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Driver speed compliance following automatic incident detection: Insights from a naturalistic driving study

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ABSTRACT

Automatic incident detection (AID) systems and variable speed limits (VSLs) can reduce crash probability and traffic congestion. Studies based on loop detector data have shown that AID systems decrease the variation in speeds between drivers. Despite the impact on driver behaviour characteristics, most mathematical models evaluating the effect of AID systems on traffic operations do not capture driver response realistically.

This study examines the main factors related to driver speed compliance with a sequence of three VSLs triggered by an AID system. For this purpose, the variable speed limit database of the executive agency of the Dutch Ministry of Infrastructure and Water Management (Rijkswaterstaat) was integrated into the UDRIVE naturalistic driving database for passenger car data collected in the Netherlands. The video data were annotated to analyse driver glance behaviour and secondary task engagement. A logistic regression model was estimated to predict driver speed compliance after each VSL in the sequence.

The results reveal that the factors predicting compliance to the VSLs differ based on which of the three VSLs the driver is subjected to. Low speeds and accelerations before the gantry, approaching a slower leader, high proportion of time with eyes-on-road and close consecutive gantries were associated with high compliance with the first VSL in the sequence (i.e., indicating a speed limit of 70 km/h with flashing attention lights). Low speeds and accelerations before the gantry, close consecutive gantries and a small number of lanes resulted in high compliance with the second VSL (i.e., a speed limit of 50 km/h with flashing attention lights). Low speeds before the gantry and close consecutive gantries were linked to high compliance with the third VSL (i.e., indicating a speed limit of 50 km/h). Although further investigations based on a larger sample are needed, these findings are relevant to the development of human-like driving assistance systems and of traffic simulations that assess the impact of AID systems on traffic operations realistically.

1. Introduction

Dynamic traffic management systems can reduce traffic congestion and crash rates. These systems provide real-time traffic information to drivers using variable message signs (VMSs) and dynamically change the speed limits using variable speed limits (VSLs). VMSs and VSLs aim to improve driver responsiveness to the traffic conditions downstream by reducing the speed differences between road sections and road users. Low speeds and small speed differences within lanes are associated with lower crash probability (Aarts and Van Schagen, 2006; Choudhary et al., 2018). Various traffic management measures have been implemented to maintain an optimal traffic flow and to decrease the crash probability depending on the type of incident (e.g., crash, traffic jam, weather conditions) (Fuhs, 2010). Since the 1980s, European and American motorways have been equipped with automatic incident detection (AID) systems that inform drivers upstream of incidents downstream (Martens, 2013). The Dutch AID system activates a sequence of (at least) three VSLs. The system activates a 50 km/h VSL downstream a loop detector that registers a mean vehicle speed lower than 35 km/h. In addition, the system activates a 70 km/h and a 50 km/h VSLs with flashing attention lights on the first and on the second gantry upstream to warn the drivers approaching the congestion tail to decrease their speed gradually.

The intended effect of the AID system is that drivers increase their awareness, decrease their speed, and maintain a larger time headway.

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These improvements in driver behaviour should result in a lower probability of driver errors and crashes. However, unintended impacts of AID systems on driver behaviour (*behavioural adaptations*) have been reported (Martens, 2013). The activation of the system might distract drivers in their control task and result in sudden braking or steering responses. Due to overreliance on the system in the long term, drivers might maintain higher speeds when the system is not installed, is malfunctioning, or has not detected traffic congestion yet. Drivers might also believe that the VSL corresponds to a safe speed in adverse weather conditions and increase their driving speed. Notwithstanding the potential effects on traffic operations, very few studies have analysed these behavioural adaptations based on empirical data (Martens, 2013).

Studies based on loop detector data have indicated that AID systems decrease the difference in speeds between vehicles (Hourdos et al., 2017; Smulders, 1990; Van den Hoogen and Smulders, 1994) and the maximum deceleration while approaching congestion (Van Lint et al., 2020). Loop detectors measure the speeds and counts of vehicles at a specific road location. Loop detector measurements are most often available at an aggregate level during a specific time interval (e.g., one minute). These measurements, however, shed limited light on the main factors that influence driver compliance with the VSLs. Driver response can be influenced by the traffic conditions, the road characteristics, and the characteristics and state of the drivers. For example, drivers might reduce their speed voluntary as a response to the VSL active on the gantry or they could be forced to reduce their speed when the lead vehicle slows down. In addition, drivers may fail to comply with the VSLs because they are distracted. Distracting tasks that require eyes off-road such as using a hand-held phone, reading, writing, reaching for objects, and looking at external objects are associated with the highest crash risk (Dingus et al., 2016). These behavioural mechanisms can be investigated in-depth based on data of individual drivers collected in naturalistic driving studies (Carsten et al., 2013). Insights from driver psychology and human factors are relevant to the development of advanced driving assistance systems (Bengler et al., 2014; Merat and Lee, 2012) and of microscopic traffic flow simulations (Hamdar et al., 2020; McDonald et al., 2019; Saifuzzaman and Zheng, 2014; Van Lint and Calvert, 2018).

