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Adaptations in driver deceleration behaviour with automatic incident detection: A naturalistic driving study

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ABSTRACT

Traffic congestion and crash rates can be reduced by introducing variable speed limits (VSLs) and automatic incident detection (AID) systems. Previous findings based on loop detector measurements have revealed that drivers reduce their speeds while approaching traffic congestion when the AID system is active. Notwithstanding these behavioural effects, most microscopic traffic flow models assessing the impact of VSLs do not describe driver response accurately.

This study analyses the main factors that influence driver deceleration behaviour while approaching traffic congestion with and without VSLs. The Dutch VSL database was linked to the driver behaviour data collected in the UDRIVE naturalistic driving study. Driver engagement in secondary tasks and glance behaviour were extracted from the video data. Linear mixed-effects models predicting the characteristics of deceleration events were estimated.

The results show that the maximum deceleration is high when approaching a slower leader, when driving at high speeds and short distance headways, and close to the beginning of traffic congestion. The minimum time headway is short when driving at high speeds and changing lanes. Certain drivers showed higher decelerations and shorter time headways than others. Controlled for these main factors, smaller maximum decelerations were found when the VSLs were present and visible, and when the gantries were within close proximity. These factors could be incorporated into microscopic traffic simulations to evaluate the impact of AID systems on traffic congestion more realistically. Further research is needed to clarify the link between engagement in secondary tasks, glance behaviour and deceleration behaviour.

1. Introduction

Real-time traffic information and dynamic speed limits can contribute to reduce crash risk, traffic congestion, and levels of emission. Real-time traffic information is communicated to drivers using variable message signs (VMSs) and speed limits are dynamically regulated using variable speed limits (VSLs). VMSs and VSLs have been widely implemented to increase driver awareness of the traffic situation downstream and reduce the variation in speed across road users and road sections. The

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introduction of VSLs has resulted in a significant decrease in the number of injury crashes, which can be mainly attributed to a reduction in rear-end crashes (De Pauw, Daniels, Franckx, & Mayeres, 2018). To decrease the crash rates and maintain the traffic flow, different traffic management techniques are used in case of dense traffic, accidents, adverse weather conditions, construction works, and special events (Fuhs, 2010). An example of a traffic management technique is automatic incident detection (AID). AID systems have been installed on motorways to warn drivers of slow moving traffic downstream in several European countries and in the United States since the 1980s (Martens, 2013). In the Netherlands, the AID system registers when the driving speed is lower than 35 km/h using loop detectors and sets a VSL of fifty kilometres per hour on the gantries downstream from that point. The first and the second gantry upstream indicate seventy flashing VSL and fifty flashing VSL to allow drivers to reduce their speed in time while approaching traffic congestion.

AID systems might have both intended and unintended impacts (*behavioural adaptations*) on driver behaviour (Martens, 2013). The intended impacts are that drivers reduce their speed, increase their time headway, and improve their attention. Previous studies have shown that VSLs can increase speed homogeneity (Van Nes, Brandenburg, & Twisk, 2010) and speed compliance (Hoogendoorn, Harms, Hoogendoorn, & Brookhuis, 2012; Lee & Abdel-Aty, 2008). These changes in driver behaviour should reduce driver error and crash probability while approaching traffic congestion. Despite the potential impacts on traffic safety, there is very little empirical evidence of behavioural adaptations with AID systems (Martens, 2013). Previous studies have shown that drivers could reduce the speed in the segment where the VMS is displayed and compensate for the reduction by increasing their speed downstream (Boyle & Mannering, 2004). Furthermore, drivers might fail to notice unexpected changes in the VSLs (Harms & Brookhuis, 2016) and may have a lower ability to detect VSL changes with flashing lights and waves (Harms & Brookhuis, 2017).

Previous studies have shown that AID systems can reduce the speed differences between vehicles (Hourdos, Liu, Dirks, Liu, Huang, Sun, & Xiao, 2017; Smulders, 1990; Van den Hoogen & Smulders, 1994) and the average maximum deceleration while approaching traffic congestion (Van Lint et al., 2020). These studies were based on data collected with loop detectors, which measure vehicle speeds and counts at specific locations and most often provide aggregated measurements during a certain interval of time (e.g., one minute). Road operators are currently interested in understanding whether the investment in roadside VSLs is a cost-effective strategy for the future (Van Lint et al., 2020). With the introduction of new in-vehicle technologies, in-vehicle systems could be used for sensing the traffic conditions downstream and regulate the speed. Loop detector measurements, however, provide limited insights into the main elements that impact driver behaviour while approaching traffic congestion. Driver behaviour might be influenced by the characteristics of the traffic flow, the road, and the drivers. For instance, drivers could decrease their speed because the next vehicle ahead (direct leader) slows down or because they see the VSLs on the gantries. Furthermore, drivers may fail to respond to the VSLs because they are looking off-road and are engaged in non-driving tasks. Rear end crashes may occur when a lead vehicle suddenly brakes while the driver is not paying attention to the forward roadway (Dingus et al., 2006). The highest crash risk is related to tasks as phoning with a hand-held device, reaching for objects in the cabin, writing, reading and observing objects outside (Dingus et al., 2016). A deeper understanding of these behavioural mechanisms can be achieved by analysing data of individual drivers collected in naturalistic driving experiments (Carsten, Kircher, & Jamson, 2013). Section 1.1 provides an overview of existing studies on driver behaviour with congestion warning systems and variable speed limits. Section 1.2 presents the research gaps and the research objectives.

1.1. Background

This section discusses driving simulator studies and on-road studies analysing the impact of in-vehicle and roadside congestion warning messages on driver behaviour on motorways. Notably, most studies available in literature focused on in-vehicle congestion warnings including a text message or a pictogram. To date, the impact of VSLs on traffic congestion have been mainly analysed at an aggregate level based on loop detector data (for a review, see Jomaa, Yella, and Dougherty (2013)).

Several studies have analysed the impact of in-vehicle congestion warning systems on driver behaviour on motorways in driving simulator experiments. Alm and Nilsson (2000) showed that drivers reduced their speed earlier, had a lower level of self-reported workload, and maintained a similar minimum distance to the congestion tail with the warning messages. Van Driel, Hoedemaeker, and Van Arem (2007) found that the warnings resulted in a lower percentage of time headways shorter than two seconds while approaching traffic congestion. In a follow-up study, Brookhuis, Van Driel, Hof, Van Arem, and Hoedemaeker (2009) showed that congestion warnings did not have an impact on the mental workload measures. Popiv, Rommerskirchen, Bengler, Duschl, and Rakic (2010) found that drivers started to brake earlier and with smaller maximum decelerations with the warning system. Similarly, Totzke, Naujoks, Mühlbacher, and Krüger (2012) found that drivers started to decelerate in advance when they were informed about the distance to the beginning of a congestion tail that required a sudden deceleration. Messages without the distance to the congestion tail and messages that required a smooth deceleration did not have an impact. In a follow up study, Naujoks and Totzke (2014) found higher maximum speeds, lower minimum time to collision in light traffic, and higher engagement in secondary tasks when the system was available than when it was not available. When the system was available, old drivers showed a larger reduction in minimum time to collision while young drivers showed higher engagement in secondary tasks. To summarize, these studies analysed the effect of few independent factors on driver responses to in-vehicle VMSs using descriptive statistics and statistical tests.

Few studies investigated the effect of roadside congestion warning messages on driver behaviour based on driver simulator experiments. Reinolsmann et al. (2018) analysed the impact of different VMS locations, designs, and distances from congestion on speed, maximum deceleration, and glance behaviour in motorways using descriptive statistics. The results showed that congestion warning messages installed on gantries one kilometre before the beginning of congestion resulted in lower speeds and smaller maximum decelerations than no warning messages. Drivers who drove at high speeds decelerated harder and closer to the beginning of congestion. Glances were shorter and more frequent on VMSs installed on gantries than on cantilevers. They concluded that the impact of congestion warning messages on driver behaviour is influenced by visibility conditions and proximity to the incident.

Very few studies have analysed the impact of advisory systems on driver performances on the motorway based on on-road experiments. Farah et al. (2012) analysed the impact of different in-vehicle VMSs (e.g., traffic congestion, roadworks, weather) based on data collected in a controlled on-road experiment (pre-set route). The results showed that most drivers reduced their speeds (mean reduction = 8.5 km/h) after receiving a congestion warning message. Based on the same experiment, Farah and Koutsopoulos (2014) investigated the impact of in-vehicle VMSs on driver acceleration and deceleration behaviour in a car-following model. The results showed that drivers older than 45 decelerated less when the system was on. The authors concluded that the warning system harmonizes the responses of drivers from different age groups and has a beneficial impact on traffic safety.

Recent studies have also developed models that predict driver behaviour with VSLs based on SHRP2 naturalistic driving data. Wang, Hallmark, Savolainen, and Dong (2018) analysed the vehicle speed on rural two-lane horizontal curves in different traffic conditions as a function of road geometry, posted speed limit, VSLs and driver characteristics. They selected traces on curves with a high posted speed limit (45 mph or 55 mph) and calculated the mean speed in each curve. In a regression model, they found that the mean speed was lower when the VSL was activated. In addition, the mean speed decreased with sharper curves and lower posted speed limits, when guardrails and arrow signs were installed, when a direct leader was present, when driving at night, when the driver was a female, and when the driver was older than 25 years.

