, drivers had a high deceleration 0.17% of the time (12 10-s intervals). When a slower lead vehicle was present for part or all the time (5,946 10-s intervals), drivers had a short time to collision 0.13% of the time (8 10-s intervals). To explore whether the treatment period or the automation level had an impact on a high deceleration or on a short time to collision, we selected 7,163 10-s intervals in which the deceleration was lower than 4 m/s^2 and 5,938 10-s intervals in which the time to collision was higher than 3 s. A high deceleration was observed immediately after 13 intervals (0.18%). Four events occurred during the baseline condition (2,452 10-s intervals) and 9 events during the experimental condition with the ACC and the LKS (4,710 10-s intervals). We observed 7 events with the ACC and the LKS inactive (3,672 10-s intervals), 3 events with the ACC inactive and the LKS active (423 10-s intervals), and 3 events with the ACC and the LKS active (2,919 10-s intervals) in the previous interval. A short time to collision was observed immediately after 7 intervals (0.12%). Three events occurred in the baseline condition (1,861 10-s intervals) and 4 events in the experimental condition with the ACC and the LKS (3,568 10-s intervals). We observed 4 events with the ACC and the LKS inactive (2,716 10-s intervals), 1 event with the ACC active and the LKS inactive (48 10-s intervals), and 2 events with the ACC and the LKS active (2,275 10-s intervals) in the previous interval. The number of events did not allow us to test statistically the effect of the treatment period or of the automation level on a high deceleration and on a short time to collision.

Table 1
Statistics of the logistic regression model predicting driver speeding during the following 10-s interval. The goodness of fit measures are computed using ML estimation approach.

Statistics	
Number of parameters related to the explanatory variables (K)	12
Number of drivers	10
Number of 10-s intervals	4537
Constant log likelihood L(c)	– 820
Final log likelihood $L(\widehat{\beta})$	– 351
Adjusted likelihood ratio index (rho-bar-squared) $\overline{\rho}^2 = 1- \frac{(L(\widehat{\beta})-K)}{L(c)}$	0.558

Table 2
Estimation results of the logistic regression model predicting driver speeding during the following 10-s interval. The explanatory variables are based on the mean values during the current 10-s interval. The parameters are estimated using REML approach.

Variable	Description	Parameter	Estimate	z stat.	p-value
–	Alternative specific constant	α^S	– 8.69	– 13.78	$3.45 \bullet 10^{-43}$
Driver behaviour characteristics and traffic density					
DiffSpeed	Difference between the current speed limit and the speed of the subject vehicle in km/h	$\beta^S_{DiffSpeed}$	0.414	12.71	$5.18 \bullet 10^{-37}$
Acc	Acceleration of the subject vehicle in m/s^2	β^S_{Acc}	7.19	10.01	$1.45 \bullet 10^{-23}$
RelSpeed	Relative speed (lead vehicle speed – subject vehicle speed) in m/s	$\beta^S_{RelSpeed}$	0.610	4.36	$1.32 \bullet 10^{-5}$
MidOutLane	Binary variable equal to one when the vehicle is in one of the middle lanes or in the outmost lane	$\beta^S_{MidOutLane}$	−1.97	– 4.63	$3.64 \bullet 10^{-6}$
ACC system, LKS systems and treatment period					
A_{ACC}	Binary variable equal to one when ACC is active, and LKS is active or inactive	$\beta^S_{A\_ACC}$	– 0.834	– 3.20	0.00135
AAc_{ACC}	Binary variable equal to one when ACC is active and accelerate, and LKS is active or inactive	$\beta^S_{AAc\_ACC}$	2.60	2.65	0.00815
$TimeA_{ACC}$	Logarithm of the time after ACC activation when LKS is active or inactive	$\beta^S_{TimeA\_ACC}$	0.482	2.43	0.0152
Road and environment characteristics					
DiffSpeedLimit	Difference between the speed limit in the next 10-s interval and the current speed limit in km/h	$\beta^S_{DiffSpeedLimit}$	– 0.368	– 7.02	$2.24 \bullet 10^{-12}$
LaneNum34	Binary variable equal to one when the number of lanes is three or four	$\beta^S_{LaneNum34}$	– 0.536	– 2.17	0.0303
MornPeak, EveOffPeak, Weekend	Binary variable equal to one during morning peak hours and evening off-peak hours in the working week and during weekends	$\beta^S_{MP,EOP,WE}$	0.541	2.18	0.0293
Vehicle brand, driver characteristics and unobserved heterogeneity					
Brand B	Binary variable equal to one when the vehicle brand is B	β^S_{BrandB}	– 1.80	– 3.04	0.00236
DriExp	Years of driving experience	β^S_{DriExp}	– 0.0932	– 3.57	$3.53 \bullet 10^{-4}$
δ^S_n	Trip-specific error term	ζ^S	0.804	–	–

Drivers had a time gap shorter than one second most often when the speed was high, the acceleration was low, the time gap was short, and when they were approaching a slower leader. In addition, drivers had a short time gap most often when the ACC was inactive and/or when the LKS was activated for a longer period of time, and during the last weeks of the baseline condition. The distributions of these variables differed significantly between conditions in which drivers had a time gap shorter than one second and conditions in which they did not have a time gap shorter than one second.

The number and the proportion of 10-s intervals in each group for the categorical explanatory variables when drivers were speeding or when they had a time gap shorter than one second were investigated (Appendix B, Table B2). The Pearson's Chi-squared test of independence was computed to understand the relationship between the different groups when five or more 10-s intervals were available in each group. This test indicated a significant relationship between each individual explanatory variable and the safety relevant behaviour observed. Drivers were more likely to speed when driving in the innermost lane, when the loop detectors were not available, in the baseline condition, and when the ACC and LKS were inactive. Furthermore, drivers were more likely to speed when the posted speed limit was 100 km/h, when the road section had three or more lanes, during weekends, summer and morning peak hours, and when their annual mileage was between 30,000 and 40,000 km. For these variables, the percentage of 10-s intervals differed significantly between situations in which drivers were speeding and in which drivers were not speeding. Drivers were more likely to have a time gap shorter than one second when the leader changed, when driving in the innermost lane, and when loop detectors were not available. In addition, they were more likely to have a short time gap when driving manually in the baseline condition, when the ACC was inactive, when transferring control, during morning peak hours, during dawn, dusk and dark, and when their annual mileage was between 30,000 and 40,000 km. For these variables, the percentage of 10-s intervals differed significantly between conditions in which drivers had a time gap shorter than one second and conditions in which they did not have a time gap shorter than one second.

3.2. Speeding behaviour

This section describes the final model predicting speeding behaviour in the following 10-s interval. The analysis was based only on 10-s intervals in which drivers were not speeding and a lead vehicle was detected as described in section 3.1. Table 1 presents the goodness-of-fit measures and Table 2 presents the estimation results. In Table 1, the adjusted likelihood ratio index shows that the inclusion of the explanatory variables and of the trip-specific error term in the final model resulted in a 55.8% improvement in goodness of fit compared to the model that contains only a constant. In Table 2, all parameters related to the explanatory variables are statistically significant at the 5% level. The alternative specific constant is significant and negative, meaning that drivers are less likely to speed everything else being equal.

3.2.1. Driver behaviour characteristics and traffic density

Several driver behaviour characteristics of the subject vehicle and of the lead vehicle had a significant effect on speeding behaviour. Drivers were more likely to speed in the following 10-s interval when the difference between the vehicle speed and the current speed limit was small. Furthermore, they were more likely to speed when the acceleration was high and when the lead vehicle had a higher speed than the subject vehicle. Controlled for the main factors mentioned above, the speed of the subject vehicle and the time gap did not have a significant effect. A motorbike or a truck as a lead vehicle instead of a passenger car, and a change of the lead vehicle did not have an impact on speeding. Drivers were less likely to speed when they were driving in one of the middle lanes or in the outermost lane than in the innermost lane. Driving in the middle lanes or in the outermost lane had a similar effect on speeding. The level of traffic density in the road section did not have a significant impact.

3.2.2. ACC system, LKS systems and treatment period

The system state and the time after the activation of the ADAS significantly influenced speeding behaviour. Drivers were less likely to speed when the ACC was active and more likely to speed when the ACC was overruled by pressing the gas pedal (i.e., ACC active accelerate) than in manual driving. When the ACC was active or active accelerate, the effect on speeding did not differ significantly between brands of vehicles. LKS active and ACC inactive did not have a significant effect. Controlled for the system states, transitions of control between the ACC, the LKS and manual control did not have a significant effect on speeding. When the ACC was active, drivers were more likely to speed a long time after the system had been activated. The impact of time after activation did not differ significantly between vehicle brands. The time after the driver had resumed manual control or had overruled the system did not have a significant impact. Controlled for the other significant factors, the experimental condition did not show a significant effect. There were no significant differences in speeding between different weeks in the experiment.

3.2.3. Road and environment characteristics

Certain road segment characteristics had a significant effect on speeding behaviour. Drivers were more likely to speed when the posted speed limit in the next 10-s interval was lower than the posted speed limit in the current 10-s interval. The lane curvature and the lane width did not have a significant effect. The number of lanes in the road section influenced speeding significantly. Drivers were less likely to speed when the road section had three or four lanes and the number of lanes did not change during the 10-s interval. Sections with five and six lanes did not have a significant effect. Some times of the day and days of the week had a significant impact on speeding behaviour. During the working week, drivers were more likely to speed in morning peak hours and evening off-peak hours than during the other times of the day. Furthermore, they were more likely to speed during weekends. The impacts of these times of the day and of the week were similar. Evening peak hours, light conditions and seasons did not have a significant effect.

3.2.4. Vehicle brand, driver characteristics and unobserved heterogeneity

Certain driver characteristics and the vehicle brand had a significant effect on speeding. Brand B vehicles were less likely to speed than brand A vehicles[5]. Drivers who had more years of driving experience were less likely to speed. When controlling for the years of driving experience, the age and the annual mileage did not have a significant effect. The trip-specific error term led to a significant improvement in goodness of fit, while the driver-specific and the system state-specific error terms did not. This means that there were significant differences between trips that were not captured by the explanatory variables, while there was no evidence of unobserved differences between drivers and between system states.