1.1. Empirical studies and models for driver responses to roadside messages

Several studies based on driving simulator experiments have found both intended and unintended impacts of roadside VMSs and VSLs on driver behaviour characteristics. Regarding intended impacts, drivers significantly reduce the mean speed (Boyle and Mannering, 2004), the speed variation (Van Nes et al., 2010), and the maximum deceleration while approaching traffic congestion (Reinolsmann et al., 2018) in the road sections where the messages are displayed. Drivers show higher compliance and shorter eye fixation times when the speed limits are posted on electronic signs installed on gantries above each lane than on standard traffic signs, rotation panels and electronic signs installed on roadside poles or carriageway gantries (Hoogendoorn et al., 2012). Some studies, however, also found unintended impacts of VMSs and VSLs on driver behaviour. Drivers might increase their speed downstream the incident to compensate for the speed reduction (Boyle and Mannering, 2004), they may fail to detect unforeseen changes in the VSLs on familiar roads (Harms and Brookhuis, 2016), and they may have a lower capability to recognize changes in the VSLs with waves and flashing lights (Harms and Brookhuis, 2017).

Few studies have developed mathematical models that predict driver responses to VSLs and they were based on data collected in driving simulator experiments. Lee and Abdel-Aty (2008) analysed the degree of speed change and the compliance with VSLs and VMSs using logistic regression models. In the model predicting the speed regulation (binary variable), drivers were assumed to have changed their speed when the difference between the speed 200 m upstream and 200 m downstream the VSL sign was higher than 8 km/h (5 mph). The results showed that drivers were more likely to change their speed when they had already changed their speed at previous signs. In addition, they were more likely to reduce their speed at VSLs in light traffic, and to increase their speeds at VMSs after the end of the congestion tail. In the compliance model, drivers were assumed to comply with the VSLs when the difference between their speed 200 m downstream the VSL sign and the speed limit was smaller than 8 km/h (5 mph). The findings showed that drivers were more likely to comply with one sign when they had already complied with the previous signs and when the VSL reduction was gradual. Conran and Abbas (2018) developed a microscopic traffic flow model that incorporates driver compliance with VSLs. They defined the degree of compliance for each individual driver as the ratio between the actual speed change (difference between the speed upstream and the speed downstream the VSL) and the desired speed change (difference between the speed upstream and the VSL). In a regression model, they found that driver compliance is high when the VMSs inform drivers of the speed reduction in advance, when the posted speed limit is equal to 100 km/h, and when the speed change implied by the VSL is small. The compliance model was incorporated into a microscopic traffic flow model to improve its prediction accuracy and assess the impacts of VSLs on traffic safety (Conran and Abbas, 2017). Further analysis based on on-road experiments is needed to investigate the validity of these findings for real traffic situations.

Recently, driver response to the VSLs has also been analysed using mathematical models based on naturalistic driving data collected in the SHARP2 project. Wang et al. (2018) investigated the impact of road geometry, VSLs, posted speed limits and driver characteristics on the mean speed on horizontal curves in rural roads. They chose curves with a posted speed limit equal to 72 km/h or 89 km/h (45 mph or 55 mph). In a regression model, they found that the mean speed on the curve was low in case of small curve radius, low posted speed limit, active VSL, arrow signs and guardrail, lead vehicle, night time, female driver, and driver older than 25. The main limitation of this model with respect to the present study is that it focuses on speed behaviour on horizontal curves in rural roads only, as opposed to motorways including straight road sections.