1.2. Knowledge gap and research objective

Previous studies have analysed the impact of congestion VMSs on driver behaviour based on data collected in driving simulator experiments. Most studies analysed the effect of in-vehicle VMSs and only Reinolsmann et al. (2018) analysed the impact of roadside VMSs. These studies investigated the impact of a limited number of factors using descriptive statistics and statistical tests. Few studies were based on on-road experiments and proposed a comprehensive analysis of the main factors influencing driver response to VMSs and VSLs while approaching traffic congestion. Farah et al. (2012) and Farah and Koutsopoulos (2014) focused on in-vehicle warning messages only based on data collected in a controlled on-road experiment. Wang et al. (2018) focused on the impact of VSLs on curves in rural roads only based on naturalistic driving data. In addition, these studies did not capture explicitly the impact of glance behaviour and secondary task engagement on the deceleration behaviour characteristics (for a review on glance behaviour, secondary task engagement, and driver performances based on naturalistic driving data, see Varotto, Jansen, Bijleveld, & Van Nes (2021)).

The research objective of the current study is to identify the main factors influencing driver deceleration behaviour while approaching traffic congestion with and without the AID system. The maximum deceleration (Popiv et al., 2010; Reinolsmann et al., 2018; Van Driel et al., 2007; Van Lint et al., 2020) and the minimum time headway (Naujoks & Totzke, 2014) during the events (event characteristics) are analysed to capture adaptations in the longitudinal control task of drivers. The maximum deceleration is used as an indicator of driver aggressiveness while approaching traffic congestion. The minimum time headway is chosen as a measure of the quality of the longitudinal control task when following a vehicle. These behavioural characteristics are often used to describe driver response in microscopic traffic models and to identify safety relevant traffic situations. The impact of the traffic conditions, driver characteristics, glance behaviour, secondary task engagement and characteristics of the environment (e.g., VSLs active or inactive on the gantries) on the event characteristics are analysed using linear mixed-effects models. For this analysis, the driver behaviour data collected in the UDRIVE naturalistic driving study (Van Nes, Bärgman, Christoph, & Van Schagen, 2019) were linked to the Dutch VSL database and the state of the driver was extracted from the video data. Naturalistic driving studies are particularly suitable to analyse driver management of different task activities because participants are not directly instructed to engage in secondary tasks as in driving simulator and test track experiments (Carsten et al., 2013). The integrated database was used to extract events in which the AID system was active in another study (Varotto et al., 2021). In that study, we analysed the main factors influencing driver compliance with the VSLs, which was defined based on the speed of the driver downstream the gantry. In a logistic regression model, we found that the factors associated with speed compliance differ depending on which VSL the driver encounters.

The paper is structured as follows. Section 2 presents the naturalistic driving database, the VSL database, the annotation method of the driver state, and the statistical analysis methods. Section 3 describes the linear mixed-effects models predicting the maximum deceleration and the minimum time headway during events while approaching traffic congestion. Finally, Section 4 presents the main factors influencing the event characteristics and recommendations for future research.

2. Method

The method section presents the naturalistic driving data, the data processing procedures and the data analysis methods in this study. Section 2.1 describes the naturalistic driving database used in the present study. Section 2.2 describes the procedure to match the driver behaviour data with the national road database, the gantry locations, and the VSLs posted in each gantry using the GPS coordinates and the timestamps. Section 2.3 describes how the deceleration events while approaching traffic congestion were extracted from the driver behaviour data. Section 2.4 presents the annotation procedure of the video data during the events. Section 2.5 introduces the linear mixed-effects models developed to analyse the main factors influencing driver deceleration behaviour.

2.1. UDRIVE database

Passenger car driver behaviour data were collected in the Netherlands within the UDRIVE project (Van Nes et al., 2019). Thirty-three drivers with a minimum mileage of 10,000 km per year were recruited in the population of the Netherlands and participated in the experiment. The sample comprised eighteen males and fifteen females. Three drivers were 18–29 years old, ten 30–39 years old, nine 40–49, and eleven 50–65 years old. Before joining the experiment, all drivers were instructed on the project and signed a standard informed consent form. The UDRIVE data acquisition system was installed in ten leased vehicles (Renault Clio IV). The instrumented vehicles were driven by each participant for six months in 2015–2017. One vehicle was shared by multiple participants in the same household. The data acquisition system registered, amongst others, date and time, GPS coordinates, speed, acceleration, distance headway and leader speed (from MobilEye smart camera), and seven video cameras recording the road environment, the driver and the passenger (Fig. 1). The data were registered at 1 Hz frequency (GPS position) and 10 Hz frequency (e.g., speed). In total, 230,842 km were driven in 3727 h.

2.2. Variable speed limit database and road database

The executive agency of the Dutch Ministry of Infrastructure and Water Management (Rijkswaterstaat) provided the variable speed limits posted on the Dutch motorway network in 2015–2017. Each state change of a specific gantry at a certain time is registered in the variable speed limit database as a single observation. The position of each gantry is identified by the number of the motorway and the closest hectometre pole (maximum error due to hectometre pole spacing = 50 m). The variable speed limits were integrated into to the UDRIVE database by projecting location-based information (e.g., car position, gantry positions) to a common hectometre pole grid. First, the coordinates in the UDRIVE database were transformed from the GPS system into the Dutch grid (Rijksdriehoek [RD]) system. Next, each RD coordinate was linked to the closest road in

Fig. 1. Seven camera views of the UDRIVE database at the encounter of an active VSL: front left, front centre, front right, cockpit, driver face, cabin, and feet. Faces have been covered to respect the privacy of the participating driver and passengers. This figure was originally presented in Varotto et al., (2021).

the National Road Database (Nationaal Wegenbestand) (Rijkswaterstaat, 2017). The closest road calculated was compared to the closest road calculated in the previous observations to account for potential errors in the coordinates. The number of the motorway, the driving direction, and an identification number for the road section were retrieved from the National Road Database. The closest gantry in front of (next gantry) and behind (previous gantry) the driver were identified by projecting the RD coordinates on a hectometre pole grid and comparing the hectometre pole numbers with the National Road Database. The state of the gantry, the date and time of the last state change, and the distance to the gantry were assigned to each RD coordinate in the UDRIVE database. The executive agency of the Dutch Ministry of Infrastructure and Water Management provided also the road number and the hectometre number of the road sections where the electronic speed control was active. These data were incorporated into the UDRIVE database.

2.3. Event selection

The events were identified based on the driver behaviour characteristics of the subject vehicle and of the leader (speed, acceleration, distance headway and relative speed) in the UDRIVE database. The original data extracted from the database were resampled at 10 Hz and synchronized using linear interpolation. The road type was identified based on the classification in the road database and the posted speed limit in the UDRIVE database. We analysed only observations on road segments classified as motorway mainline and with a posted speed limit between 100 km/h and 130 km/h. In this study, traffic congestion was identified as a situation in which the mean speed of the subject vehicle and of the direct leader were lower than 70 km/h for at least 10 s. This assumption was made in order to include congestion situations with and without gantries and AIDs. The mean speed was chosen based on the mean speeds at level of service (LOS) E proposed by the Highway Capacity Manual (Transportation Research Board, 2010) (80 km/h) and suggested by the SHRP2 codebook (Virginia Tech Transportation Institute, 2015) (between 50 and 75 km/h depending on the posted speed limit). In these traffic conditions, any disruptions of the traffic stream can create a wave that propagates upstream and produce a breakdown. We did not analyse situations in which traffic congestion was not detected or traffic congestion was detected at less than 2500 m after the entrance of the motorway. The analysis focused only on events that occurred on the motorway segment closer than 2500 m before the beginning of traffic congestion. In this motorway segment, a direct leader was present all the time or part of the time. The events were discarded when the distance to the previous and to the next gantry were unknown or when the gantry states were unknown. The events were detected based on the longitudinal deceleration and on the speed of the subject vehicle. The event was considered of interest when three conditions were met. First, the subject vehicle decelerated more than 0.5 m/s^2 for a minimum duration of 1 s. Second, the speed at the beginning of the event was higher than 50 km/h. Third, the speed decrement during the event was larger than 5 km/h. The event terminated when the vehicle decelerated less than 0.5 m/s^2. This threshold was selected to exclude small decelerations that might be part of regular driving behaviour as suggested by Deligianni, Quddus, Morris, Anvuur, and Reed (2017). Multiple events were detected for each congestion situation when a single driver decelerated and accelerated multiple times. When the end of an event and the beginning of the next event occurred within 1 s, the two events were merged. This interval was chosen because it is similar to the reaction time of drivers. The above criteria imply that there was no fixed event duration.

2.4. Annotation

The videos related to each event were manually inspected and coded by four annotators using a dedicated toolbox developed in Microsoft Visual Studio 2017. The visualization toolbox allowed the annotators to load trips, to pause and play videos at a self-chosen playback speed, and to perform annotation using an array of labelled buttons. The annotation was conducted during three weeks in July 2019. During the first day, the annotators received a formal training consisting in the annotation of five events and a plenary consultation to achieve a common agreement on the variables annotated. The events were randomly distributed across the four annotators.