3.2.5. Effect of the explanatory variables on the probability of speeding behaviour

To investigate the effect of changes in the explanatory variables on speeding behaviour, the speeding probability was calculated for 10-s intervals in which all variables were maintained fixed except for one variable that was altered. The features of the baseline 10-s interval were selected based on the mean conditions in which speeding was observed. In the baseline 10-s interval, the difference between the speed of the subject vehicle and the current speed limit was 2.94 km/h, the acceleration was 0.166 m/s^2, the relative speed

[5] In compliance with the agreements with the vehicle manufacturers, the vehicle brand was anonymised due to the limited number of drivers and vehicles available.

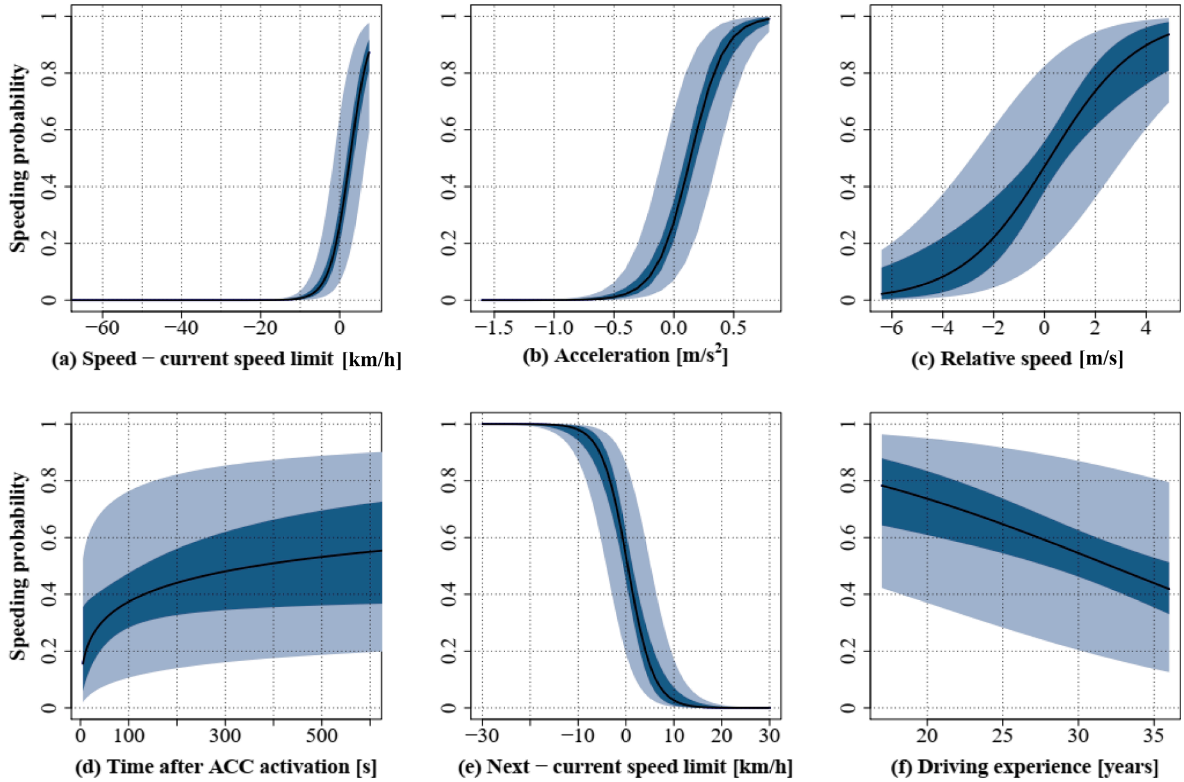

Fig. 3. Effect of the numerical explanatory variables on the speeding probability in the following 10-s interval. The variables are based on the mean values during the current 10-s interval. Black solid lines indicate the marginal means, dark blue ribbons denote the 95% confidence intervals, and light blue ribbons indicate the 95% prediction intervals. The variables are listed as follows: (a) speed − current speed limit, (b) acceleration, (c) relative speed, (d) time after the ACC activation, (e) next speed limit − current speed limit, (f) driving experience. The minimum and the maximum of the axis scales are selected based on the values observed in the data.

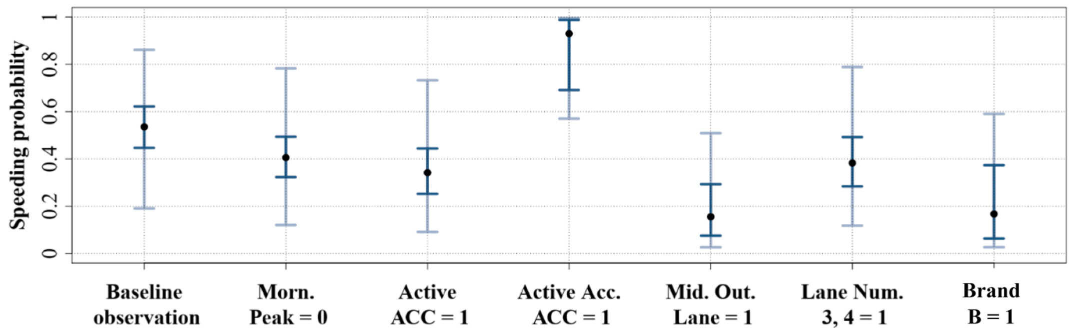

Fig. 4. Effect of the categorical explanatory variables on the speeding probability in the following 10-s interval. The variables are based on the values during the current 10-s interval. Black dots indicate the marginal means, dark blue error bars denote the 95% confidence intervals, and light blue error bars indicate the 95% prediction intervals.

was 0.451 m/s, the driver was driving manually, the time of the day was morning peak hour, and the years of driving experience were 30. The speeding probability in the baseline 10-s interval was 53.6%. The results are provided in Fig. 3 for the numerical variables and in Fig. 4 for the categorical variables. All findings are in agreement with the previous results presented in this section. In Fig. 3, it can be seen that the variables that have the highest impact on the speeding probability are: a small difference between the subject vehicle speed and the current speed limit; a large difference between the next speed limit and the current speed limit; a high acceleration of the subject vehicle. Controlled for these main factors, a high relative speed, ACC active and accelerate, and the trip-specific error term have a large effect on the speeding probability. An out-of-sample validation analysis of the model in Table 2 is presented in Appendix C. For all validation subsamples, the final model shows higher prediction accuracy than a logistic regression model that contains only a constant. The result indicates that the final model is useful to predict the behaviour of drivers not comprised in the estimation sample.

Table 3
Statistics of the logistic regression model predicting a time gap shorter than one second during the following 10-s interval. The goodness of fit measures are computed using ML approach.

Statistics	
Number of parameters related to the explanatory variables (K)	9
Number of drivers	10
Number of 10-s intervals	3731
Constant log likelihood $L(c)$	− 1206
Final log likelihood $L(\widehat{\beta})$	− 640
Adjusted likelihood ratio index (rho-bar-squared) $\overline{\rho}^2 = 1 - \frac{(L(\widehat{\beta})-K)}{L(c)}$	0.462

Table 4
Estimation results of the logistic regression model predicting a time gap shorter than one second during the following 10-s interval. The explanatory variables are based on the mean values during the current 10-s interval. The parameters are estimated using ML approach.

Variable	Description	Parameter	Estimate	z stat.	p-value
–	Alternative specific constant	α^T	− 3.29	− 17.17	$4.78 \bullet 10^{-66}$
Driver behaviour characteristics and traffic density					
Speed	Speed of the subject vehicle in km/h	β^T_{Speed}	0.0118	2.43	0.0150
Accel	Acceleration of the subject vehicle in m/s^2	β^T_{Accel}	3.91	9.08	$1.06 \bullet 10^{-19}$
TimeGap	Time gap (front bumper to rear bumper) in s	$\beta^T_{TimeGap}$	− 8.88	− 14.80	$1.48 \bullet 10^{-49}$
RelSpeed	Relative speed (lead vehicle speed – subject vehicle speed) in m/s	$\beta^T_{RelSpeed}$	− 1.76	− 15.31	$6.19 \bullet 10^{-53}$
LeadChanged	Binary variable equal to one when there was a change of lead vehicle	$\beta^T_{LeadChanged}$	1.98	6.45	$1.12 \bullet 10^{-10}$
MidOutLane	Binary variable equal to one when the vehicle is in one of the middle lanes or in the outmost lane	$\beta^S_{MidOutLane}$	− 0.562	− 2.52	0.0119
ACC system, LKS systems and treatment period					
A_{ACC_BrandA}	Binary variable equal to one when the ACC is active in the current and the following 10-s interval, the LKS is active or inactive, and the vehicle brand is A	$\beta^T_{A\_ACC\_BrandA}$	− 2.67	− 14.96	$1.31 \bullet 10^{-50}$
A_{ACC_BrandB}	Binary variable equal to one when the ACC is active in the current and the following 10-s interval, the LKS is active or inactive, and the vehicle brand is B	$\beta^T_{A\_ACC\_BrandB}$	− 0.850	− 2.29	0.0220
$TimeA_{ACC\_BrandA}$	Logarithm of the time after the ACC activation when LKS is active or inactive, manual control is not resumed and the vehicle brand is A	$\beta^T_{TimeA\_ACC\_BrandA}$	− 0.348	− 2.67	0.00766

3.3. Time gap shorter than one second

This section describes the final model predicting a time gap shorter than one second in the following 10-s interval. The analysis was based only on 10-s intervals in which a lead vehicle was detected and the current time gap was longer than one second as described in section 3.1. Table 3 presents the goodness-of-fit measures and Table 4 presents the estimation results. The adjusted likelihood ratio index shows that the inclusion of the explanatory variables in the final model resulted in a 46.1% improvement in goodness of fit compared to the model that contains only a constant. In Table 4, all parameters related to the explanatory variables are statistically significant at the 5% level. The alternative specific constant is significant and negative, meaning that drivers are less likely to have a time gap shorter than one second everything else being equal.