1.2. Glance behaviour and secondary task engagement in naturalistic driving studies

A number of studies focused on the relationship between glance behaviour and driving performances based on naturalistic driving data. Naturalistic driving studies are particularly suited to investigate driver management of different tasks because participants' behaviour in driving simulator and test track experiments tend to be biased by an instruction effect (Carsten et al., 2013). Peng et al. (2013) analysed the impact of glance behaviour and secondary task engagement on lane keeping performance. They compared three types of inattention during 3 s-intervals: eyes-off-road (i.e., the driver glanced away from the forward road), eyes-on-road inattentive (i.e., the driver looked forward while being engaged in non-driving tasks) and eyes-on-road attentive (i.e., the driver looked forward and was not engaged in non-driving tasks). Controlling for the roadway type, the lane width and the speed in a regression model, they found that drivers swerved more (i.e., high standard deviation of the lateral position) when they had eyes-off-road for a duration longer than 2 s compared to when they were attentive. Tivesten and Dozza (2014) analysed the effect of secondary task engagement and surrounding vehicles on glance behaviour. They compared eyes-on-road (i.e., the driver looked forward, at the other road users or at the mirrors to monitor the traffic situation) and eyes-off-road (i.e., the driver glanced away from the road forward) when the driver engaged in phone tasks and during the 30 s prior. The following glance metrics were analysed: percentage of time with eyes-on-road, maximum off-road glance duration, percentage of off-road glances longer than 2 s, the off-road glance frequency, and total off-road glance time. The results showed that drivers have lower proportions of long off-road glances when turning, when following a leader, and when an upcoming vehicle was present. The authors concluded that the percentage of eyes-on-road is a metric suitable to analyse visual allocation in different driving situations, whereas glance frequency and percentage of long off-road glances are the best metrics to distinguish between different secondary tasks. Morando et al. (2016) analysed drivers' glance behaviour during safety relevant situations when adaptive cruise control was engaged. Glance behaviour was analysed in terms of location (i.e., the area the eyes are directed to) and eccentricity (i.e., the radial angle between the glance location and the forward direction). They classified the glance locations as on-path, centre stack, driver information module, phone, interior object, passenger, eyes closed, rear-view mirror, side mirror or window, forward windshield not on-path, and over the driver shoulders. The results showed that the percentage of glances to the forward path increased over time in anticipation of the threat. The main cue that attracted the attention of the driver was the deceleration of the subject vehicle. The main conclusion from these naturalistic driving studies is that there is a significant relation between driver glance behaviour, engagement in secondary tasks, and driver performance.

1.3. Knowledge gap and research objective

Few studies have analysed the main factors determining driver compliance with the VSLs using statistical models. The models developed by Lee and Abdel-Aty (2008) and Conran and Abbas (2018) were based on data collected in driving simulator experiments and gained limited insights for driving behaviour in real traffic. Very few studies have analysed the main factors associated with driver response to the VSLs based on naturalistic driving data. The only example is the study by Wang et al. (2018), who used naturalistic data to model driver behaviour on curves in rural roads with VSLs. Despite the impact of glance behaviour and secondary task engagement on driver performance, none of these studies analysed the effect of the driver state on compliance with the VSLs.

The objective of this study is to investigate the main factors associated with driver compliance with the VSLs within an AID sequence (i.e., 70 km/h with flashing lights, followed by 50 km/h with flashing lights and 50 km/h) based on naturalistic driving data. In this study, driver compliance with the VSLs is defined based on the speed observed downstream the VSL sign and the minimum value for legal speed violations. A logistic regression model was developed to analyse the impact of several factors observed upstream the gantry (traffic conditions, driver state, environment characteristics and driver characteristics) on speed compliance downstream the gantry. For this purpose, the national road and variable speed limit databases of the executive agency of the Dutch Ministry of Infrastructure and Water Management (Rijkswaterstaat) were integrated into the naturalistic driving passenger car data collected in the Netherlands in the UDRIVE project (Van Nes et al., 2019). The driver state was annotated based on the video data. In another study based on these data, we analysed the main factors influencing the deceleration behaviour of drivers approaching the congestion tail with and without the AID system (Varotto et al., 2020). We found that presence and visibility of the VSLs triggered by the AID system resulted in smaller maximum decelerations and larger minimum time headways in dense traffic conditions. The objective of this study is relevant to the development of driving assistance systems that can anticipate driver response to the VSLs and intervene by increasing driver attention or regulating the speed. This objective is also relevant to the development of microscopic traffic flow models that assess the effect of VSLs on traffic congestion realistically.