For each event, the following variables were coded once: weather circumstances (limited sight or not), density of the environment (open, half open, closed), and whether the driver took an exit lane by the end of the event. Three variables were annotated in the 5 s before the beginning of the event at a frame-by-frame resolution. These variables were: glance direction (eyes on and off road), secondary task engagement (yes or no), and gantry visibility (gantry not visible, gantry visible and VSL inactive, gantry visible and VSL active). The driving lane (counted from the central reservation) and a variable that indicated if the driver was passing a weaving section, entry lane, or exit lane were annotated at a frame-by-frame resolution in the 5 s before and during the event. The gantry passing time (if present) and the variable speed limit within the driving lane were annotated both during the 5 s before the event and during the event itself. The annotation of the driving lane allowed us to recognise if drivers were subject to the AID sequence when the VSLs differed across the driving lanes. Notes on playback errors (e.g., video not loading or asynchronous camera views) and on drivers with sunglasses (i.e., impossible glance annotation) were used to remove the associated events from analysis. The annotators manually coded the level of traffic density (low, medium, high traffic density) in the interval 10 s after the beginning of traffic congestion (i.e., following the events). The level of traffic density was defined based on the levels of service (LOS A-B, LOS C-D, LOS E-F) in the Highway Capacity Manual (Transportation Research Board, 2010). This classification of the traffic density levels was used in the SHRP2 project (Virginia Tech Transportation Institute, 2015) and has shown high levels of inter-rater reliability in previous studies (Hankey, Perez, & McClafferty, 2016). If the traffic density was classified as low, the corresponding events were removed from subsequent analyses. The interrater reliability of the annotation was investigated based on statistical measures as described in Varotto et al. (2021). The variables analysed in Section 3 resulted to be eligible based on the reliability tests. Measures based on secondary task engagement, weather conditions, presence of ramps and weaving sections did not meet the reliability criteria and were excluded from the analysis.

2.5. Statistical analysis

The main factors influencing the maximum deceleration and the minimum time headway (event characteristics) are analysed in linear mixed-effects models. Linear mixed-effects models allow to investigate the unconditional marginal effect of several explanatory variables on the event characteristics capturing correlations between repeated observations for the same driver (Deligianni et al., 2017; Farah, Bianchi Piccinini, Itoh, & Dozza, 2019; Oviedo-Trespalacios, Haque, King, & Washington, 2017; Varotto, Farah, Bogenberger, Van Arem, & Hoogendoorn, 2020; Varotto, Farah, Toledo, Van Arem, & Hoogendoorn, 2018). The models predicting the event characteristics (EvChar) for driver n at time t are given by equation (1):

$$\mathrm{Y_n(t)} = \mu + \boldsymbol{\lambda} \cdot \mathbf{X_n(t)} + \gamma \cdot \vartheta_\mathrm{n} + \omega \cdot \upsilon_\mathrm{n}(\mathrm{t}) \tag{1}$$

where μ is the mean, $\boldsymbol{\lambda}$ is the vector of parameters related to the explanatory variables $\mathbf{X_n(t)}$, γ is the parameter associated with the driver-specific error term $\vartheta_\mathrm{n} \sim \mathrm{N}(0,1)$, and ω is the parameter associated with the observation-specific error term $\upsilon_\mathrm{n}(\mathrm{t}) \sim \mathrm{N}(0,1)$. Relevant explanatory variables that can be included are the driver behaviour characteristics of the subject vehicle and of the direct leader, driver glance behaviour metrics, driver characteristics, characteristics of the motorway segment and of the environment. The driver-specific error term captures unobserved preferences that influence all responses by the same individual driver. The probability density function of the event characteristics conditional on the value of ϑ_n is given in Eq. (2):

$$P(Y_n(t) = log(EvChar_n(t))|\vartheta_n) = \frac{1}{\omega}\phi\left(\frac{log(EvChar_n(t)) - \mu - \boldsymbol{\lambda} \cdot \boldsymbol{X_n(t)} - \gamma \cdot \vartheta_n}{\omega}\right) \tag{2}$$

The linear mixed-effects models were estimated using the package ‘nlme’ (Pinheiro, Bates, DebRoy, Sarkar, & R Core Team, 2019), which allows to explicitly define a residual variance-covariance structure and to choose maximum likelihood (ML) or restricted maximum likelihood (REML) estimation methods. REML methods produce unbiased estimates of the residual variance-covariance parameters accounting for the loss in degrees of freedom due to the estimation of the fixed effects (Harville, 1977). The marginal and conditional R^2 measures were calculated using the package ‘MuMIn’ (Barton, 2019) in the software R (R Core Team, 2019). The marginal R^2_m captures the variance explained by the fixed factors while the conditional R^2_c captures the variance explained by both fixed and random factors (Nakagawa, Johnson, & Schielzeth, 2017; Nakagawa & Schielzeth, 2013). The estimated marginal means of the event characteristics were calculated using the package ‘ggeffects’ (Lüdecke, 2018). The estimated means, the confidence intervals and the prediction intervals were calculated changing one independent variable while keeping all the other variables fixed. The confidence intervals capture the uncertainty about the fixed effect parameters while the prediction intervals capture the uncertainty about both fixed and random effect parameters.

In this study, the event characteristics are assumed to be influenced by the driver behaviour characteristics at the beginning of the event and by the glance behaviour metrics registered 3 s before the beginning of the event. The time interval was chosen based on previous studies in literature (Peng, Boyle, & Hallmark, 2013). Other time intervals (2 s and 5 s) were also explored and resulted in similar findings. We investigated bivariate correlations between the event characteristics and the explanatory variables using both Pearson-product moment correlations ($\mathrm{r_P}$) and Spearman rank-order correlations ($\mathrm{r_S}$). We selected the explanatory variables in the final specification of the linear mixed-effects models depending on their interpretation (non-redundant variables) and statistical significance (p-value < 0.05). All continuous variables were centred in the mean value. The impact of each explanatory variable was tested statistically by comparing alternative model specifications using ML estimation methods and likelihood ratio tests. We tested first the variable that resulted to have a high or medium correlation with the event characteristics. Variables that had a very similar interpretation (e.g., different glance behaviour metrics) were separately included in the model. The correlation matrix of the parameters was inspected each time the model was estimated. This stepwise procedure allowed us to detect potential cases of multicollinearity between explanatory variables. Substantial changes in the parameters when a variable was added or a significant likelihood ratio test when the parameters of multiple variables were non-significant were considered potential indicators of multicollinearity. Explanatory variables that had a similar interpretation were tested separately against each other and merged when they did not have a significantly different effect on the event characteristics. Variables that did not have a significant effect were omitted one by one. When a variable was missing for some observations (e.g., a direct leader was not identified by the MobilEye and the distance headway was unavailable), we included a binary variable indicating the missing values in addition to the original variable (dummy variable adjustment method). Different specifications of the residual covariance parameters were compared using REML estimation methods and likelihood ratio tests. Congestion-specific and trip-specific error terms did not result in a significant improvement in goodness of fit and therefore were not included in the final specification of the models.

3. Results

The result section discusses the main factors influencing the characteristics of deceleration events while approaching traffic congestion. Section 3.1 provides an overview of the events using descriptive statistics. Section 3.2 discusses the estimation results of the linear mixed-effects models predicting the maximum deceleration and the minimum time headway. Section 3.3 presents the out-of-sample validation analysis of the linear mixed-effects models estimated.

3.1. Descriptive statistics

Using the selection procedure described in Section 2.3, we identified 645 traffic congestion situations. In the first 10-s of the congestion situations, all of which were validated through annotation, the mean of the subject vehicle mean speed was 55.52 km/h and the mean of the speed standard deviation was 6.830 km/h. We identified 1060 deceleration events while approaching the beginning of traffic congestion. These events occurred in 440 distinct trips by 29 drivers. The number of events per congestion situation was between 1 and 8 (Median = 1) and the number of events per driver was between 2 and 116 (Median = 30.00). The event duration was between 1.1 s and 24.9 s (Median = 4.700 s, Mean = 5.709 s). The maximum deceleration during the events was between 0.550 m/s^2 and 8.761 m/s^2 (Median = 1.500 m/s^2, Mean = 1.715 m/s^2). A direct leader was present (all the time or part of the time) in 1028 events. The minimum time headway during these events was between 0.1163 s and 5.508 s (Median = 1.101 s, Mean = 1.336 s).

A direct leader was present at the beginning of 90.19% of the events. Most events occurred within 2000 m before the next gantry (94.62%) or within 2000 m after the previous gantry (93.77%). In addition, 32.17% of the events occurred when the next gantry was closer than 2000 m and a VSL within the AID sequence was active on the driving lane: 14.53% when the seventy flashing VSL was active, 12.26% when the fifty flashing VSL was active, and 5.38% when the fifty VSL was active. To gain insights into the general characteristics of these events, we present the descriptive statistics of the driver behaviour characteristics and the characteristics of the road segment in Table 1. The mean values suggest that drivers decelerated more often when they were close to the beginning of traffic congestion and when they approached a slower vehicle.

We conducted correlation analysis to investigate the relations between the maximum deceleration, the minimum time headway, the traffic conditions, the infrastructure characteristics, and the driver characteristics. High maximum decelerations were observed close to the beginning of traffic congestion ($r_P = -0.32$, $r_S = -0.45$). The correlations between the maximum deceleration and the other explanatory variables available were weak ($|r| < 0.20$). Short minimum time headways were observed when a leader was present ($r_P = -0.38$, $r_S = -0.25$) and the distance headway was short ($r_P = 0.77$, $r_S = 0.76$) at the beginning of the event. The correlations with the other explanatory variables were weak ($|r| < 0.20$). Further analysis is needed to capture the impact of multiple explanatory variables simultaneously on the maximum deceleration and on the minimum time headway.

3.2. Linear mixed-effects models

3.2.1. Maximum deceleration

This section describes the model selection procedure and presents the results of the final model predicting the maximum deceleration. As discussed in section 2.5, the final model is the outcome of an extensive selection procedure, in which several model specifications were estimated and compared using statistical tests. The next paragraphs describe which explanatory variables were tested, which tests were significant and which direction significant impacts had. The description follows the order in which the variables were tested in the model development phase. We did not detect potential cases of multicollinearity between the explanatory variables. The equation of the final model is presented in Appendix A, Eq. (3). The goodness-of-fit measures are reported in Table 2 and the estimation results in Table 3. The logarithmic transformation of the maximum deceleration is consistent with the empirical findings and resulted in a significant improvement in goodness of fit compared to a linear specification. Most parameters related to the explanatory variables in Table 3 are statistically significant at the 5% level. The R^2 measures indicate that the explanatory variables capture 25.7% of the variability in the maximum deceleration and that the driver-specific error term captures an additional 3.4%.