3.3.1. Driver behaviour characteristics and traffic density

The driver behaviour characteristics of the subject vehicle and of the lead vehicle had a significant effect on a time gap shorter than one second. Drivers were more likely to have a short time gap in the following 10-s interval when the speed and the acceleration were high. In addition, they were more likely to have a short time gap when the current time gap was short, when they were approaching a slower leader, and when there was a change of lead vehicle. Approaching a motorbike or a truck did not have an impact on a time gap shorter than one second. Drivers were less likely to have a short time gap when they were driving in one of the middle lanes or in the outmost lane than in the innermost lane. Driving in one of the middle lanes and in the outmost lane had a similar effect. The level of traffic density did not have a significant effect.

3.3.2. ACC system, LKS systems and treatment period

The states of the ADAS significantly influenced short time gaps. Drivers were less likely to have a time gap shorter than one second when the ACC was active in the current 10-s interval and in the following 10-s interval. When the ACC was deactivated or overruled by pressing the gas pedal, the effect was similar to manual driving. When the ACC was active, the effect did not differ significantly between LKS states but differed significantly between vehicle brands. Drivers were less likely to have a short time gap in brand A vehicles than in brand B vehicles. ACC active and accelerate, LKS active and ACC inactive did not have a significant effect on time gaps shorter than one second. Similarly, transitions from manual control to ACC control or to LKS control did not have a significant impact on the time gap. Drivers were less likely to have a time gap shorter than one second when the ACC had been activated for a long period of time

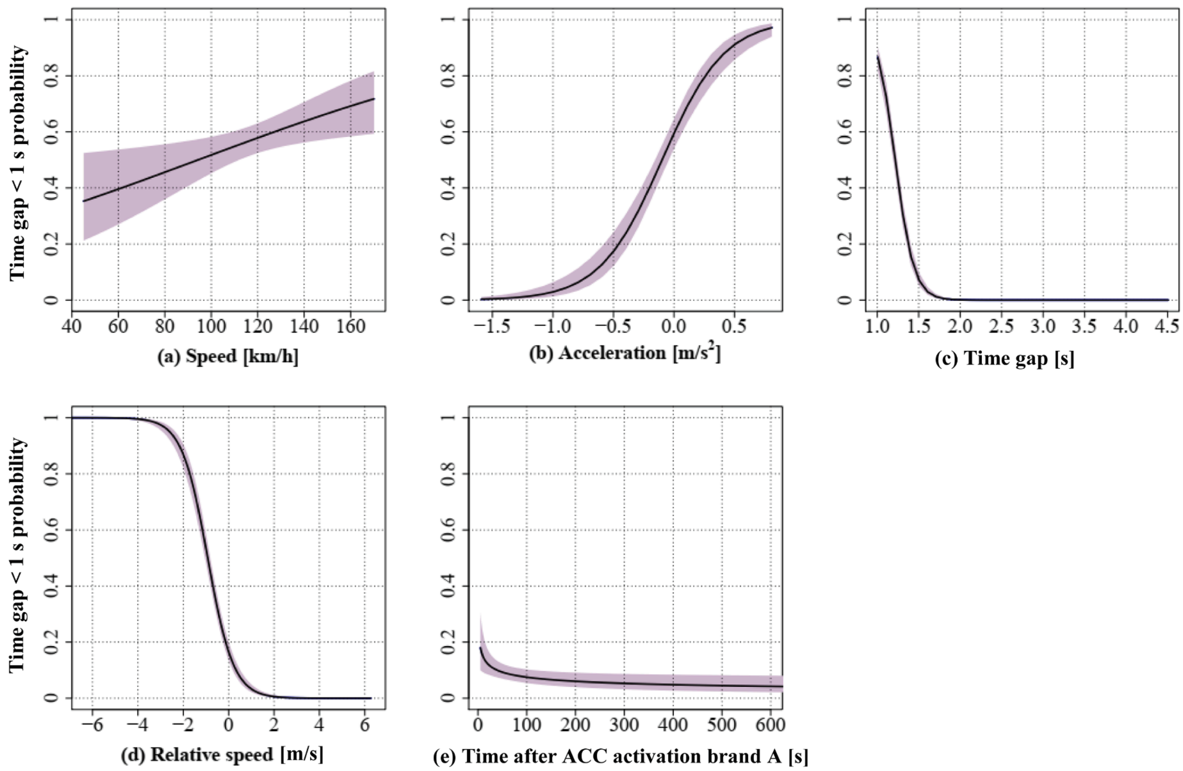

Fig. 5. Effect of the numerical explanatory variables on the probability of a mean time gap shorter than one second during the following 10-s interval. The variables are based on the mean values during the current 10-s interval. Black solid lines indicate the marginal means and purple ribbons denote the 95% confidence intervals. The variables are listed as follows: (a) speed, (b) acceleration, (c) time gap, (d) relative speed, (e) time after the ACC activation in brand A vehicles. The minimum and the maximum of the axis scales are selected based on the values observed in the data.

in brand A vehicles. The time after the driver had activated the ACC in brand B vehicles, had overruled the ACC and had resumed manual control did not have a significant effect on time gaps shorter than one second. Controlled for the states of the ACC and the LKS, the experimental condition and the week in each condition did not have a significant impact.

3.3.3. Road and environment characteristics

The characteristics of the road segment (lane curvature, lane width, number of lanes, and posted speed limit) did not have a significant effect on time gaps shorter than one second. The characteristics of the environment (season of the year, lightening conditions, weekends, peak and off-peak hours) also did not have a significant effect.

3.3.4. Vehicle brand, driver characteristics and unobserved heterogeneity

Controlled for the main factors identified, the type of vehicle and the driver characteristics had a significant effect on a time gap shorter than one second. There were no significant differences between vehicle brands in manual driving. The annual mileage, the years of driving experience and the age of the drivers did not have a significant impact. The driver-specific, the trip-specific and state-specific error terms did not lead to a significant improvement in the goodness of fit. This means that there was no evidence of unobserved differences between drivers, trips and system states.

3.3.5. Effect of the explanatory variables on the probability of a time gap shorter than one second

To investigate the effect of changes in the explanatory variables on a time gap shorter than one second, the probability of a short time gap was calculated for 10-s intervals in which all variables were maintained fixed except for one variable that was altered. The features of the baseline 10-s interval were selected based on the mean conditions in which a short time gap was observed. In the baseline 10-s interval, the speed of the subject vehicle was 116 km/h, the acceleration was – 0.0288 m/s^2, the time gap was 1.19 s, the relative speed was – 1.08 m/s, and the driver was driving manually. The probability of a short time gap in the baseline 10-s interval was 56.7%. The results are provided in Fig. 5 for the numerical variables and in Fig. 6 for the categorical variables. All findings are in agreement with the previous results presented in this section. In Fig. 5, it can be seen that the variables that have the highest impact on a time gap shorter than one second are a low relative speed, a short current time gap and a high acceleration. In Fig. 6, the variables that have the highest impact are a change of lead vehicle, and ACC active in brand A vehicles. An out-of-sample validation analysis of the model in Table 4 is presented in Appendix C. For all validation subsamples, the final model has higher prediction accuracy than a

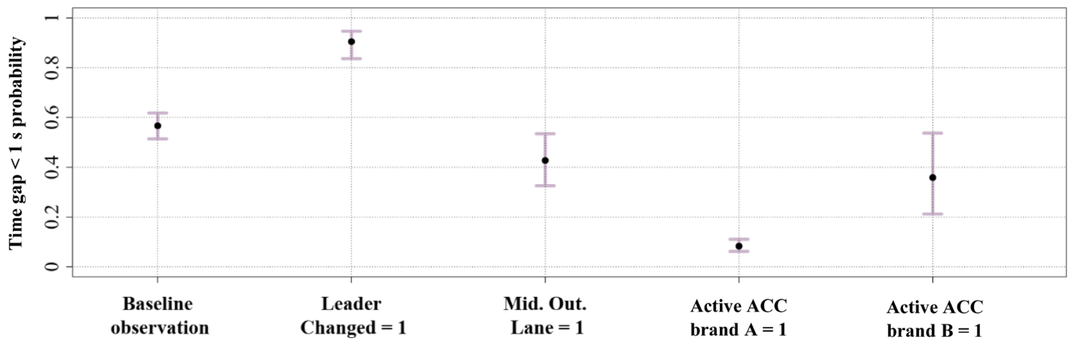

Fig. 6. Effect of the categorical explanatory variables on the probability of a mean time gap shorter than one second during the following 10-s interval. The variables are based on the mean values during the current 10-s interval. Black dots indicate the marginal means and purple error bars denote the 95% confidence intervals.

logistic regression model that contains only a constant. The finding shows that the final model is suitable to predict the behaviour of drivers not included in the estimation sample.

4. Discussion and conclusion

This study investigated the factors that influence changes in the longitudinal control of drivers with full-range adaptive cruise control (ACC) and lane keeping system (LKS) (SAE Level 2 automation). To the best of the authors' knowledge, this is the first study analysing the factors influencing speeding and a time gap shorter than one second based on a large-scale naturalistic driving dataset with ACC and LKS (10 drivers and a mean distance driven of 12,442 km/driver). Statistical tests and logistic regression models were used to analyse the effect of multiple explanatory variables, observed during the current 10-s interval, on the probability that drivers were speeding or had a time gap shorter than one second during the following 10-s interval. The results showed that, overall, drivers were less likely to speed and they were also less likely to have a time gap shorter than one second in the experimental condition with the ACC and the LKS and that, controlled for the current driver behaviour characteristics, drivers were less likely to speed and to have a short time gap when the ACC was active. The main conclusion from this study is that, based on these two indicators, the ACC and the LKS systems have a positive impact on the longitudinal vehicle control.