2. Method

2.1. UDRIVE database

The driver behaviour data were collected within the UDRIVE project in the Netherlands (Van Nes et al., 2019). Thirty-three participants were recruited in the Dutch population using advertisements, social media and the internal network. A minimum mileage of 10,000 km per year was considered a pre-requisite. Eighteen participants were males and fifteen were females. Three participants were aged between 18 and 29, ten between 30 and 39, nine between 40 and 49, and eleven between 50 and 65. All participants were briefed about the project using standard protocols and signed a written informed consent form. Ten passenger vehicles (Renault Clio IV) were leased and equipped with the data acquisition system (DAS) developed in the UDRIVE project. Free use of the leased vehicle exclusive of the fuel costs was given to the participants as an incentive. Each participant drove the instrumented vehicle for six months between 2015 and 2017. Participants belonging to the same household shared the same vehicle but were considered different drivers. The DAS recorded, amongst others, date and time, GPS position, speed, acceleration, distance headway (from MobilEye smart camera), leader speed (from MobilEye), and videos from seven cameras recording the driver and the surrounding environment (Fig. 1). The data were recorded at a frequency of 1 Hz (GPS position) and 10 Hz (e.g., speed, acceleration). In total, the participants drove 230,842 km in 3,727 h (Christoph et al., 2019).

2.2. Road database and variable speed limit database

The variable speed limits of the Dutch motorway network in the period between January 1st, 2015 and December 31st, 2017 were provided by the executive agency of the Dutch Ministry of Infrastructure and Water Management (Rijkswaterstaat). Each observation in the variable speed limit database corresponds with a state change of a specific gantry at a certain time. The exact coordinates of each gantry were not available. The gantry position was obtained by mapping each gantry to the closest hectometre pole, the coordinates of which were available. Due to the hectometre spacing, the maximum error in the gantry position is 50 m.

To link the different databases, the vehicle positions in the UDRIVE database and the gantry positions in the variable speed limit database were projected to a common hectometre pole grid. First, the GPS coordinates in the UDRIVE database were converted to the Dutch grid (Rijksdriehoek) projection. The closest road in the National Road Database (Nationaal Wegenbestand) (Rijkswaterstaat, 2017) was estimated for each Rijksdriehoek coordinate. Possible errors in the GPS coordinates were accounted for by comparing the current estimate of the closest road with the closest road estimated in previous data points. Through the road database, we obtained the motorway number, the driving direction and the road section identification number. We identified the closest gantry at each moment in front of the driver (hereafter: next gantry) and behind the driver (hereafter: previous gantry) by projecting the Rijksdriehoek coordinates on a hectometre pole grid and comparing the resulting hectometre pole numbers with the road database. Thus, each Rijksdriehoek coordinate in the UDRIVE database was assigned a gantry state, the date and time of the last change, and the distance to the gantry. Multiple states are possible in different lanes on the same gantry simultaneously. In addition, Rijkswaterstaat provided information on the presence of electronic speed control, specified in terms of the road number and the hectometre number. These data were also integrated in the UDRIVE database.

2.3. Event selection

The events were defined as the following sequence of gantry states: 70 km/h VSL with flashing lights (hereafter: 70-flashing VSL [*70*]), 50

Fig. 1. Views of seven video cameras in the UDRIVE data when encountering an active VSL: road front left, road front centre, road front right, vehicle cockpit, face of the driver, vehicle cabin, and feet of the driver. The face of the driver and of the passenger have been blurred due to privacy reasons.

km/h VSL with flashing lights (hereafter: 50-flashing VSL [*50*]) and 50 km/h VSL (hereafter: 50 VSL [50]). The VSLs are lane specific and different VSLs can be active simultaneously on the same gantry. To understand whether the driver is subject to an AID sequence, the driving lane is needed. Given that the driving lane is not available in the UDRIVE database, the events were initially selected including all situations in which the AID sequence was active in at least one lane. A prerequisite for event selection was that three different physical gantries were passed by the driver. The gantry states are updated when the loops detect that congestion has moved upstream or downstream. Therefore, the gantry states might have been updated while the driver was passing through the AID sequence. The driver might have seen the 70-flashing VSL on the first gantry and the 50-flashing VSL being substituted by the 50 VSL on the second gantry. Events including such state changes were removed from subsequent analysis.

2.4. Annotation

Four annotators manually inspected and coded the videos related to the events. A dedicated toolbox written in Microsoft Visual Studio 2017 was developed for annotation. Using the toolbox, the annotators load the selected trips, paused and played the videos at a self-chosen speed, and pressed labelled buttons to annotate. The annotation was completed in three weeks in July 2019. The first day was used for training the annotators. The training session consisted in the annotation of five events by each annotator and a plenary discussion to reach a mutual understanding on the variables annotated. Twelve randomly selected events were processed by all annotators to examine the degree of agreement. The other events were randomly assigned to one of the annotators. The annotation was executed from 500 m before the 70-flashing VSL to 200 m after the first 50 VSL of the AID sequence.