Most driver behaviour characteristics of the subject vehicle and of the direct leader have a significant impact on the maximum deceleration. Drivers decelerated less aggressively at lower speeds. They also decelerated less when there was no

Table 1
Statistics of the driver behaviour characteristics and the characteristics of the road segment at the beginning of the events.

Variable	Description	Min.	Median	Mean	Max.
Speed	Speed of the subject vehicle in km/h	70.14	97.16	97.79	130.7
DHW	Distance headway (front bumper to rear bumper) in m	5.079	35.34	41.40	122.1
Relative speed	Relative speed (leader speed - subject vehicle speed) in km/h	– 48.57	– 4.667	– 6.089	22.35
DistCong	Distance to the beginning of traffic congestion in m	20.68	330.5	583.19	2498
DistNextGantry	Distance to the next gantry in m	2.58	251.7	754.7	33,494
DistPrevGantry	Distance from the previous gantry in m	9.14	312.21	1678	43,671

Table 2
Statistics of the linear mixed-effects model predicting the maximum deceleration. The log likelihood measures are calculated using ML methods while the R^2 measures using REML methods.

Statistics	
Number of parameters associated with the explanatory variables	9
Number of drivers	29
Number of observations	1060
Constant log likelihood	− 880
Final log likelihood	− 703
$R^2_m = \frac{\sigma_f^2}{\sigma_f^2+(\gamma^D)^2+(\omega^D)^2}$	0.257
$R^2_c = \frac{\sigma_f^2+(\gamma^D)^2}{\sigma_f^2+(\gamma^D)^2+(\omega^D)^2}$	0.291

Table 3
Estimation results of the linear mixed-effects model predicting the maximum deceleration. The parameters are estimated using REML methods. The driver behaviour characteristics and the characteristics of the road segment are measured at the beginning of each single event. The R package 'nlme' used for model estimation provides the test statistics of the fixed effects only.

Variable	Description	Parameters	Estimate	t-stat.	p-value
–	Mean maximum deceleration	μ^D	0.585	8.08	< 0.0005
Speed	Speed of the subject vehicle in km/h	λ^D_{Speed}	0.00999	7.38	< 0.0005
RelSpeed	Relative speed (leader speed - subject vehicle speed) in km/h	$\lambda^D_{RelSpeed}$	− 0.0133	− 6.91	< 0.0005
DHW	Distance headway (front bumper to rear bumper) in m	λ^D_{DHW}	− 0.00501	− 6.21	< 0.0005
NoLead	Binary variable equal to 1 when there is no leader	λ^D_{NoLead}	− 0.288	− 4.82	< 0.0005
DistCong	Distance to the beginning of traffic congestion in m	$\lambda^D_{DistCong}$	− 0.000453	− 16.79	< 0.0005
NextGantryClose	Binary variable equal to 1 when the next gantry is closer than 2000 m	$\lambda^D_{GantryClose}$	− 0.0839	− 2.34	0.020
PrevGantryClose	Binary variable equal to 1 when the previous gantry is closer than 2000 m	$\lambda^D_{GantryClose}$	− 0.0839	− 2.34	0.020
pGantryVisAct	Proportion of time when the gantry is visible and active during the 3 s before the beginning of the event	$\lambda^D_{pGantryVisAct}$	− 0.0855	− 2.24	0.025
*Next*70*,*50**	Binary variable equal to 1 when the next gantry is closer than 2000 m, the AID is active on the driving lane, and the next VSL is *70* or *50*	$\lambda^D_{Next*70*,*50*}$	− 0.126	− 3.73	0.0002
Age	Age of the driver in years	λ^D_{Age}	0.00377	1.84	0.076 [a]
ϑ^D_n	Driver-specific error term	γ^D	0.102	–	–
υ^D_n	Observation-specific error term	ω^D	0.466	–	–

Note: [a] the parameter associated with the driver age resulted in a significant improvement in goodness of fit based on the likelihood ratio test and ML estimation methods.

direct leader, when the distance headway was large, and when they were following a faster vehicle (positive relative speed). Drivers decelerated less when they were far from the beginning of traffic congestion. Changing lane during the event did not have an impact on the maximum deceleration.

Certain characteristics of the road segment influenced significantly the maximum deceleration. Drivers decelerated less when the previous or the next gantry were within 2000 m. The impact of distance to the previous and to the next gantry were tested separately against each other and did not differ significantly. Moreover, drivers decelerated less when they were close to the next gantry, when the AID sequence was active on the driving lane, and when the next VSL was either seventy flashing or fifty flashing. The impact did not differ significantly between seventy flashing and fifty flashing VSLs. Proximity to the fifty VSL within an AID sequence did not have a significant impact on the maximum deceleration. The number of lanes did not have a significant impact. The presence of an electronic speed control system did not have a significant impact on the maximum deceleration. Exiting the motorway at the end of the event did not influence significantly the maximum deceleration.

The visibility of the gantry had a significant impact on the maximum deceleration. Drivers decelerated less aggressively when the proportion of time during which the gantry was visible and active was higher. The glance behaviour of the driver did not have a significant impact on the maximum deceleration. Likewise, proportion of time with eyes off road, percentage of long glances off road, and count of switches between on and off-road glances did not have a significant impact.

Younger drivers decelerated less than older drivers. The gender did not have a significant impact on the maximum deceleration. The driver-specific error term resulted in a significant improvement in goodness of fit, meaning that certain drivers decelerated differently from others. Congestion-specific and trip-specific error terms did not improve the model significantly, indicating that no evidence was found for differences in the maximum deceleration between congestion situations and trips.

To analyse the effect of changes in the explanatory variables on the maximum deceleration, the maximum deceleration was calculated for observations in which only one variable was changed while keeping all the other variables fixed (speed:

97.79 km/h; distance headway: 41.41 m; relative speed: – 6.089 km/h; distance to congestion onset: 583.19 m; previous and next portal: closer than 2000 m; portal visibility: 23.0% of the time; AID sequence: inactive; driver age: 45 years old). The characteristics of the baseline observation were chosen based on the mean values in the sample. The maximum deceleration associated with the baseline observation was equal to 1.517 m/s^2. Fig. 2 presents the results for the continuous variables and Fig. 3 presents the results for the nominal variables. All results are consistent with previous discussions in this section. When we compare the different variables, we notice that low relative speeds have the strongest impact on the maximum deceleration. In addition, high speeds, short distance headways, proximity to the beginning of congestion, and the driver-specific error term have a large impact on the maximum deceleration.

3.2.2. Minimum time headway

This section presents the results of the final model predicting the minimum time headway. To develop this model, several model specifications were estimated and compared using statistical tests as described in Section 2.5. The next paragraphs describe the explanatory variables tested, the test results and the direction of significant impacts. The equation of the final model is presented in Appendix A, Eq. (4). The goodness-of-fit measures are presented in Table 4 and the estimation results in Table 5. The logarithmic transformation of the minimum time headway is consistent with empirical findings and resulted in a significant improvement in goodness of fit compared to a linear specification. All parameters associated with the explanatory variables in Table 5 are statistically significant at the 5% confidence level. The R^2 measures show that the explanatory variables capture 72.1% of the variability in the minimum time headway and that the driver-specific error term captures an additional 0.6%.

Most driver behaviour characteristics of the subject vehicle and of the direct leader have a significant impact on the minimum time headway. Drivers had larger time headways at lower speeds. They also had larger time headways when there was no direct leader at the beginning of the event (i.e., when they were approaching a new leader), when the distance headway was large, and when they were approaching a faster vehicle (positive relative speed). The logarithmic transformation of the distance headway resulted in a significant improvement in goodness of fit compared to a linear specification. The minimum time headway was larger when the driver did not change lane during the event. The distance to the beginning of traffic congestion did not have a significant impact on the minimum time headway.

In terms of characteristics of the road segment, four significant effects on the minimum time headway were found. Drivers had larger time headways when they were closer than 2000 m to the next gantry, the AID sequence was active on the