4.1. Main findings

4.1.1. Speeding

The results of the model revealed that the main factors determining speeding in the following 10-s interval are a small difference between the speed of the subject vehicle and the current speed limit, a large difference between the next speed limit and the current speed limit, and a high acceleration of the subject vehicle. These results are in line with previous findings in manual driving by Yu et al. (2019), who showed that the current speed, the current acceleration, and a low posted speed limit are among the main determinants of speeding at a sighting distance away. We conclude that the current driver behaviour characteristics and the posted speed limit are among the main determinants of speeding behaviour in the following 10-s interval. In addition, drivers were more likely to speed when the lead vehicle had a higher speed and when driving in the innermost lane. These results show that drivers speed when the current traffic situation allows it.

Notably, the state of the ACC and of the LKS systems had a significant impact on speeding. Overall, drivers were less likely to speed when the ACC was active. This result confirmed previous findings on inappropriate speeds at ramps with ACC and LKS (Várhelyi et al., 2020) but is in contrast with previous findings with ACC systems active at medium–high speeds (Alkim et al., 2007). The result can be explained by the ability of the system to maintain a consistent target speed as opposed to manual speed control, while differences with previous ACC systems could be explained by different system characteristics (e.g., possibility to directly adapt the target speed to the speed limit). However, drivers were more likely to speed when the ACC was active and accelerate and, when the system was active, they were more likely to speed when a long time had passed after the system activation. Previous findings have shown that, when the ACC is active, drivers are less likely to overrule the system a long time after the activation than to maintain the system active or to increase the target speed (Varotto et al., 2017, 2018). These results can be explained by the fact that drivers have to overrule the system or increase the target speed if they desire to speed when the system is active.

Driver speeding behaviour is influenced by the characteristics of the road, the day of the week, and the time of the day. Controlled for the other significant variables, drivers were less likely to speed when the road section had three or four lanes instead of two lanes only. The result is in line with previous findings in manual driving, showing that drivers are less likely to speed when the road section has more than two lanes (Ghasemzadeh and Ahmed, 2019). Further analysis is needed to link the result to road characteristics that were not analysed in the current study. For instance, drivers might be less likely to speed in proximity to connections between motorway segments or when a speed control system is enforced. Further analysis is also needed to investigate the impact of road sections with five and six lanes, which should correspond to major interchanges in the road network. Drivers were more likely to speed during morning peak hours and evening off-peak hours in the working week and during weekends. The results partially confirm previous findings in manual driving on higher speeding probability during morning peak hours than during afternoon hours (Ghasemzadeh and Ahmed, 2019) and during weekends (Richard et al., 2020). During morning peak hours, drivers might feel a higher time pressure to reach their destination in time due to work commitments. It is interesting to notice a similar type of behaviour during evening off-peak hours and weekends, when leisure and social activities take place. Further research is needed to link this behaviour to habits and attitudes of the Dutch population. In addition, there were significant differences in speeding between trips that were not captured by the explanatory variables. A possible interpretation could be that, in certain trips, drivers felt more time pressure due to unobserved factors (e.g., being late for an appointment).

Interestingly, the results showed a significant difference between vehicle brands and drivers. Participants driving brand B vehicles were less likely to speed than participants driving brand A vehicles. Setting and adjusting the ACC speed was similar in the two vehicle brands. Further analysis is needed to understand whether the finding can be explained by differences between participants (e.g., risk-taking behaviour) and by differences between brands (e.g., HMI, supported target speed in certain road sections, or engine type) that we did not investigate. Finally, drivers who had more years of driving experience were less likely to speed. The result shows that drivers are more likely to comply with the speed limit with increasing driving experience and confirms previous findings in manual driving on driving experience (Yu et al., 2019) and age (Bao et al., 2020). More experienced and older drivers show risk-taking behaviour less often.

4.1.2. Time gap shorter than one second

The results of the model revealed that the main factors determining a time gap shorter than one second during the following 10-s interval are: a low relative speed, a short current time gap and a high acceleration of the subject vehicle. These results partially reflect previous findings showing a short minimum time gap while approaching traffic congestion in case of a short distance gap and a low relative speed at the beginning of the deceleration event (Varotto et al., 2021a). We conclude that the current driver behaviour characteristics are among the main determinants of a short time gap during the following 10-s interval. Drivers were also more likely to have a short time gap when driving at a high speed and in the innermost lane. These factors could be interpreted as indicators of driver aggressiveness and risk-taking behaviour. In addition, drivers were more likely to have a short time gap when the lead vehicle changed. In these situations (e.g., a vehicle cuts in), the driver and the ACC system require a certain time to adapt the speed and restore a safe time gap.

The state of the ACC and of the LKS systems had a significant impact on time gaps shorter than one second. Drivers were less likely to have a time gap shorter than one second when the ACC was activated. Previous studies with ACC systems inactive at low speeds have shown similar results, reporting a smaller proportion of short time gaps with the system (Alkim et al., 2007; Malta et al., 2012; NHTSA, 2005; Schakel et al., 2017). This finding is consistent with the fact that the shortest target time gap of most ACC systems is one second. When the systems were active, however, the probability of a short time gap was lower in brand A vehicles than in brand B vehicles. The result suggests that there are important differences between ACC systems in terms of the target time gaps available and of the system ability to maintain a target time gap in different traffic situations. These differences between ACC systems appear to be in contrast with recent findings based on test track experiments (Makridis et al., 2021) and should be further investigated. In brand A vehicles, short time gaps were also less likely after a long time had passed since the activation of the ACC system. An explanation could be that the system requires some time to adjust the time gap to the target time gap when it is activated.

In contrast to speeding behaviour, the results did not show evidence of differences in time gaps shorter than one second between vehicle brands, drivers and trips. In manual driving, there was no difference between brand A and brand B vehicles. Driver age did not have a significant impact as shown in a previous study (Bao et al., 2020).

4.2. Recommendations for future research

This study investigated the factors affecting speeding behaviour and time gaps shorter than one second in a broad range of traffic circumstances that did not involve lane changes on Dutch motorways. The data included only situations in which the lane, the system state, the target speed and the target time gap did not change for 20 s or longer and the speed limit detected by the MobilEye® smart camera matched the posted speed limit based on the map data. Trips during the night between 19 h and 6 h were not included in the analysis because the semi-dynamic speed limits that could be enforced were not available. Further studies are needed to generalize the findings to situations in which drivers change lanes, interact with the system multiple times during a 20-s interval, drive during the night and are subjected to variable speed limits. We also explored the maximum deceleration and the minimum time to collision in these traffic circumstances but the number of safety relevant events (e.g., maximum deceleration higher than 4 m/s^2 or minimum time to collision shorter than 3 s) was too limited to conduct a statistical analysis. To assess the impact of the ACC and the LKS on these indicators, further studies are needed including a wider range of traffic situations.

The main factors analysed in this study were the driver behaviour characteristics, the traffic density, the ACC and LKS states, the treatment period and exposure week, the road characteristics, the vehicle brand, and the driver characteristics. Further analysis based on a larger sample of 10-s intervals is needed to investigate differences between situations in which both the ACC and the LKS were active and situations in which only one system was active, since we had a small number of 10-s intervals available only. Lateral assistance systems could have an indirect effect on the longitudinal control as shown in previous driving simulator studies (Miller and Boyle, 2018; Strand et al., 2014). Similarly, further analysis based on a larger sample of 10-s intervals is needed to assess the effect of transitions from ACC or LKS control to manual control, and changes in the longitudinal control when manual control is resumed (Pauwelussen and Feenstra, 2010; Varotto et al., 2020). Learning effects with the systems over time should be further investigated in experiments with a longer duration and in which the baseline and the treatment condition are randomized.

The analysis can be further extended based on annotation of the video data. The videos can be used to extract information on the environment and on the state of the driver. Based on previous studies in manual driving, speeding and a time gap shorter than one second can be influenced by the weather conditions (Ahmed and Ghasemzadeh, 2018; Ghasemzadeh and Ahmed, 2019; Ghasemzadeh et al., 2018; Kong et al., 2020), the visibility of the speed signs (Varotto et al., 2021a), driver glance behaviour (Varotto et al., 2021b) and driver engagement in non-driving tasks (Morgenstern et al., 2020; Papadimitriou et al., 2019; Precht et al., 2017). These factors might be linked to the usage of the ACC and the LKS (e.g., drivers could engage in non-driving tasks more often when the systems are activated) and have a different impact on the behaviour of drivers.

The sample of participants in the current study was not representative of the general driving population and therefore the generalizability of the findings is limited. The number of participants was relatively small (10) and only consisted of males between the age of 39 and 55 years old. Similarly, the variability in terms of annual mileage and years of driving experience was limited. A larger and more heterogeneous sample of participants is needed to further investigate differences between drivers, which can be explained by personality traits and driving styles (Paschalidis et al., 2020). In addition, each participant drove only one of the two vehicle brands available. To generalize the results to other brands of vehicles and systems, further analysis including a wider variety of vehicle brands with both electric and conventional vehicles is needed. Finally, the findings should be complemented by the in-depth analysis of real crashes with ADAS based on accident data (Dutch Safety Board, 2019).

4.3. Recommendations for practice

The data collection methods (naturalistic driving data) and the statistical analysis methods (logistic regression model) proposed in this study are appropriate to investigate changes in driver behaviour that are relevant for traffic safety in real traffic conditions. The results have a higher level of external validity and a lower level of controllability than results based on other data collection methods such as driving simulator experiments. The findings allow us to predict the probability of observing speeding and a short time gap during the following 10-s interval in different traffic situations. The results are relevant to researchers, organizations and policymakers developing legislation for advanced driver assistance systems and evaluating the effect of these systems on traffic operations.