For each event, the variables listed below were annotated once: weather conditions (limited visibility), density of the surrounding environment (open, half open, closed), and motorway exited by the driver at the end of the event. The gantry passing times and the VSL active on the driver's lane were annotated three times during each event. The variables listed below were annotated at a frame-by-frame resolution during the event: glance direction (eyes off- and on-road, where on-road is defined as any glance through the front window), gantry visibility (gantry visible and VSL active, gantry visible and VSL inactive, gantry not visible), driving lane (counted from the centre of the road), type of road section (motorway mainline, weaving section, entry lane, or exit lane), and engagement in secondary tasks (yes or no). Secondary tasks were operationalised according to the codebook of the UDRIVE project (Carsten et al., 2017), consisting of phone use, electric device use, eating, drinking, smoking, reading, writing, grooming, talking, and singing. By combining the presence of an AID sequence (i.e., [*70*], [*50*], [50]) per lane with annotation of the driving lane, it was possible to identify whether drivers were subject to the AID regime at any given time, even if they did not drive through the whole sequence (e.g., due to lane changes). Furthermore, notes made by the annotators on playback errors (e.g., inaccurate synchronization between the camera views or video not loading) and on drivers wearing sunglasses (i.e., glance annotation impossible) were used to delete the corresponding events from subsequent analysis.

2.5. Data analysis methods

2.5.1. Interrater reliability of annotation

The agreement achieved in the annotation was analysed by comparing the variables coded in twelve events processed by all four annotators based on statistical measures. Several variables derived from the data annotated (e.g., proportion of time with eyes-on-road and count of switches between eyes on and off road) were compared to understand which ones could be included into the statistical analysis. Krippendorff's alpha was used as the primary measure of reliability, where values higher than 0.67 were considered as acceptable for analysis (Krippendorff, 2004). Jeni et al. (2013) demonstrated that Krippendorff's alpha is underestimated for variables with a skewed distribution. Therefore, percentage agreement was used as secondary measure of reliability, calculated only for variables with a Krippendorff's alpha below 0.67 and a significantly skewed distribution. We used a criterion of 80 % agreement across twelve events to determine which of those variables could be used in subsequent analysis.

Krippendorff's alpha was calculated using the R package 'irr' (Gamer et al., 2019). The R package 'moments' (Komstra and Novomestky, 2015) was used to test if the variables that did not meet the minimum threshold of Krippendorff's alpha were significantly skewed. If so, the percentage agreement, including a tolerance margin of 10 %, was calculated with the R package 'irr' (Gamer et al., 2019) as an indicator of the interrater reliability.

2.5.2. *Descriptive analysis and statistics*

The driver speed profiles and the distance to the gantries during the events were analysed. Driver compliance was assessed separately after each VSL sign as shown in Fig. 2. Drivers complied if the difference between the speed of the subject vehicle 200 m downstream the gantry and the VSL was lower than 6 km/h. This speed threshold was chosen based on the minimum value for legal speed violations in the Netherlands. The distance to the gantry was selected based on results from a previous study (Lee and Abdel-Aty, 2008), showing that drivers gradually regulate their speed in proximity to the VSL sign and compliance can be best assessed 200 m downstream the gantry. We analysed the mean driver behaviour characteristics and glance behaviour metrics registered 200−300 m upstream the gantry to understand whether the conditions upstream could explain driver compliance downstream. This interval was chosen based on the mean distance at which drivers started to decelerate when the VSL signs were active (250 m). At this distance, a driver monitoring system and a driving assistance system may predict whether drivers are likely to comply with the VSLs and intervene by increasing the attention of the driver or regulating the speed. Differences in the conditions upstream when drivers complied and did not comply with the VSLs were compared using descriptive statistics (mean and standard deviation) and statistical tests (two-sample Kolmogorov-Smirnov tests and Chi-squared test of independence).

2.5.3. *Logistic regression model*

The main factors associated with driver compliance with the VSLs are analysed in a logistic regression model. Logistic regression models allow to capture the impact of multiple explanatory variables on the observed behaviour of drivers accounting for correlations between repeated observations over time (Farah et al., 2019; Obeid et al., 2017; Paschalidis et al., 2018; Varotto et al., 2017, 2018). Driver compliance with each VSL is defined as described in Section 2.5.2. The latent regression functions for complying (C) and not complying (NC) with the VSLs for driver *n* at time *t* are given by Eqs. (1)–(2):