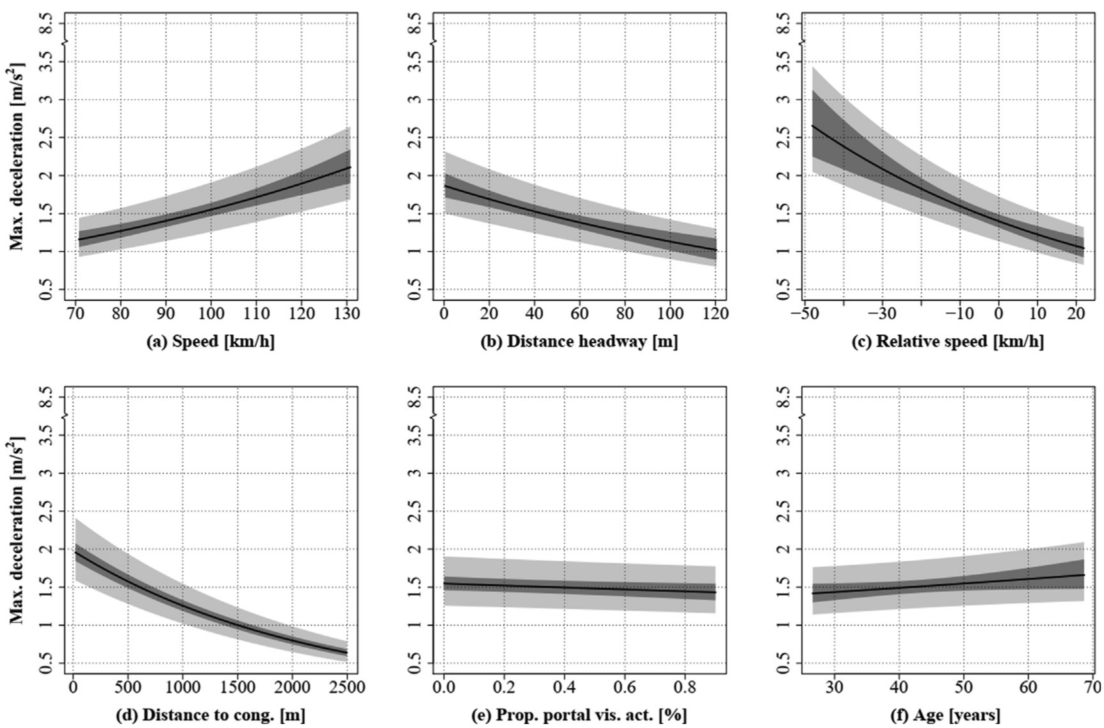

Fig. 2. Impact of the continuous explanatory variables on the maximum deceleration during the event. Black solid lines denote the marginal means, dark grey ribbons indicate the 95% confidence intervals, and light grey ribbons denote the 95% prediction intervals. The variables are listed as follows: (a) speed, (b) distance headway, (c) relative speed, (d) distance to the beginning of congestion, (e) proportion of time when the portal is visible and active, (f) driver age. The axis scales are chosen based on the minimum and the maximum values available in the data. To improve the readability, the vertical axis is interrupted at maximum deceleration equal to 3.75 m/s^2.

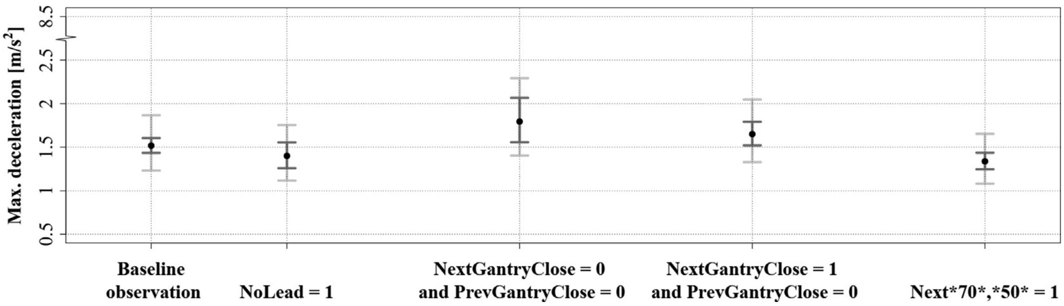

Fig. 3. Impact of the nominal explanatory variables on the maximum deceleration during the event. Black dots denote the marginal means, dark grey error bars indicate the 95% confidence intervals, and light grey error bars denote the 95% prediction intervals. The vertical axis scale is chosen based on the minimum and the maximum values available in the data. To improve the readability, the axis is interrupted at maximum deceleration equal to 2.75 m/s^2.

Table 4
Statistics of the linear mixed-effects model predicting the minimum time headway. The log likelihood measures are calculated using ML methods while the R^2 measures using REML methods.

Statistics	
Number of parameters associated with the explanatory variables	7
Number of drivers	29
Number of observations	1028
Constant log likelihood	− 898
Final log likelihood	− 231
$R^2_m = \frac{\sigma_f^2}{\sigma_f^2+(\gamma^D)^2+(\omega^D)^2}$	0.721
$R^2_c = \frac{\sigma_f^2+(\gamma^D)^2}{\sigma_f^2+(\gamma^D)^2+(\omega^D)^2}$	0.727

Table 5
Estimation results of the linear mixed-effects model predicting the minimum time headway. The parameters are estimated using REML methods. The driver behaviour characteristics and the characteristics of the road segment are measured at the beginning of each single event. The R package 'nlme' used for model estimation provides the test statistics of the fixed effects only.

Variable	Description	Parameters	Estimate	t-stat.	p-value
–	Mean minimum time headway	μ^T	0.0508	2.54	0.011
Speed	Speed of the subject vehicle in km/h	λ^T_{Speed}	− 0.0136	− 17.26	< 0.0005
RelSpeed	Relative speed (leader speed - subject vehicle speed) in km/h	$\lambda^T_{RelSpeed}$	0.00692	5.57	< 0.0005
DHW	Distance headway (front bumper to rear bumper) in m	λ^T_{DHW}	0.908	44.02	< 0.0005
NoLead	Binary variable equal to 1 when there is no leader	λ^T_{NoLead}	3.94	48.27	< 0.0005
LaneChange	Binary variable equal to 1 when one or more lane changes are executed during the event	$\lambda^T_{LaneChange}$	− 0.307	− 8.07	< 0.0005
Next50	Binary variable equal to 1 when the next gantry is closer than 2000 m, the AID is active on the driving lane, and the next VSL is 50	λ^T_{Next50}	0.105	2.46	0.014
Prev50	Binary variable equal to 1 when the previous gantry is closer than 2000 m, the AID was active on the driving lane, and the previous VSL was 50	λ^T_{Prev50}	0.105	2.46	0.014
Female	Binary variable equal to 1 when the driver is a female	λ^T_{Female}	0.0711	2.55	0.017
ϑ^T_n	Driver-specific error term	γ^T	0.0461	–	–
υ^T_n	Observation-specific error term	ω^T	0.302	–	–

driving lane, and the next VSL was fifty. A similar impact was found immediately after the fifty VSL. Several other factors did not reach statistical significance. The distance from the previous gantry and to the next gantry did not have a significant impact on the minimum time headway, neither did proximity to the seventy and the fifty flashing VSLs within an AID sequence. The number of lanes did not have a significant impact. The presence of an electronic speed control system did not have a significant impact on the minimum time headway. Exiting the motorway at the end of the event did not influence significantly the minimum time headway.

The glance behaviour of the driver did not have a significant impact on the minimum time headway. Proportion of time with eyes off road, percentage of long glances off road, and count of switches between on and off-road glances did not have a significant impact. In addition, the visibility of the gantry did not have a significant impact on the minimum time headway.

Female drivers had larger minimum time headways than male drivers. The age did not have a significant impact. The driver-specific error term resulted in a significant improvement in goodness of fit based on the log likelihood values, meaning that certain drivers had a different minimum time headway from others. Congestion-specific and trip-specific error terms did not improve the model significantly, indicating that no significant differences in time headways were found between congestion situations and trips.

The effect of changes in the explanatory variables on the minimum time headway was analysed by calculating the minimum time headway for observations in which only one variable was changed while keeping all the other variables fixed. In the baseline observation, the speed was equal to 97.57 km/h, the distance headway was 41.41 m, and the relative speed was − 6.278 km/h. Furthermore, an AID sequence was not active on the driving lane, the previous and the next portal were closer than 2000 m, and the driver was male. The characteristics of the baseline observation were chosen based on the mean values in the sample. The minimum time headway associated with the baseline observation was equal to 1.197 s. Fig. 4 presents the results for the continuous variables and Fig. 5 presents the results for the nominal variables. All findings are consistent with previous discussions in this section. When we compare the different variables, we notice that short distance headways at the beginning of the event have the strongest impact on the minimum time headway. Controlled for the initial distance headways, we observe that high speeds and changing lanes also have a large impact on the minimum time headway.

3.3. Validation analysis

This section provides a validation analysis of the linear mixed-effects models in Table 3 and Table 5 compared to linear mixed-effects models that contain only the constant. The purpose of this validation analysis is to understand the ability of the models to predict the behaviour of individual drivers not included in the estimation sample. The models should be applied to other empirical databases to understand their prediction abilities. Given that no other similar databases are available, an out-of-sample approach has been used. The models were estimated based on the observations of 80% of the drivers and validated based on the observations of the 20% of the drivers not included in the estimation sample. We used a five-fold cross validation method due to the small number of drivers (Hastie, Tibshirani, & Friedman, 2009). We randomly assigned the drivers to five groups, estimated the models on four groups, and validated the models on the group not included in the estimation sample. We repeated the procedure five times.

The performances of the models on the validation samples were evaluated based on the Root Mean Square Error (RMSE) of the model with constants only and of the linear mixed-effects models. The RMSE captures the prediction errors between the maximum deceleration (or the minimum time headway) predicted by the model and the maximum deceleration (or the minimum time headway) observed. The smaller the RMSE, the higher the accuracy achieved.

The RMSE of the models on the validation samples are presented in Table 6 (maximum deceleration) and in Table 7 (minimum time headway). The last column of each table presents the accuracy improvement. The results indicate that the linear mixed-effects models have smaller mean prediction errors than the models with constants only on all validation samples. Comparing the results in Table 7, we note that the linear mixed-effects model predicting the minimum time headway shows the smallest accuracy improvement when it is validated on group 1. This result means that certain drivers in this group showed a different behaviour in maintaining a minimum time headway than the other drivers. Further research is needed to explain the source of these differences that might be related to driving styles or personality traits. The main conclusion is that the linear mixed-effects models developed are suitable to forecast the behaviour of individual drivers not included in the estimation sample.