Developers of automated vehicles intending to detect and prevent speeding and time gaps shorter than one second may incorporate the factors identified in this study. Based on the results, future research should develop automated vehicle systems that anticipate driver behaviour and regulate the longitudinal control when drivers are likely to speed or keep a short time gap. These systems should also account for variations between drivers based on personal characteristics and within drivers based on the driver behaviour characteristics of the subject vehicle and of the lead vehicle, the system state, and the road characteristics. In addition, the results highlight the importance of developing systems that are accepted by drivers in a broader range of traffic circumstances. These systems are expected to reduce the probability of speeding and time gaps shorter than one second. Choice models can be incorporated into the systems to detect the circumstances in which drivers are likely to resume manual control (Varotto et al., 2017, 2018).

The realism of microscopic traffic simulations assessing the effect of the ACC and the LKS systems on crash rates and on traffic congestion could be improved by including the factors identified in this study. The findings have shown a large variability within and between drivers in speeding behaviour and in maintaining a short time gap, that can be explained by the traffic circumstances, the system states, the road characteristics, and the driver characteristics. To date, most traffic simulations are not based on findings in naturalistic driving experiments (Ciuffo et al., 2018). Recent studies have made the first steps to develop car-following models based on on-road data with ACC (Gunter et al., 2019; Li et al., 2021; Makridis et al., 2020; Milanés and Shladover, 2014). In these models, speeding and short time gaps should be described as a function of the system state and of the instantaneous behaviour characteristics as presented in this study. The models should also predict the conditions in which the system is used and explicitly capture behavioural changes related to the system state. Implementing such an advanced car-following model into a microscopic traffic flow simulation, one could more accurately forecast the impact of the ACC and the LKS on crash rates and traffic congestion.

CRediT authorship contribution statement

Silvia F. Varotto: Conceptualization, Data curation, Formal analysis, Methodology, Software, Supervision, Project administration, Validation, Visualization, Writing – original draft, Writing – review & editing. **Celina Mons:** Data curation, Writing – original draft, Writing – review & editing. **Jeroen H. Hogema:** Investigation, Writing – original draft, Writing – review & editing. **Michiel Christoph:** Data curation, Writing – review & editing. **Nicole van Nes:** Project administration, Writing – review & editing. **Marieke H. Martens:** Investigation, Project administration, Writing – review & editing.

Declaration of Competing Interest

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

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Appendix A. Data processing

A.1. Database integration and synchronization

All measurements collected from different vehicles were harmonised in terms of units and sign definitions and parsed into a common database. This procedure guaranteed that, for all vehicles, the states of the ACC and the LKS were coded in a unified manner, irrespective of the definitions in the original data. Each trip collected was linked to the participant identification number and to the experimental condition. The GPS coordinates were used to link map data retrieved from OpenStreetMap (https://www.openstreetmap.org). The map data included the road category, the number of lanes and the posted speed limit during 6–19 h. Furthermore, the GPS coordinates and the timestamps were used to link the traffic data for all roads equipped with loop detectors (i.e., motorways and large provincial roads). The original loop detector measurements were processed using the Adaptive Smoothing Method (ASM) to estimate the mean traffic conditions as functions of time and space (Treiber and Helbing, 2002). As a result, the traffic speed (km/h) and the traffic flow (veh/h) over all lanes in the carriageway were calculated with a spatial resolution of 200 m and a temporal resolution of 60 s.

For the Tesla vehicle, the ACC and the LKS system states were not collected during the experiment because the data were distributed over more CAN busses than the data logger could register. For this vehicle, the system states and the confidence level of the system states were extracted in post-processing using automated analysis of the dashboard videos. Initially, all data were logged using the original time stamps. To harmonise the different timestamps, all data were synchronised to one common clock signal with a 10 Hz frequency.

A.2. Variable definition

The variables collected during the experiment and in the post-processing phase were further elaborated to derive the variables relevant to the current study. The speed and the acceleration of the subject vehicle were directly available based on CAN bus measurements. The obstacle identification number, the obstacle type, the distance gap and the relative speed from the MobilEye® smart camera were defined only when a lead vehicle was detected in the lane in front of the subject vehicle. When the speed of the subject vehicle was higher than zero, the time gap was calculated based on the distance gap and the subject vehicle speed. The obstacle types available were passenger vehicles, trucks, or motorbikes. Changes of lead vehicle were identified based on changes of obstacle identification number. The lane width was calculated based on the distance to the lane markings measured by the MobilEye® smart camera. The driving lane was identified based on the type of lane marking detected (solid or dashed). Three types of lanes were distinguished: innermost lane (i.e., fastest lane), middle lanes and outmost lane (i.e., slowest lane). The lane curvature was directly provided by the MobilEye® camera.

The posted speed limit and the number of lanes in the road section were based on the map data. The traffic density was calculated based on the mean traffic flow and speed in the loop detector data and the number of lanes in the road section. As suggested by Knoop and Daamen (2017), unreliable loop detector measurements (mean speeds lower than 36 km/h, and mean speeds lower than 72 km/h at densities lower than 22 veh/km/lane) were classified as missing values. On motorways, three levels of traffic densities were distinguished based on the levels of service in the Highway Capacity Manual (Transportation Research Board, 2010): “low density” when the mean density was lower than 11 veh/km/lane (HCM level of service A and B), “medium density” when the mean density was between 11 and 22 veh/km/lane (HCM level of service C and D), and “high density” when the density was higher than 22 veh/km/lane (HCM level of service E and F).

The system states were determined based on the ACC state, the LKS state, and the gas pedal. Six different systems states were identified: ACC and LKS inactive, ACC active and LKS inactive, ACC active accelerate (i.e., overruled by pressing the gas pedal) and LKS inactive, ACC inactive and LKS active, ACC active accelerate and LKS active, and ACC active and LKS active. The state ACC inactive and LKS active was only applicable to BMW vehicles.

The exposure week was calculated using the starting date in the experimental condition and the date in the timestamp. The timestamp was also used to calculate the time of the day, the day of the week, and the season of the year. Based on typical traffic patterns in the Netherlands (Duivenvoorden, 2010), four periods of the day were defined: morning peak hours (7:00–9:00 h), morning off-peak hours (9:00–16:00 h), evening peak hours (16:00–18:00 h), and evening off-peak hours (18:00–7:00 h). The light conditions were determined based on the timestamps, the GPS coordinates and the sunlight times for that specific date and location calculated using the R package “suncalc” (Thieurmel and Elmarhraoui, 2019). Four light conditions were distinguished: dawn (from the beginning of the morning civil twilight to the beginning of the sunrise), daylight (from the beginning of the sunrise to the end of the sunset), dusk (from the end of the sunset to the end of the evening civil twilight), and night (from the end of the evening civil twilight to the beginning of the morning civil twilight).

The driver characteristics (age, years of driving experience and annual mileage) were determined based on the questionnaires. Experience with ADAS, expectations towards automation, acceptance of automation, and levels of usefulness and satisfaction with the systems were not included as independent variables in the present analysis because the variability in the sample was limited.

A.3. Data selection and reduction

Valid observations were identified based on the systems available and the map data in the integrated database. We only analysed segments in which the state of the ACC and the LKS systems were available for BMW vehicles and were detected with the highest level of confidence for Tesla vehicles based on image processing. In addition, we only selected segments in which the road type was classified as motorway (i.e., carriageway with main traffic flow), the posted speed limit was 100 km/h or higher based on the map data, and the lane markings were detected with the highest level of confidence by the MobilEye® smart camera. As shown by Geurts et al. (2022), the latter requirement was needed to ensure good lane change detection. We only chose segments in which the posted speed limit based on the map data was equal to the posted speed limit detected by the MobilEye® smart camera. Segments in which other road signs (e.g., electronic speed limits) were detected by the MobilEye® smart camera, and segments during 19–6 h when semi-dynamic speed limits could have been enforced were excluded from the analysis. Lane changes were detected based on sudden changes in the distances to the left and right lane markings. The 10-s intervals before and after each lane change were discarded from analysis.

We identified segments longer than 20 s in which the lane, the system state, the target speed and the target time gap did not change. This period of time was chosen to identify steady state driving as suggested by Morando et al. (2019). Driving segments that did not meet the inclusion criteria were discarded. The data were reduced using chunking technique (Dozza et al., 2013). The 10-s intervals before and after each ACC control transition, target speed regulation and target time gap regulation were selected in each segment. The remaining segments were divided into non-overlapping 10-s intervals. Intervals shorter than 10 s were discarded. The mean and the standard deviation of the variables defined in section A.2 were calculated for each valid 10-s interval. This interval of time was chosen based on previous studies (Morando et al., 2019; Pauwelussen and Feenstra, 2010; Varotto et al., 2020).

Appendix B. Data analysis

Table B1 and Table B2

Table B1
Mean, standard deviation and two-sample Kolmogorov-Smirnov test (p-value) of the numerical explanatory variables when the drivers were speeding (S) or not speeding (NS) and when they had a time gap shorter than one second (T) and did not have a time gap shorter than one second (NT).