$$C_n(t) = \alpha^C + \beta^C \cdot X_n^C(t) + \varepsilon_n^C(t) \tag{1}$$

$$NC_n(t) = 0 + \varepsilon_n^{NC}(t) \tag{2}$$

where α^C is the constant, β^C is the vector of parameters related to the explanatory variables $X_n^C(t)$, and $\varepsilon^C(t)$ and $\varepsilon^{NC}(t)$ are logistic-distributed error terms. Relevant explanatory variables that can be included in the latent regression function are the driver behaviour characteristics of the subject vehicle and of the lead vehicle, driver glance behaviour metrics, driver characteristics, characteristics of the motorway segment and of the environment. The driver behaviour characteristics and glance behaviour metrics influencing compliance with each VSL are defined as described in Section 2.5.2. Eq. (1) can also include a driver-specific error term and an event-specific error term, capturing unobserved preferences that influence all situations by the individual driver over time and in the same event. The probability of complying with the VSL is presented in Eq. (3):

$$P(Y_n(t) = 1) = \frac{\exp\left(\alpha^C + \beta^C \cdot X_n^C(t)\right)}{1 + \exp\left(\alpha^C + \beta^C \cdot X_n^C(t)\right)} \tag{3}$$

The parameters α and β are estimated using maximum likelihood methods in the R package 'Apollo' (Hess and Palma, 2019). The variables included in the final specification of the model were chosen based on their meaning (i.e., non-redundant variables) and statistical significance. The explanatory variables were assumed to have a different impact on compliance after the 70-flashing VSL, the 50-flashing VSL and the 50 VSL. Differences between VSLs were tested statistically by comparing alternative model specifications using the likelihood ratio test. Variables that did not have a significantly different impact on compliance between VSLs were merged and variables that did not have a significant impact on any VSLs were omitted. When an explanatory variable was not available for part of the observations (e.g., the distance headway was missing because a leader was not detected by the MobilEye), a binary variable denoting the missing values was included in the latent regression function in addition to the variable of origin (dummy variable adjustment method).

3. Results

3.1. *Interrater reliability of annotation*

Table 1 shows the list of derived variables that were considered eligible for analysis based on the results of the reliability tests using twelve events coded by four annotators. As described in Section 2.5.1, derived variables were considered eligible when the Krippendorff's alpha was higher than 0.67, or when the distribution was significantly skewed and the percentage agreement was higher than 80 %. In total, fifteen derived variables met these criteria. Derived measures based on engagement in secondary tasks did not meet the reliability criteria. The weather conditions related to the visibility for the driver were not reliably interpreted. The timing of the presence of weaving sections, exit lanes, and entry lanes was not reliably annotated.

3.2. *Descriptive analysis and statistics*

This section analyses 603 observations associated with 201 valid events. These events were observed in 185 distinct journeys by 27 drivers. The number of events per driver was between 1 and 32 (M = 7.44, SD = 6.86). Overall, 33.83 % of the drivers complied with the speed limit after the 70-flashing sign (68 observations), 59.70 % after the 50-flashing sign (120 observations), and 71.64 % after the 50 sign (144 observations). A lead vehicle was present most of the time when

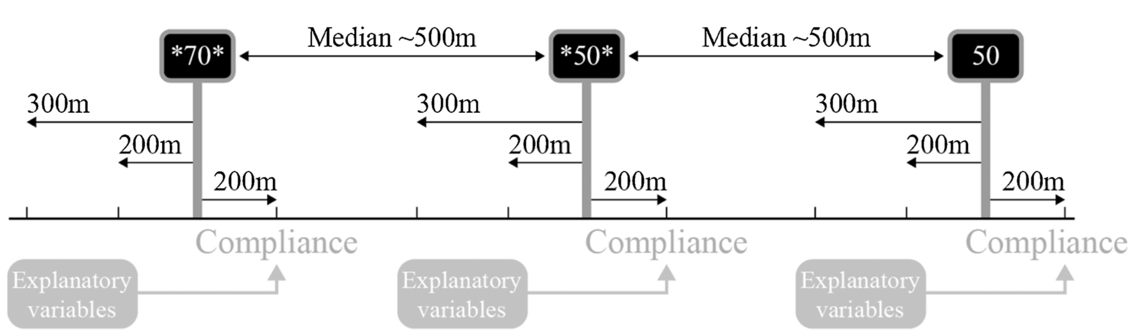

Fig. 2. Driver compliance during the events (70-flashing VSL, 50-flashing VSL and 50 VSL). The main factors influencing compliance are calculated 200 m to 300 m before each gantry. Compliance is assessed based on the speed 200 m after each gantry.

Table 1
List of variables considered eligible for analysis based on the results of the interrater reliability tests using twelve events coded by four annotators.