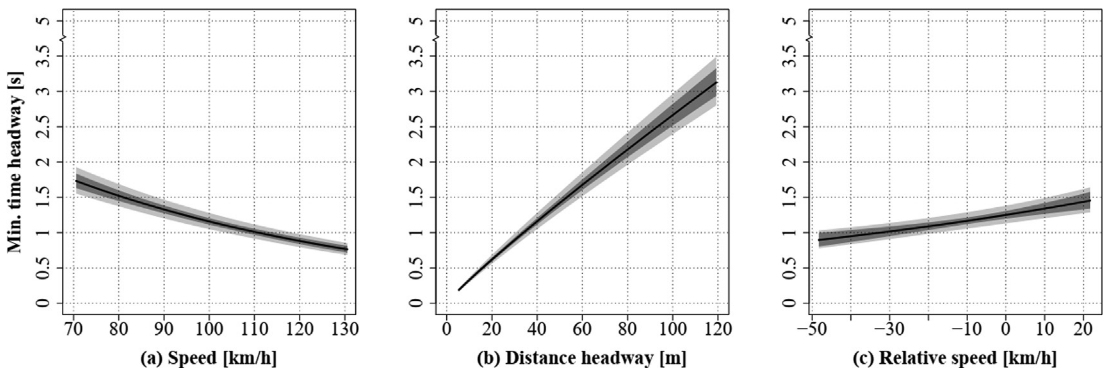

Fig. 4. Impact of the continuous explanatory variables on the minimum time headway during the event. Black solid lines denote the marginal means, dark grey ribbons indicate the 95% confidence intervals, and light grey ribbons denote the 95% prediction intervals. The variables are listed as follows: (a) speed, (b) distance headway, (c) relative speed. The axis scales are chosen based on the minimum and the maximum values available in the data. To improve the readability, the vertical axis is interrupted at minimum time headway equal to 3.75 s.

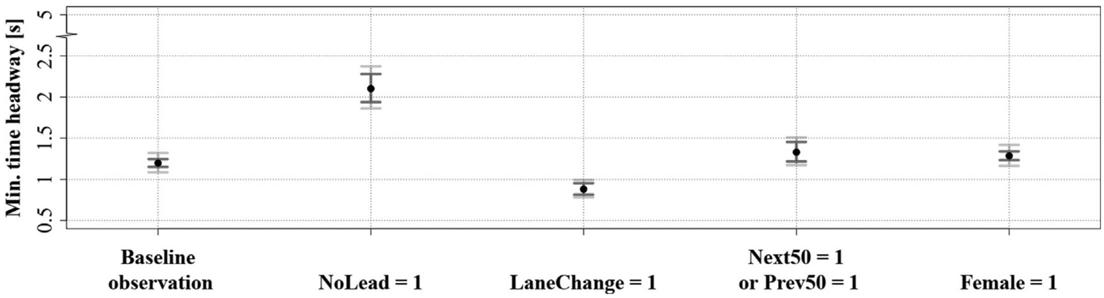

Fig. 5. Impact of the nominal explanatory variables on the minimum time headway during the event. Black dots denote the marginal means, dark grey error bars indicate the 95% confidence intervals, and light grey error bars denote the 95% prediction intervals. The vertical axis scale is chosen based on the minimum and the maximum values available in the data. To improve the readability, the axis is interrupted at minimum time headway equal to 2.75 s.

Table 6
Five-fold cross validation of the linear mixed-effects model predicting the maximum deceleration. C indicates the model that contains only the constant and $\hat{\beta}$ denotes the linear mixed-effects model.

Validation subsample	Drivers	Observations	RMSE($\mathbf{c}$)	RMSE$\left(\hat{\beta}\right)$	$\frac{\text{RMSE}(\mathbf{c})-\text{RMSE}\left(\hat{\beta}\right)}{\text{RMSE}(\mathbf{c})}$
1	6	208	0.555	0.473	0.1480
2	5	212	0.595	0.493	0.1703
3	6	213	0.505	0.454	0.0997
4	6	215	0.538	0.454	0.1560
5	6	212	0.600	0.525	0.1262
M	5.80	212	0.559	0.480	0.1400
SD	0.45	2.55	0.040	0.030	0.0276

Table 7
Five-fold cross validation of the linear mixed-effects model predicting the minimum time headway. C indicates the model that contains only the constant and $\hat{\beta}$ the linear mixed-effects model.

Validation subsample	Drivers	Observations	RMSE($\mathbf{c}$)	RMSE$\left(\hat{\beta}\right)$	$\frac{\text{RMSE}(\mathbf{c})-\text{RMSE}\left(\hat{\beta}\right)}{\text{RMSE}(\mathbf{c})}$
1	6	204	0.5800	0.3933	0.3218
2	5	203	0.5725	0.2822	0.5071
3	6	208	0.6270	0.3054	0.5129
4	6	208	0.5640	0.2692	0.5226
5	6	205	0.5742	0.2834	0.5065
M	5.80	206	0.5835	0.3067	0.4742
SD	0.45	2.06	0.0250	0.0501	0.0854

4. Discussion and conclusions

This study analysed the main factors influencing driver deceleration behaviour while approaching traffic congestion with VSLs. For this purpose, naturalistic driving data collected in the UDRIVE project were analysed using linear mixed-effects models. This data analysis method allows to capture the impact of multiple explanatory variables and unobserved correlations between observations for the same driver. The maximum deceleration and the minimum time headway were investigated as indicators of driver aggressiveness and control task quality while approaching traffic congestions. These indicators have been used in previous studies (Naujoks & Totzke, 2014; Popiv et al., 2010; Reinolsmann et al., 2018; Van Driel et al., 2007; Van Lint et al., 2020). The results showed that low speeds, large distance headways, approaching a faster vehicle, proximity to the gantries and the presence of VSLs on the gantries resulted in significantly smaller maximum decelerations and larger minimum time headways during the events. The findings in this study must be interpreted with caution, due to limitations related to the data collection method, the sample of participants, and the AID system analysed. The main conclusion from this study is that proximity to the gantries and presence of VSLs have a beneficial impact on deceleration behaviour while approaching traffic congestion. Section 4.1 discusses the main findings, Section 4.2 presents recommendations for future research, and Section 4.3 presents recommendations for practice.

4.1. Main findings

The results showed that the main factors influencing large maximum decelerations are approaching a slower vehicle, high speeds, short distance headways, proximity to the beginning of traffic congestion, and the driver-specific error term. A possible interpretation could be that drivers decelerate more aggressively to reduce their speed quicker when they perceive a higher feeling of risk and task difficulty (Fuller, 2011) due to the current traffic situation. In addition, drivers can be influenced by the traffic conditions further downstream when approaching traffic congestion. The significant differences between drivers might be explained by individual driving styles, usage of navigation systems providing traffic advice, and familiarity with traffic congestion at specific locations (e.g., commuting from home to work). Controlled for these main factors, closer proximity to the gantries and presence of the seventy and fifty flashing VSLs resulted in smaller maximum decelerations. These results are in line with previous findings on roadside VSLs based on loop detector data (Van Lint et al., 2020) and on in-vehicle and roadside VMSs in driving simulator experiments (Popiv et al., 2010; Reinolsmann et al., 2018; Totzke et al., 2012). Interestingly, smaller decelerations were also observed when the gantry was visible and active for a larger percentage of time before the beginning of the event. The findings suggest that drivers decelerate less aggressively when they see active gantries. Further research is needed to investigate the potential link between glances and deceleration behaviour.

The results revealed that the main factors related to short minimum time headways, controlled for short initial distance headways, are high speeds and changing lane during the event. A possible interpretation could be that drivers accept shorter time headways when they want to experience higher feeling of risk and task difficulty (high speeds). In addition, drivers could accept higher risks for a short period of time while changing lanes. Controlled for these main factors, proximity to the gantry with the fifty VSL resulted in larger minimum time headways. This finding suggests that situations with high perceived risk occur less often when the VSLs are active in dense traffic conditions. Further research is needed to analyse the effect of glances on minimum time headway.

4.2. Recommendations for future research

This study analysed the main factors influencing deceleration behaviour while approaching traffic congestion on Dutch motorways in a wide range of traffic situations, mostly non-safety critical. For instance, 56.9% of the events have a minimum time headway larger than 1 s, which has been commonly used as a threshold for the identification of critical time headways in previous studies (De Waard & Brookhuis, 1997; Fairclough, May, & Carter, 1997; Vogel, 2003). Therefore, the results cannot be directly generalized to deceleration behaviour in safety critical traffic situations. Future studies are recommended to focus on analysing the impact of the AID system on driver behaviour in safety critical situations based on a larger sample of observations. The events were selected based on a minimum speed reduction (5 km/h) over a duration between 1.1 s and 24.9 s. Although further analysis is necessary, the main findings in this study are expected to be robust to more restrictive criteria in terms of event duration around the median values (e.g., between 3 s and 7 s). Caution is needed to generalize the findings to event durations in the extreme values, which might capture different types of behaviour. For example, during short events, drivers usually pressed the brake pedal in response to the immediate traffic situation. In contrast, during long events, drivers were more likely to release the gas pedal or shift gears than to press the brake pedal. Future studies are recommended to explore the link between event durations and characteristics based on a larger sample. In the current analysis, a single value of the event characteristics (e.g., minimum time headway) during a time interval (i.e., the event) is used as dependent variable. The analysis could be extended to account for the time dimension by using an aggregated value of the event characteristics (e.g., mean time headway, or percentage of time when the time headway is shorter than one second) during the event. To explore this direction, we included the mean event characteristics as dependent variables instead of the minimum and of the maximum values in the models presented in Table 3 and in Table 5. All results were consistent with the findings discussed in this study in terms of direction of the impact. Certain variables had a smaller impact on the mean values than on the extreme values (e.g., proximity to the gantries and proportion of time when the gantry is visible and active in the models predicting the deceleration). Although further analysis is necessary, the main factors identified in this study are expected to have a similar impact on the mean deceleration and on the mean time headway during the events. Another interesting direction for future research could be to investigate driver response time to traffic congestion. Further work is also required to generalize the findings, which are affected by the characteristics of the Dutch AID system, to other types of AID systems.