		Mean and standard deviation				Two sample KS test: p-value	
Variable	**Description**	**S**	**NS**	**T**	**NT**	**S vs. NS**	**T vs. NT**
Driver behaviour characteristics and traffic density							
Speed	Mean speed of the subject vehicle in km/h	116.0 (12.34)	104.6 (14.91)	116.1 (16.85)	107.2 (16.81)	$<2.2\bullet10^{-16}$	$6.66\bullet10^{-16}$
Accel	Mean acceleration of the subject vehicle in m/s^2	0.1661 (0.2049)	−0.003400 (0.2367)	−0.02876 (0.2784)	0.01382 (0.2257)	$<2.2\bullet10^{-16}$	$1.11\bullet10^{-5}$
TimeGap	Mean time gap (front bumper to rear bumper) in s	1.069 (0.4205)	1.196 (0.4743)	1.186 (0.2018)	1.431 (0.4749)	$2.30\bullet10^{-4}$	$<2.2\bullet10^{-16}$
RelSpeed	Relative speed (lead vehicle speed − subject vehicle speed) in m/s	0.4507 (2.209)	− 0.03224 (1.305)	−1.076 (1.557)	−0.03379 (1.043)	$4.70\bullet10^{-14}$	$<2.2\bullet10^{-16}$
ACC system, LKS systems and treatment period							
Time A_{ACC}	Time after the ACC activation in s	–	138.3 (100.7)	176.2 (42.43)	151.1 (108.4)	–	0.897
Time AAc	Time after overruling ACC by pressing the gas pedal in s	5.050 (0.000)	17.33 (16.32)	15.10 (15.49)	20.28 (13.84)	0.395	0.497
Time A_{LKS}	Time after the LKS activation in s	90.76 (107.8)	93.76 (82.92)	118.3 (103.3)	71.13 (58.65)	0.287	$7.61\bullet10^{-3}$
Time $A_{ACC, LKS}$	Time after the ACC and LKS activation in s	151.2 (126.2)	124.0 (129.9)	97.65 (106.1)	130.1 (133.0)	$9.53\bullet10^{-4}$	0.128
WeekB	Week number in the baseline condition	2.904 (1.551)	3.128 (1.278)	3.115 (1.281)	2.807 (1.247)	0.101	0.0414
WeekE	Week number in the experimental condition	4.872 (2.534)	4.796 (2.359)	5.048 (2.432)	4.778 (2.420)	0.908	0.857
Road and environment characteristics							
Lane Curv	Absolute value of the lane curvature in 1/km	0.09437 (0.09684)	0.07980 (0.09100)	0.08436 (0.09504)	0.07825 (0.09120)	0.0269	0.197
Lane Width	Lane width in m	3.392 (0.0629)	3.391 (0.06635)	3.385 (0.06268)	3.385 (0.06469)	0.0244	0.986
Vehicle brand and driver characteristics							
DrivExp	Experience of the driver in years	30.47 (4.446)	32.34 (4.609)	31.60 (4.468)	31.94 (4.839)	$6.31\bullet10^{-13}$	0.151
Age	Age of the driver in years	49.84 (3.806)	51.37 (3.913)	50.89 (3.752)	50.98 (4.086)	$6.31\bullet10^{-13}$	0.151

Table B2
Number and percentage of 10-s intervals in each system state when the drivers were speeding (S) or not speeding (NS) and when they had time gaps shorter than one second (T) and did not have time gaps shorter than one second (NT). The Pearson's Chi-squared test of independence was computed to test the relationship between the different groups when five or more 10-s intervals were available in each group.

		10-s intervals (proportion per group)				Chi-Squared test: p-value	
Variable	**Description**	**S**	**NS**	**T**	**NT**	**S vs. NS**	**T vs. NT**
Driver behaviour characteristics and traffic density							
Motorbike	No	199 (99.5%)	4305 (99.26%)	365 (98.65%)	3338 (99.3%)	–	0.274
	Yes	1 (0.50%)	32 (0.74%)	5 (1.35%)	23 (0.68%)		
Truck	No	199 (99.5%)	4219 (97.28%)	368 (99.46%)	3256 (96.88%)	–	–
	Yes	1 (0.5%)	118 (2.72%)	2 (0.54%)	105 (3.12%)		
Leader changed	No	193 (96.5%)	4217 (97.23%)	332 (89.73%)	3261 (97.02%)	0.693	$4.79•10^{-12}$
	Yes	7 (3.5%)	120 (2.77%)	38 (10.27%)	100 (2.98%)		
Lane	Innermost lane	191 (95.5%)	3302 (76.14%)	331 (89.46%)	2447 (72.81%)	$3.49•10^{-10}$[a]	$1.60•10^{-11}$
	Middle lane	7 (3.5%)	482 (11.11%)	24 (6.49%)	444 (13.21%)		
	Outermost lane	2 (1.0%)	553 (12.75%)	15 (4.05%)	470 (13.98%)		
Traffic density level	Light	21 (10.5%)	562 (12.96%)	39 (10.54%)	465 (13.84%)	$2.58•10^{-7}$[b]	0.0156
	Medium	32 (16%)	1253 (28.89%)	92 (24.86%)	942 (28.03%)		
	High	2 (1%)	213 (4.91%)	9 (2.43%)	139 (4.14%)		
	Not available	145 (72.5%)	2309 (53.24%)	230 (62.16%)	1815 (54.0%)		
ACC system, LKS systems and treatment period							
Automation level	ACC and LKS inactive	130 (65.0%)	1952 (45.01%)	264 (71.35%)	1049 (31.21%)	$5.94•10^{-8}$[c]	$3.59•10^{-66}$[e]
	ACC active and LKS inactive	0 (0%)	50 (1.15%)	2 (0.54%)	36 (1.07%)		
	ACC active accelerate and LKS inactive	0 (0%)	5 (0.12%)	0 (0%)	2 (0.06%)		
	ACC inactive and LKS active	12 (6.0%)	315 (7.26%)	36 (9.73%)	140 (4.17%)		
	ACC active accelerate and LKS active	3 (1.5%)	34 (0.78%)	6 (1.62%)	12 (0.36%)		
	ACC and LKS active	55 (27.5%)	1981 (45.68%)	62 (16.76%)	2122 (63.14%)		
Transition of control	None	200 (100%)	4318 (99.56%)	365 (98.65%)	3348 (99.61%)	–	0.0319[f]
	Driver controls long. control	0 (0%)	12 (0.28%)	3 (0.81%)	9 (0.27%)		
	Driver controls lat. control	0 (0%)	0 (0%)	0 (0%)	0 (0%)		
	ACC controls long. control	0 (0%)	5 (0.12%)	2 (0.54%)	2 (0.06%)		
	LKS controls lat. control	0 (0%)	2 (0.05%)	0 (0%)	2 (0.06%)		
Treatment period	Baseline	83 (41.5%)	1446 (33.34%)	183 (49.46%)	691 (20.56%)	0.0209	$2.85•10^{-35}$
	Experimental	117 (58.5%)	2891 (66.66%)	187 (50.54%)	2670 (79.44%)		
Road and environment characteristics							
Speed limit	100 km/h	95 (47.5%)	1062 (24.49%)	116 (31.35%)	1166 (34.69%)	$5.62•10^{-14}$	0.209
	120 km/h	54 (27.0%)	1171 (27.0%)	80 (21.62%)	774 (23.03%)		
	130 km/h	51 (25.5%)	2104 (48.51%)	174 (47.03%)	1421 (42.28%)		

(continued on next page)

Table B2 (*continued*)

Variable	Description	10-s intervals (proportion per group) S	NS	T	NT	Chi-Squared test: p-value S vs. NS	T vs. NT
N lanes	Two	98 (49.0%)	2790 (64.33%)	231 (62.43%)	1983 (59.00%)	$2.53{\bullet}10^{-11}$	0.368[g]
	Three	64 (32.0%)	1123 (25.89%)	96 (25.95%)	934 (27.79 %)		
	Four	18 (9.0%)	289 (6.66%)	30 (8.11%)	266 (7.91%)		
	Five	9 (4.5%)	99 (2.28%)	11 (2.97%)	123 (3.66%)		
	Six	11 (5.5%)	36 (0.83%)	2 (0.54%)	55 (1.64%)		
Weekend	No	167 (83.5%)	4031 (92.94%)	345 (93.24%)	3050 (90.75%)	$1.37{\bullet}10^{-6}$	0.135
	Yes	33 (16.5%)	306 (7.06%)	25 (6.76%)	311 (9.25%)		
Light condition	Dawn	3 (1.5%)	119 (2.74%)	11 (2.97%)	49 (1.46%)	0.0439[d]	0.0427[h]
	Daylight	194 (97.0%)	4037 (93.08%)	342 (92.43%)	3197 (95.12%)		
	Dusk	1 (0.5%)	57 (1.31%)	3 (0.81%)	52 (1.55%)		
	Dark	2 (1.0%)	124 (2.86%)	14 (3.78%)	63 (1.87%)		
Season year	Spring	64 (32.0%)	1967 (45.35%)	170 (45.95%)	1417 (42.16%)	$1.16{\bullet}10^{-6}$	0.129
	Summer	98 (49.0%)	1584 (36.52%)	136 (36.76%)	1310 (38.98%)		
	Autumn	29 (14.5%)	356 (8.21%)	31 (8.38%)	388 (11.54%)		
	Winter	9 (4.5%)	430 (9.91%)	33 (8.92%)	246 (7.32%)		
Time day	Morning peak	57 (28.5%)	839 (19.35%)	92 (24.86%)	558 (16.6%)	0.00210	$1.67{\bullet}10^{-4}$
	Morning off peak	76 (38.0%)	1550 (35.74%)	128 (34.59%)	1317 (39.18%)		
	Evening peak	43 (21.5%)	1357 (31.29%)	90 (24.32%)	1017 (30.26%)		
	Evening off peak	24 (12.0%)	591 (13.63%)	60 (16.22%)	469 (13.95%)		
Vehicle brand and driver characteristics							
Vehicle brand [i]	A	196 (98.0%)	3665 (84.51%)	326 (88.11%)	2954 (87.89%)	–	0.970
	B	4 (2.0%)	672 (15.49%)	44 (11.89%)	407 (12.11%)		
Annual mileage	20.000 – 30.000 km	30 (15.0%)	1324 (30.53%)	77 (20.81%)	1072 (31.90%)	$5.10{\bullet}10^{-26}$	$2.74{\bullet}10^{-9}$
	30.000 – 40.000 km	144 (72.0%)	1499 (34.56%)	193 (52.16%)	1208 (35.94%)		
	greater than 40.000 km	26 (13.0%)	1514 (34.91%)	100 (27.03%)	1081 (32.16%)		

[a] Outermost lane was grouped with middle lane;
[b] High traffic density was grouped with medium traffic density;
[c] ACC active and LKS inactive was grouped with ACC active and LKS active, while ACC active accelerate was grouped with ACC inactive and LKS inactive;
[d] Dawn was grouped with dusk and dark;
[e] ACC active and LKS inactive was grouped with ACC active and LKS active, while ACC active accelerate and LKS inactive was grouped with ACC active accelerate and LKS active;
[f] All transition types were grouped together;
[g] Six lanes was grouped with five lanes;
[h] Dusk was grouped with dark;
[i] In compliance with the agreements with the vehicle manufacturers, the vehicle brand was anonymised due to the limited number of drivers and vehicles available.