Annotated variable	Definition annotated variable	Valid derived variables
Glance direction	*On road* (driver looks outside forward) or *off road* (driver looks sideways or inside the vehicle).	Proportion of time with eyes-on-road Proportion of time with eyes-off-road Count of switches between eyes on and off road Proportion of time with eyes-off-road for a minimum duration of 2 s Proportion of time eyes with eyes-on-road for a minimum duration of 2 s Count of off-road glances with a minimum duration of 2 s
Gantry visibility	*Not visible* (portal too far away or blocked view), *visible* (portal visible and not active), *visible and active* (portal visible and active irrespective of readability).	Proportion of time when the portal is visible and not active Proportion of time when the portal is not visible Proportion of time when the portal is visible and active
Driving lane	*Lane number* counted from the centre of the road (most central = 1). If the number of lanes changes, the count starts again from the centre.	Proportion of time in lane one Proportion of time in lane two Proportion of time in lane three Proportion of time in lane four
Density of the environment	*Open* (no trees, bushes, buildings), *half-open* (occasional trees, bushes, building) or *closed* (dense forestation or buildings).	Open environment versus non-open environment (closed, semi-open)
Exiting the motorway	*Yes* (driver has passed the blocks to exit the motorway at the end of the event), *no* (driver is on the motorway at the end of the event).	Binary variable indicating if the driver exited the motorway at the end of the event

the drivers complied: 97.06 % of the observations after the 70-flashing VSL (vs. 89.47 % when they did not comply); 96.67 % of the observations after the 50-flashing VSL (vs. 87.65 % when they did not comply); 97.92 % of the observations after the 50 VSL (vs. 92.98 % when they did not comply).

To gain insights into the conditions in which drivers complied after each VSL sign, we present the mean and the standard deviations of the continuous variables expressing the driver behaviour characteristics, the road segment characteristics, the driver characteristics, and the driver state when drivers complied and did not comply with each VSL in Table 2. Comparing the mean values in Table 2, we notice that drivers complied more often when the mean speeds before the gantries were lower, when the distance headways were smaller, when approaching a slower vehicle, and when the next gantry was closer. In addition, two-sample Kolmogorov-Smirnov tests were performed to test the similarity of the distributions (not of the means) between the two groups for each VSL. The speed distributions differed significantly between the two groups before the 70-flashing and the 50-flashing VSLs (p-value $<$ 0.005). The distance headway distributions differed significantly between the two groups before the 50-flashing VSL (p-value = 0.007). The relative speed distributions before the 70-flashing VSL differed significantly (p-value = 0.054). The distributions of the distance to the portals differed significantly between the two groups before the 70-flashing VSL (p-value = 0.005). The distributions of all other variables in Table 2 did not differ significantly between the two groups. The main conclusion from this analysis is that the driver behaviour characteristics and the characteristics of the road segment can have a significant impact on compliance with the VSLs.

The number and the percentage of observations in each group based on the nominal variables are presented in Table 3. The Chi-squared test of independence was calculated to test the relation between these variables and compliance with each VSL. Table 3 shows that there is a small number of observations available when the road environment was open, the electronic speed control was active, and the driver exited the motorway after the 50 VSL. Statistical tests on these variables were not conducted. The Chi-squared test of independence between closed and non-closed environment and between male and female drivers showed non-significant results. Further analysis is needed to understand the impact of these factors on compliance with the VSLs.

Table 2
Mean and standard deviation of the driver behaviour characteristics and the characteristics of the road segment when the drivers complied (C) and did not comply (NC) with each VSL. The driver behaviour characteristics and the driver state are measured 200-300 m before the gantry. Compliance is assessed 200 m after the gantry.