The number of participants in this study was relatively small (29) and the sample was not representative of the driving population in terms of gender, age, and driving experience. The generalizability of the results towards the general driving population is limited. For instance, the results showed that older drivers decelerated more aggressively than younger drivers in the sample. However, this finding cannot be generalized to young drivers (18–21 years) and elderly drivers (>= 65 years) in the general driving population, because they were not included in the sample. The results of the validation analysis indicated that future studies should analyse more in-depth the impact of driver characteristics on deceleration behaviour in order to improve the prediction accuracy of the models. Furthermore, all participants in this study drove a single vehicle model. Further research is needed to generalize the results to other vehicle types and to vehicles equipped with in-vehicle warning systems and advanced driving assistance systems as adaptive cruise control, which was not available in the instrumented vehicle.

More research using different annotation methods is needed to assess the impact of secondary task engagement on driver behaviour while approaching traffic congestion. In the current study, secondary task involvement was operationalized according to the codebook used in the UDRIVE project (Carsten, et al., 2017). However, the interrater reliability of the annotated secondary tasks was too low (Varotto et al., 2021), and therefore secondary tasks were not included in the analysis. An alternative operationalization of secondary task engagement or an annotation procedure focusing on secondary tasks only might result in more reliable measures. In addition, the annotation could be extended to include the visibility of traffic congestion during the events and the type of incident that caused congestion (e.g., road works or crashes). These factors might have an impact on the responses of drivers and should be further investigated.

4.3. Recommendations for practice

The data collection methods (naturalistic driving data, variable speed limit database, and manual annotation) and the data analysis methods (linear mixed-effects models) proposed in this study are suitable to in-depth analyse adaptations in driver behaviour in real traffic conditions. The analysis of this integrated database provides insights that have a high level of external validity, which cannot be achieved by other empirical data collection methods. The results allow us to quantify explicitly the maximum deceleration and the minimum time headway of drivers while approaching traffic congestion in different circumstances. The findings are of interest to policymakers, companies, and researchers developing intelligent transport systems and assessing the impact of these systems on traffic operations.

Driving assistance systems intending to mimic a human driving style while approaching traffic congestion may benefit from including the main factors found in this study. Based on the current findings, future studies should focus on developing systems that regulate the longitudinal control task based on the maximum deceleration drivers would apply and the minimum time headway drivers would keep. These systems should also accommodate variability between drivers based on individual characteristics and within drivers based on characteristics of the infrastructure, including proximity to gantries and presence of VSLs. To improve driver response when the VSLs on the gantries are not directly visible, the VSLs could also be provided in in-vehicle devices using infrastructure to vehicle communication systems. Driving assistance systems grounded on these findings should be adopted by drivers in a wider variety of traffic conditions.

The realism of microscopic traffic flow models that evaluate the impact of VSLs on traffic operations could be enhanced by incorporating the main factors found in this study. The results in this study have indicated that there is a large variability between and within drivers in deceleration behaviour, that can be explained by the traffic conditions, proximity to the gantries, presence and visibility of VSLs, and observed and unobserved driver characteristics. To the best of the authors' knowledge, previous traffic simulation models have not been based on findings in naturalistic driving experiments. Based on the empirical results in this study, future research should focus on developing a car-following model that describes driver deceleration while approaching traffic congestion as a function of the instantaneous behaviour characteristics. This advanced car-following model should explicitly account for adaptation effects related to the proximity to gantries and to the presence of VSLs (analogous to the car-following models including driver distraction by Hoogendoorn, Van Arem, and Hoogendoorn (2013) and Saifuzzaman, Zheng, Mazharul Haque, and Washington (2015)). Such an advanced car-following model can be implemented into a microscopic traffic flow simulation to predict the impact of VSLs on traffic operations with a higher level of accuracy.

CRediT authorship contribution statement

Silvia F. Varotto: Conceptualization, Data curation, Formal analysis, Methodology, Software, Validation, Visualization, Writing - original draft, Writing - review & editing. **Reinier Jansen:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Project administration, Software, Supervision, Validation, Visualization, Writing - original draft, Writing - review & editing. **Frits Bijleveld:** Data curation, Formal analysis, Software, Supervision, Writing - review & editing. **Nicole Nes:** Conceptualization, Funding acquisition, Project administration, Writing - review & editing.

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Appendix A

This section describes the equations of the final linear mixed-effects models predicting the maximum deceleration and the minimum time headway. The maximum deceleration $\mathrm{MaxDec_n(t)}$ and the minimum time headway $\mathrm{MinTHW_n(t)}$ during the event at time t for driver n are presented in Eqs. (3) and (4):

$$\begin{aligned}\log(\mathrm{MaxDec_n(t)}) = {} & \mu^{\mathrm{D}} + \lambda^{\mathrm{D}}_{\mathrm{Speed}} \cdot \mathrm{Speed(t)} + \lambda^{\mathrm{D}}_{\mathrm{RelSpeed}} \cdot \mathrm{RelSpeed(t)} + \lambda^{\mathrm{D}}_{\mathrm{DHW}} \cdot \mathrm{DHW(t)} + \lambda^{\mathrm{D}}_{\mathrm{NoLead}} \cdot \mathrm{NoLead(t)} \\ & + \lambda^{\mathrm{D}}_{\mathrm{DistCong}} \cdot \mathrm{DistCong(t)} + \lambda^{\mathrm{D}}_{\mathrm{GantryClose}} \cdot \mathrm{PrevGantryClose(t)} + \lambda^{\mathrm{D}}_{\mathrm{GantryClose}} \cdot \mathrm{NextGantryClose(t)} \\ & + \lambda^{\mathrm{D}}_{\mathrm{Next}*70*,*50*} \cdot \mathrm{Next}*70*,*50*(\mathrm{t}) + \lambda^{\mathrm{D}}_{\mathrm{pGantryVisAct}} \cdot \mathrm{pGantryVisAct(t)} + \lambda^{\mathrm{D}}_{\mathrm{Age}} \cdot \mathrm{Age_n} \\ & + \gamma^{\mathrm{D}} \cdot \vartheta^{\mathrm{D}}_{\mathrm{n}} + \omega^{\mathrm{D}} \cdot \upsilon^{\mathrm{D}}_{\mathrm{n}}(\mathrm{t}) \end{aligned} \tag{3}$$

$$\log(\mathrm{MinTHW_n(t)}) = \mu^{\mathrm{T}} + \lambda^{\mathrm{T}}_{\mathrm{Speed}} \cdot \mathrm{Speed(t)} + \lambda^{\mathrm{T}}_{\mathrm{RelSpeed}} \cdot \mathrm{RelSpeed(t)} + \lambda^{\mathrm{T}}_{\mathrm{DHW}} \cdot \log(\mathrm{DHW(t)}) + \lambda^{\mathrm{T}}_{\mathrm{NoLead}} \cdot \mathrm{NoLead(t)} + \lambda^{\mathrm{T}}_{\mathrm{LaneChange}} \cdot \mathrm{LaneChange(t)} + \lambda^{\mathrm{T}}_{\mathrm{Next50}} \cdot \mathrm{Next50(t)} + \lambda^{\mathrm{T}}_{\mathrm{Prev50}} \cdot \mathrm{Prev50(t)} + \lambda^{\mathrm{T}}_{\mathrm{Female}} \cdot \mathrm{Female_n} + \gamma^{\mathrm{T}} \cdot \vartheta^{\mathrm{T}}_{\mathrm{n}} + \omega^{\mathrm{T}} \cdot \upsilon^{\mathrm{T}}_{\mathrm{n}}(\mathrm{t}) \quad (4)$$

where μ^{D} and μ^{T} are the mean values, λ^{D} and λ^{T} are vectors of parameters related to the explanatory variables in Table 3 and Table 5, γ^{D} and γ^{T} are the parameter associated with the driver-specific error terms $\vartheta^{\mathrm{D}}_{\mathrm{n}} \sim \mathrm{N}(0,1)$ and $\vartheta^{\mathrm{T}}_{\mathrm{n}} \sim \mathrm{N}(0,1)$, and ω^{D} and ω^{T} are the parameters associated with the observation-specific error terms $\upsilon^{\mathrm{D}}_{\mathrm{n}}(\mathrm{t}) \sim \mathrm{N}(0,1)$ and $\upsilon^{\mathrm{T}}_{\mathrm{n}}(\mathrm{t}) \sim \mathrm{N}(0,1)$.

References

Alm, H., & Nilsson, L. (2000). Incident warning systems and traffic safety: A comparison between the PORTICO and MELYSSA test site systems. *Transportation Human Factors, 2*, 77–93.

Barton, K. (2019). MuMIn: Multi-Model Inference.

Boyle, L. N., & Mannering, F. (2004). Impact of traveler advisory systems on driving speed: Some new evidence. *Transportation Research Part C: Emerging Technologies, 12*, 57–72.

Brookhuis, K. A., Van Driel, C. J. G., Hof, T., Van Arem, B., & Hoedemaeker, M. (2009). Driving with a congestion assistant; mental workload and acceptance. *Applied Ergonomics, 40*, 1019–1025.

Carsten, O., Hibberd, D., Bärgman, J., Kovaceva, J., Pereira Cocron, M. S., Dotzauer, M., Utesch, F., Zhang, M., Stemmler, E., Guyonvarch, L., Sagberg, F., & Forcolin, F. (2017). Driver Distraction and Inattention. In UDRIVE Deliverable 43.1: EU FP7 Project UDRIVE Consortium.

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

De Pauw, E., Daniels, S., Franckx, L., & Mayeres, I. (2018). Safety effects of dynamic speed limits on motorways. *Accident Analysis and Prevention, 114*, 83–89.