Appendix C. Validation analysis

A validation analysis was conducted to investigate how accurately the logistic regression models will forecast the behaviour of drivers not comprised in the estimation sample. In the analysis, the models presented in Table 2 and Table 4 were evaluated against logistic regression models that include only a constant. The best approach to assess the predictive ability of the models is to apply them to other similar databases. In this study, we conducted an out-of-sample validation because we do not have other comparable databases available. Due to the limited number of drivers available, a five-fold cross validation approach was chosen (Hastie et al., 2009). The drivers were divided into five pairs. Four pairs (80% of the drivers) were selected and the models were estimated based on the

Table C1
Validation analysis of the logistic regression model predicting speeding behaviour during the following 10-s interval. C indicates the model that includes only a constant and $\widehat{\beta}$ denotes the model in Table 2.

Validation sample	Drivers	10-s intervals	Constant log likelihood $L(c)$	Final log likelihood $L(\widehat{\beta})$	$\frac{L(\widehat{\beta})-L(c)}{L(c)}$
1	2	425	−62	−18	0.7034
2	2	754	−116	−41	0.6458
3	2	553	−260	−116	0.5535
4	2	1149	−161	−69	0.5722
5	2	850	−251	−148	0.4105
M	2	746	−170	−78	0.5771
SD	0	250.4	76.6	47.6	0.0990

Table C2
Validation analysis of the logistic regression model predicting a time gap shorter than one second during the following 10-s interval. C indicates the model that includes only a constant and $\widehat{\beta}$ denotes the model in Table 4.

Validation sample	Drivers	10-s intervals	Constant log likelihood $L(c)$	Final log likelihood $L(\widehat{\beta})$	$\frac{L(\widehat{\beta})-L(c)}{L(c)}$
1	2	425	−166	−91	0.4547
2	2	754	−208	−113	0.4554
3	2	553	−279	−129	0.5373
4	2	1149	−297	−148	0.4999
5	2	850	−272	−169	0.3785
M	2	746	−244	−130	0.4652
SD	0	250.4	49.2	27.2	0.0531

corresponding 10-s intervals. The 10-s intervals associated with the pair not included in the estimation phase (20% of the drivers) were used to validate the model. The process was replicated five times. The model performances were compared based on the final log likelihood of the models. This evaluation metric indicates which model has the highest forecasting accuracy out of sample. The forecasting accuracy is higher when the log likelihood is smaller.

The final log likelihood of the models calculated on the validation subsamples are presented in Table C1 and Table C2. The accuracy improvement of the logistic regression models compared to models that contain only a constant is shown in the last column. For all validation subsamples, the models proposed show higher prediction accuracy than the constant model. Both models show the smallest improvement in accuracy when they are validated on pair 5. This finding means that one or both drivers in this pair revealed different behaviour than the other drivers. This variability between drivers can be explained by individual characteristics as driving styles and personality traits that are not included in the final model. The findings indicate that the final models are useful to predict the behaviour of drivers not comprised in the estimation sample.

References

Ahmed, M.M., Ghasemzadeh, A., 2018. The impacts of heavy rain on speed and headway Behaviors: An investigation using the SHRP2 naturalistic driving study data. Transp. Res. Part C: Emerging Technol. 91, 371–384.

Alkim, T.P., Bootsma, G., Hoogendoorn, S.P., 2007. Field Operational Test "The Assisted Driver", 2007 IEEE Intelligent Vehicles Symposium, pp. 1198-1203.

Banks, V.A., Eriksson, A., O'Donoghue, J., Stanton, N.A., 2018. Is partially automated driving a bad idea? Observations from an on-road study. Appl. Ergonomics 68, 138–145.

Banks, V.A., Stanton, N.A., 2016. Keep the driver in control: Automating automobiles of the future. Appl. Ergonomics 53, 389–395.

Bao, S., Wu, L., Yu, B., Sayer, J.R., 2020. An examination of teen drivers' car-following behavior under naturalistic driving conditions: With and without an advanced driving assistance system. Accid. Anal. Prev. 147, 105762.

Brooks, M., Kristensen, K., van Benthem, K., Magnusson, A., Berg, C., Nielsen, A., Skaug, H., Maechler, M., Bolker, B., 2017. glmmTMB Balances Speed and Flexibility Among Packages for Zero-inflated Generalized Linear Mixed Modeling. The R J. 9 (2), 378–400.

Carsten, O., Kircher, K., Jamson, S., 2013. Vehicle-based studies of driving in the real world: The hard truth? Accident Anal. Prevention 58, 162–174.

Ciuffo, B., Makridis, M., Toledo, T., Fontaras, G., 2018. Capability of current car-following models to reproduce vehicle free-flow acceleration dynamics. IEEE Trans. Intelligent Transp. Syst. 19 (11), 3594–3603.

De Waard, D., Brookhuis, K.A., 1997. Behavioural adaptation of drivers to warning and tutoring messages: Results from an on-the-road and simulator test. Heavy Vehicle Syst. 4 (2–4), 222–234.

Dozza, M., Bärgman, J., Lee, J.D., 2013. Chunking: A procedure to improve naturalistic data analysis. Accid. Anal. Prev. 58, 309–317.

Duivenvoorden, K., 2010. The relationship between traffic volume and road safety on the secondary road network. In: SWOV Institute for Road Safety Research, p. 25.

Dutch Safety Board, 2019. Who is in control? Road safety and automation in road traffic. Dutch Safety Board, The Hague.

Endsley, M.R., 2017. Autonomous Driving Systems: A Preliminary Naturalistic Study of the Tesla Model S. J. Cognitive Eng. Decision Making 11 (3), 225–238.

Eriksson, A., Banks, V.A., Stanton, N.A., 2017. Transition to manual: Comparing simulator with on-road control transitions. Accident Anal. Prevention 102, 227–234.

European Commission, 2020. Road safety thematic report – Speeding. European Road Safety Observatory, Brussels, European Commission, Directorate General for Transport.