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 Systems, 4*, 222–234.

Deligianni, S. P., Quddus, M., Morris, A., Anvuur, A., & Reed, S. (2017). Analyzing and modeling drivers' deceleration behavior from normal driving. *Transportation Research Record, 2663*, 134–141.

Dingus, T. A., Guo, F., Lee, S., Antin, J. F., Perez, M., Buchanan-King, M., & Hankey, J. (2016). Driver crash risk factors and prevalence evaluation using naturalistic driving data. *Proceedings of the National Academy of Sciences, 113*, 2636–2641.

Dingus, T. A., Klauer, S., Neale, V., Petersen, A., Lee, S., Sudweeks, J., Pérez, M. A., Hankey, J. M., Ramsey, D. J., Gupta, S., Bucher, C., Doerzaph, Z. R., Jermeland, J., & Knipling, R. (2006). The 100-Car Naturalistic Driving Study Phase II: Results of the 100-Car Field Experiment.

Fairclough, S. H., May, A. J., & Carter, C. (1997). The effect of time headway feedback on following behaviour. *Accident Analysis and Prevention, 29*, 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. *Transportation Research Part F: Traffic Psychology and Behaviour, 63*, 226–239.

Farah, H., & Koutsopoulos, H. N. (2014). Do cooperative systems make drivers' car-following behavior safer?. *Transportation Research Part C: Emerging Technologies, 41*, 61–72.

Farah, H., Koutsopoulos, H. N., Saifuzzaman, M., Kölbl, R., Fuchs, S., & Bankosegger, D. (2012). Evaluation of the effect of cooperative infrastructure-to-vehicle systems on driver behavior. *Transportation Research Part C: Emerging Technologies, 21*, 42–56.

Fuhs, C. (2010). *Synthesis of active traffic management experiences in Europe and the United States*. Federal Highway Administration.

Fuller, R. (2011). Chapter 2 - Driver Control Theory: From Task Difficulty Homeostasis to Risk Allostasis. In B. E. Porter (Ed.), *Handbook of Traffic Psychology* (pp. 13–26). San Diego: Academic Press.

Hankey, J. M., Perez, M. A., & McClafferty, J. A. (2016). *Description of the SHRP 2 Naturalistic Database and the Crash, Near-Crash, and Baseline Data Sets*. Blacksburg, VA: Virginia Tech Transportation Institute.

Harms, I. M., & Brookhuis, K. A. (2016). Dynamic traffic management on a familiar road: Failing to detect changes in variable speed limits. *Transportation Research Part F: Traffic Psychology and Behaviour, 38*, 37–46.

Harms, I. M., & Brookhuis, K. A. (2017). Traffic management: Assessing various countermeasures to improve detection failure of changes in speed limit signals. *Applied Ergonomics, 61*, 44–52.

Harville, D. A. (1977). Maximum likelihood approaches to variance component estimation and to related problems. *Journal of American Statistical Association, 72*, 320–338.

Hastie, T., Tibshirani, R., & Friedman, J. (2009). *The elements of statistical learning: Data mining, inference and prediction*. Springer.

Hoogendoorn, R. G., Harms, I. M., Hoogendoorn, S. P., & Brookhuis, K. A. (2012). Dynamic maximum speed limits: Perception, mental workload, and compliance. *Transportation Research Record, 2321*, 46–54.

Hoogendoorn, R. G., Van Arem, B., & Hoogendoorn, S. P. (2013). Incorporating driver distraction in car-following models: Applying the TCI to the IDM. In 16th International IEEE Conference on Intelligent Transportation Systems (ITSC 2013) (pp. 2274-2279).

Hourdos, J., Liu, Z., Dirks, P., Liu, H. X., Huang, S., Sun, W., & Xiao, L. (2017). *Development of a Queue Warning System Utilizing ATM Infrastructure System Development and Field-Testing*. Minnesota Department of Transportation.

Jomaa, D., Yella, S., & Dougherty, M. (2013). Review of the effectiveness of vehicle activated signs. *Journal of Transportation Technologies, 3*, 8.

Lee, C., & Abdel-Aty, M. (2008). Testing effects of warning messages and variable speed limits on driver behavior using driving simulator. *Transportation Research Record, 2069*, 55–64.

Lüdecke, D. (2018). ggeffects: Tidy data frames of marginal effects from regression models. *Journal of Open Source Software, 3*, 772.

Martens, M. H. (2013). Behavioural adaptation to roadway intelligent transport systems. In C. Rudin-Brown & S. Jamson (Eds.), *Behavioural Adaptation and Road Safety: Theory, Evidence and Action* (pp. 135–160). New York: CRC Press.

Nakagawa, S., Johnson, P. C. D., & Schielzeth, H. (2017). The coefficient of determination R^2 and intra-class correlation coefficient from generalized linear mixed-effects models revisited and expanded. *Journal of the Royal Society, Interface, 14*, 1–11.

Nakagawa, S., & Schielzeth, H. (2013). A general and simple method for obtaining R2 from generalized linear mixed-effects models. *Methods in Ecology and Evolution, 4*, 133–142.

Naujoks, F., & Totzke, I. (2014). Behavioral adaptation caused by predictive warning systems – The case of congestion tail warnings. *Transportation Research Part F: Traffic Psychology and Behaviour, 26*, 49–61.

Oviedo-Trespalacios, O., Haque, M. M., King, M., & Washington, S. (2017). Effects of road infrastructure and traffic complexity in speed adaptation behaviour of distracted drivers. *Accident Analysis and Prevention, 101*, 67–77.

Peng, Y., Boyle, L. N., & Hallmark, S. L. (2013). Driver's lane keeping ability with eyes off road: Insights from a naturalistic study. *Accident Analysis and Prevention, 50*, 628–634.

Pinheiro, J., Bates, D., DebRoy, S., Sarkar, D., & R Core Team (2019). nlme: Linear and Nonlinear Mixed Effects Models. In.

Popiv, D., Rommerskirchen, C., Bengler, K., Duschl, M., & Rakic, M. (2010). Effects of assistance of anticipatory driving on driver's behaviour during deceleration situations. In J. Krems, T. Petzoldt, & M. Henning (Eds.), *The Second European Conference on Human Centered Design for Intelligent Transport Systems* (pp. 133–145). Lyon: HUMANIST Publications.

R Core Team (2019). *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing.

Reinolsmann, N., Brijs, K., Brijs, T., Alhajyaseen, W., Cornu, J., & Mollu, K. (2018). Variable message sign strategies for congestion warning on motorways - A driving simulator study. *Advances in Transportation Studies: an international Journal, 45*, 77–92.
Rijkswaterstaat (2017). *Aanleverspecificatie NWB en WEGGeg*. Nationaal WegenBestand en Weggegevens Hoofdwegennet.
Saifuzzaman, M., Zheng, Z., Mazharul Haque, M., & Washington, S. (2015). Revisiting the Task-Capability Interface model for incorporating human factors into car-following models. *Transportation Research Part B: Methodological, 82*, 1–19.
Smulders, S. (1990). Control of freeway traffic flow by variable speed signs. *Transportation Research Part B: Methodological, 24*, 111–132.
Totzke, I., Naujoks, F., Mühlbacher, D., & Krüger, H. (2012). Precision of congestion warnings: Do drivers really need warnings with precise information about the congestion taiĺs position? In D. De Waard, A. H. Jamson, Y. Barnard, & O. Carsten (Eds.), *Human Factors of Systems and Technology* (pp. 235–247). Maastricht, the Netherlands: Shaker Publishing.
Transportation Research Board (2010). *HCM 2010: Highway Capacity Manual*. Washington, DC: Transportation Research Board.
Van den Hoogen, E., & Smulders, S. (1994). Control by variable speed signs: results of the Dutch experiment. In Seventh International Conference on Road Traffic Monitoring and Control, 1994. (pp. 145-149).
Van Driel, C. J. G., Hoedemaeker, M., & Van Arem, B. (2007). Impacts of a Congestion Assistant on driving behaviour and acceptance using a driving simulator. *Transportation Research Part F: Traffic Psychology and Behaviour, 10*, 139–152.
Van Lint, H., Nguyen, T. T., Krishnakumari, P., Calvert, S. C., Schuurman, H., & Schreuder, M. (2020). Estimating the safety effects of congestion warning systems using carriageway aggregate data. *Transportation Research Record*.
Van Nes, N., Bärgman, J., Christoph, M., & Van Schagen, I. (2019). The potential of naturalistic driving for in-depth understanding of driver behavior: UDRIVE results and beyond. *Safety Science, 119*, 11–20.
Van Nes, N., Brandenburg, S., & Twisk, D. (2010). Improving homogeneity by dynamic speed limit systems. *Accident Analysis and Prevention, 42*, 944–952.
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 Science, 16*, 776–806.
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. *Transportation Research Part B: Methodological, 117*, 318–341.
Varotto, S. F., Jansen, R., Bijleveld, F., & Van Nes, N. (2021). Driver speed compliance following automatic incident detection: Insights from a naturalistic driving study. *Accident Analysis and Prevention, 150*, 105939.
Virginia Tech Transportation Institute. (2015). *SHRP2 Researcher Dictionary for Video Reduction Data, Version 3.4*. Blacksburg, Virginia: Virginia Tech Transportation Institute.
Vogel, K. (2003). A comparison of headway and time to collision as safety indicators. *Accident Analysis and Prevention, 35*, 427–433.
Wang, B., Hallmark, S., Savolainen, P., & Dong, J. (2018). Examining vehicle operating speeds on rural two-lane curves using naturalistic driving data. *Accident Analysis and Prevention, 118*, 236–243.