Fairclough, S.H., May, A.J., Carter, C., 1997. The effect of time headway feedback on following behaviour. Accid. Anal. Prev. 29 (3), 387–397.
Farah, H., Bianchi Piccinini, G., Itoh, M., Dozza, M., 2019. Modelling overtaking strategy and lateral distance in car-to-cyclist overtaking on rural roads: A driving simulator experiment. Transp. Res. Part F: Traffic Psychology Behav. 63, 226–239.
Fridman, L., Brown, D.E., Glazer, M., Angell, W., Dodd, S., Jenik, B., Terwilliger, J., Patsekin, A., Kindelsberger, J., Ding, L., Seaman, S., Mehler, A., Sipperley, A., Pettinato, A., Seppelt, B.D., Angell, L., Mehler, B., Reimer, B., 2019. MIT Advanced Vehicle Technology Study: Large-Scale Naturalistic Driving Study of Driver Behavior and Interaction With Automation. IEEE Access 7, 102021–102038.
Gaspar, J., Carney, C., 2019. The Effect of Partial Automation on Driver Attention: A Naturalistic Driving Study. Hum. Factors 61 (8), 1261–1276.
Geurts, M., Hogema, J., Silvas, E., Souman, J., Rahman, A. & Hiller, J., 2022. Evaluating the Quality of Lane Change Event Detection: Effect of Situational Variables. In Proceedings of the 8th International Conference on Vehicle Technology and Intelligent Transport Systems. On-line conference: 27-29 April, 2022.
Ghasemzadeh, A., Ahmed, M.M., 2019. Quantifying regional heterogeneity effect on drivers' speeding behavior using SHRP2 naturalistic driving data: A multilevel modeling approach. Transp. Res. Part C: Emerging Technol. 106, 29–40.
Ghasemzadeh, A., Hammit, B.E., Ahmed, M.M., Young, R.K., 2018. Parametric Ordinal Logistic Regression and Non-Parametric Decision Tree Approaches for Assessing the Impact of Weather Conditions on Driver Speed Selection Using Naturalistic Driving Data. Transp. Res. Rec. 2672 (12), 0361198118758035.
Gunter, G., Stern, R., Work, D.B., 2019. Modeling adaptive cruise control vehicles from experimental data: model comparison, 2019 IEEE Intelligent Transportation Systems Conference (ITSC), pp. 3049-3054.
Harville, D.A., 1977. Maximum Likelihood Approaches to Variance Component Estimation and to Related Problems. J. Am. Statistical Assoc. 72 (358), 320–338.
Hastie, T., Tibshirani, R., Friedman, J., 2009. The elements of statistical learning: data mining, inference and prediction. Springer.
Heikoop, D.D., de Winter, J.C.F., van Arem, B., Stanton, N.A., 2019. Acclimatizing to automation: Driver workload and stress during partially automated car following in real traffic. Transp. Res. Part F: Traffic Psychology Behav. 65, 503–517.
Knoop, V.L., Daamen, W., 2017. Automatic fitting procedure for the fundamental diagram. Transportmetrica B: Transport Dynamics 5 (2), 129–144.
Knoop, V.L., Wang, M., Wilmink, I., Hoedemaeker, D.M., Maaskant, M., Van der Meer, E.-J., 2019. Platoon of SAE Level-2 Automated Vehicles on Public Roads: Setup, Traffic Interactions, and Stability. Transp. Res. Rec. 2673 (9), 311–322.
Kong, X., Das, S., Jha, K., Zhang, Y., 2020. Understanding speeding behavior from naturalistic driving data: Applying classification based association rule mining. Accident Anal. Prevention 144, 105620.
Li, T., Chen, D., Zhou, H., Laval, J., Xie, Y., 2021. Car-following behavior characteristics of adaptive cruise control vehicles based on empirical experiments. Transp. Res. Part B: Methodol. 147, 67–91.
Lu, Z., Happee, R., Cabrall, C.D.D., Kyriakidis, M., de Winter, J.C.F., 2016. Human factors of transitions in automated driving: A general framework and literature survey. Transp. Res. Part F: Traffic Psychol. Behav. 43, 183–198.
Lüdecke, D., 2018. ggeffects: Tidy Data Frames of Marginal Effects from Regression Models. J. Open Source Software 3 (26), 772.
Makridis, M., Mattas, K., Anesiadou, A., Ciuffo, B., 2021. OpenACC. An open database of car-following experiments to study the properties of commercial ACC systems. Transp. Res. Part C: Emerging Technol. 125, 103047.
Makridis, M., Mattas, K., Ciuffo, B., Re, F., Kriston, A., Minarini, F., Rognelund, G., 2020. Empirical Study on the Properties of Adaptive Cruise Control Systems and Their Impact on Traffic Flow and String Stability. Transp. Res. Rec. 2674 (4), 471–484.
Malta, L., Ljung Aust, M., Faber, F., Metz, B., Saint Pierre, G., Benmimoun, M., Schäfer, R., 2012. SP6 D6.4 Final results: Impacts on traffic safety.
Martens, M.H., Jenssen, G.D., 2012. Behavioral Adaptation and Acceptance. In: Eskandarian, A. (Ed.), Handbook of Intelligent Vehicles. Springer, London, London, pp. 117–138.
Milanés, V., Shladover, S.E., 2014. Modeling cooperative and autonomous adaptive cruise control dynamic responses using experimental data. Transp. Res. Part C: Emerging Technol. 48, 285–300.
Miller, E.E., Boyle, L.N., 2018. Behavioral Adaptations to Lane Keeping Systems: Effects of Exposure and Withdrawal. Hum. Factors 61 (1), 152–164.
Morando, A., Victor, T., Dozza, M., 2019. A Reference Model for Driver Attention in Automation: Glance Behavior Changes During Lateral and Longitudinal Assistance. IEEE Trans. Intell. Transp. Syst. 20 (8), 2999–3009.
Morgenstern, T., Schott, L., Krems, J.F., 2020. Do drivers reduce their speed when texting on highways? A replication study using European naturalistic driving data. Saf. Sci. 128, 104740.
Naujoks, F., Purucker, C., Neukum, A., 2016. Secondary task engagement and vehicle automation – Comparing the effects of different automation levels in an on-road experiment. Transp. Res. Part F: Traffic Psychol. Behav. 38, 67–82.
NHTSA, 2005. Automotive Collision Avoidance System Field Operational Test Report: Methodology and Results. National Highway Traffic Safety Administration, U.S. Department of Transportation.
Novakazi, F., Orlovska, J., Bligård, L.-O., Wickman, C., 2020. Stepping over the threshold linking understanding and usage of Automated Driver Assistance Systems (ADAS). Transp. Res. Interdisciplinary Perspect. 8, 100252.
OECD, 1990. *Behavioural adaptations to changes in the road transport system : report*. Organisation for Economic Co-Operation and Development; Obtainable from OECD Publications and Information Centre, Paris; Washington, D.C.
Openbaar Ministerie, 2021. Snelheid en te hard rijden: marges en meetcorrecties.
Orlovska, J., Novakazi, F., Lars-Ola, B., Karlsson, M., Wickman, C., Söderberg, R., 2020. Effects of the driving context on the usage of Automated Driver Assistance Systems (ADAS) -Naturalistic Driving Study for ADAS evaluation. Transp. Res. Interdisciplinary Perspect. 4, 100093.
Papadimitriou, E., Argyropoulou, A., Tselentis, D.I., Yannis, G., 2019. Analysis of driver behaviour through smartphone data: The case of mobile phone use while driving. Saf. Sci. 119, 91–97.
Paschalidis, E., Choudhury, C.F., Hess, S., 2018. Modelling the effects of stress on gap-acceptance decisions combining data from driving simulator and physiological sensors. Transp. Res. Part F: Traffic Psychol. Behav. 59, 418–435.
Paschalidis, E., Hajiseyedjavadi, F., Wei, C., Solernou, A., Hamish Jamson, A., Merat, N., Romano, R., Boer, E.R., 2020. Deriving metrics of driving comfort for autonomous vehicles: A dynamic latent variable model of speed choice. Analytic Methods in Accident Res. 28, 100133.
Pauwelussen, J., Feenstra, P.J., 2010. Driver Behavior Analysis During ACC Activation and Deactivation in a Real Traffic Environment. IEEE Trans. Intell. Transp. Syst. 11 (2), 329–338.
Precht, L., Keinath, A., Krems, J.F., 2017. Identifying the main factors contributing to driving errors and traffic violations – Results from naturalistic driving data. Transp. Res. Part F: Traffic Psychol. Behav. 49, 49–92.
Purucker, C., Berghöfer, F., Naujoks, F., Wiedemann, K., Marberger, C., 2018. Prediction of Take-Over Time Demand in Highly Automated Driving. Results of a Naturalistic Driving Study.
Richard, C.M., Lee, J., Atkins, R., Brown, J.L., 2020. Using SHRP2 naturalistic driving data to examine driver speeding behavior. J. Saf. Res. 73, 271–281.
Russell, S., Blanco, M., Atwood, J., Schaudt, W., Fitchett, V., Tidwell, S., 2018. Naturalistic Study of Level 2 Driving Automation Functions.
SAE, 2015. Operational Definitions of Driving Performance Measures and Statistics, in: International, S. (Ed.), *J2944*, Warrendale, PA.
Schakel, W.J., Gorter, C.M., Winter, J.C.F.D., Arem, B.V., 2017. Driving Characteristics and Adaptive Cruise Control ? A Naturalistic Driving Study. IEEE Intell. Transp. Syst. Mag. 9 (2), 17–24.
Singh, H., Kathuria, A., 2021. Analyzing driver behavior under naturalistic driving conditions: A review. Accid. Anal. Prev. 150, 105908.
Solís-Marcos, I., Ahlström, C., Kircher, K., 2018. Performance of an Additional Task During Level 2 Automated Driving: An On-Road Study Comparing Drivers With and Without Experience With Partial Automation. Hum. Factors 60 (6), 778–792.
Stapel, J., Mullakkal-Babu, F.A., Happee, R., 2019. Automated driving reduces perceived workload, but monitoring causes higher cognitive load than manual driving. Transp. Res. Part F: Traffic Psychol. Behav. 60, 590–605.
Strand, N., Nilsson, J., Karlsson, I.C.M., Nilsson, L., 2014. Semi-automated versus highly automated driving in critical situations caused by automation failures. Transp. Res. Part F: Traffic Psychol. Behav. 27, 218–228.
Thieurmel, B., Elmarhraoui, A., 2019. suncalc: Compute Sun Position, Sunlight Phases, Moon Position and Lunar Phase.

Transportation Research Board, 2010. HCM 2010: Highway Capacity Manual. Transportation Research Board, Washington, DC.
Treiber, M., Helbing, D., 2002. Reconstructing the spatio-temporal traffic dynamics from stationary detector data. Cooperative Transp. Dynamics 24.
Van Der Laan, J.D., Heino, A., De Waard, D., 1997. A simple procedure for the assessment of acceptance of advanced transport telematics. Transp. Res. Part C: Emerging Technol. 5 (1), 1–10.
Várhelyi, A., Kaufmann, C., Johnsson, C., Almqvist, S., 2020. Driving with and without automation on the motorway – an observational study. J. Intelligent Transp. Syst. 1–22.
Varotto, S.F., Farah, H., Bogenberger, K., Van Arem, B., Hoogendoorn, S.P., 2020. Adaptations in driver behaviour characteristics during control transitions from full-range Adaptive Cruise Control to manual driving: an on-road study. Transportmetrica A: Transport Sci. 16 (3), 776–806.
Varotto, S.F., Farah, H., Toledo, T., Van Arem, B., Hoogendoorn, S.P., 2017. Resuming Manual Control or Not?: Modeling Choices of Control Transitions in Full-Range Adaptive Cruise Control. Transp. Res. Rec. 2622 (1), 38–47.
Varotto, S.F., Farah, H., Toledo, T., Van Arem, B., Hoogendoorn, S.P., 2018. Modelling decisions of control transitions and target speed regulations in full-range Adaptive Cruise Control based on Risk Allostasis Theory. Transp. Res. Part B: Methodol. 117, 318–341.
Varotto, S.F., Jansen, R., Bijleveld, F., van Nes, N., 2021a. Adaptations in driver deceleration behaviour with automatic incident detection: A naturalistic driving study. Transp. Res. Part F: Traffic Psychol. Behav. 78, 164–179.
Varotto, S.F., Jansen, R., Bijleveld, F., van Nes, N., 2021b. Driver speed compliance following automatic incident detection: Insights from a naturalistic driving study. Accid. Anal. Prev. 150, 105939.
Vogel, K., 2003. A comparison of headway and time to collision as safety indicators. Accid. Anal. Prev. 35 (3), 427–433.
Walker, F., Boelhouwer, A., Alkim, T., Verwey, W.B., Martens, M.H., 2018. Changes in Trust after Driving Level 2 Automated Cars. J. Adv. Transp. 2018, 1045186.
Wilson, K.M., Yang, S., Roady, T., Kuo, J., Lenné, M.G., 2020. Driver trust & mode confusion in an on-road study of level-2 automated vehicle technology. Saf. Sci. 130, 104845.
Yu, B., Chen, Y., Bao, S., 2019. Quantifying visual road environment to establish a speeding prediction model: An examination using naturalistic driving data. Accid. Anal. Prev. 129, 289–298.
Zuur, A.F., Ieno, E.N., Walker, N.J., Saveliev, A.A., Smith, G.M., 2009. Mixed effects models and extensions in ecology with R. Springer, New York.