Variable	Description	*70* C	*70* C	*50* C	*50* C	50 C	50 NC
Speed	Mean speed of the subject vehicle in km/h	78.57 (16.87)	95.82 (11.87)	74.52 (16.02)	86.09 (13.78)	41.58 (20.78)	44.99 (27.08)
Acceleration	Mean acceleration of the subject vehicle in m/s^2	−0.2936 (0.3445)	−0.2050 (0.2858)	−0.3187 (0.3480)	−0.1905 (0.3139)	−0.3125 (0.4981)	−0.2349 (0.5386)
DHW	Mean distance headway (front bumper to rear bumper) in m	39.38 (20.45)	46.08 (25.12)	38.90 (21.90)	47.69 (22.21)	25.57 (18.27)	27.18 (24.18)
Relative speed	Relative speed (leader speed − subject vehicle speed) in km/h	−1.850 (7.406)	−0.1010 (7.877)	−1.650 (5.947)	−1.615 (7.185)	−2.427 (6.660)	−2.531 (8.265)
Dist NextGantry	Distance to the next gantry in m	272.9 (132.1)	327.7 (129.1)	293.1 (115.4)	316.0 (97.99)	273.2 (118.0)	271.4 (130.2)
NLanes	Number of lanes in the road section	3.221 (0.9279)	3.293 (0.7665)	3.167 (0.8534)	3.444 (0.9220)	3.403 (0.9336)	3.211 (0.9207)
Age	Driver age in years	40.68 (13.56)	42.08 (12.06)	41.60 (12.20)	41.60 (13.18)	41.22 (12.70)	42.56 (12.30)
pEyes OnRoad	Proportion of time with eyes-on-road in %	90.54 (15.64)	86.70 (20.53)	89.11 (18.96)	85.42 (21.00)	86.77 (17.77)	86.23 (22.30)
nOnOffRoad	Number of switches between eyes on/off road	0.7647 (0.9942)	0.6617 (0.8428)	0.5583 (0.8677)	0.6667 (0.8367)	1.285 (1.960)	1.386 (1.943)
pEyes OffRoad2s	Proportion of time with eyes-off-road > = 2 s in.%	0.8823 (7.276)	1.905 (12.73)	3.423 (13.41)	3.857 (15.30)	4.774 (12.80)	7.360 (21.01)
pGantryVis	Proportion of time portal visible and not active in %	8.569 (22.79)	11.45 (26.29)	9.378 (25.46)	10.93 (26.55)	14.99 (32.01)	7.180 (22.14)
pGantry VisAct	Proportion of time portal visible and active in %	37.24 (39.62)	32.79 (40.11)	39.77 (43.43)	35.04 (41.05)	33.42 (40.49)	27.66 (38.52)

Table 3
Number and percentage of observations in each group when the drivers complied (C) and did not comply (NC) with each VSL. Compliance is assessed 200 m after the gantry.

Variables	*70* C	*70* NC	*50* C	*50* NC	50 C	50 NC
Environment						
Open	2 (6.1 %)	8 (3.0 %)	4 (7.4 %)	6 (3.4 %)	8 (3.5 %)	2 (5.6 %)
Half-open	53 (75.0 %)	99 (79.1 %)	94 (71.6 %)	58 (79.7 %)	106 (80.7 %)	46 (74.6 %)
Close	12 (18.9 %)	25 (17.9 %)	20 (21.0 %)	17 (16.9 %)	28 (15.8 %)	9 (19.7 %)
Electronic speed control						
Yes	2 (2.9 %)	3 (2.3 %)	2 (1.7 %)	4 (4.9 %)	5 (3.5 %)	2 (3.5 %)
No	66 (97.1 %)	130 (97.7 %)	119 (98.3 %)	77 (95.1 %)	139 (96.5 %)	55 (96.5 %)
Exiting the motorway						
Yes	2 (2.9 %)	1 (0.8 %)	1 (0.8 %)	2 (2.5 %)	2 (1.4 %)	1 (1.8 %)
No	66 (97.1 %)	132 (99.2 %)	119 (99.2 %)	79 (97.5 %)	142 (98.6 %)	56 (98.2 %)
Gender						
Female (n = 13)	31 (45.6 %)	69 (48.1 %)	61 (50.8 %)	39 (48.1 %)	76 (52.8 %)	24 (42.1 %)
Male (n = 14)	37 (54.4 %)	64 (51.9 %)	59 (49.2 %)	42 (51.8 %)	68 (47.2 %)	33 (57.9 %)

Table 4
Statistics of the logistic regression model.

Statistics	
Number of parameters K associated with the explanatory variables	9
Number of constants	3
Number of drivers	27
Number of events	201
Number of observations	603
Constant log likelihood $L(c)$	−384
Constant Akaike information criterion	774
Constant Bayesian information criterion	787
Final log likelihood $L(\widehat{\beta})$	−319
Final Akaike information criterion	661
Final Bayesian information criterion	714
Adjusted likelihood ratio index (rho-bar-squared) $\bar{\rho}^2 = 1 - \frac{(L(\widehat{\beta})-K)}{L(c)}$	0.147

3.3. Logistic regression model

The goodness-of-fit measures and the estimation results are presented in Table 4 and Table 5 respectively. The latent regression function for complying (C) and not complying (NC) with the 70-flashing VSL (*70*), 50-flashing VSL (*50*) and 50 VSL (50) for driver *n* at time *t* are given by Eqs. (4)–(5):

$$
\begin{aligned}
C_n(t) = {} & \alpha^{[*70*]} + \alpha^{[*50*]} + \alpha^{[50]} \\
& + \beta_{Speed}^{[*70*]} \cdot [Speed*70*](t) + \beta_{Speed}^{[*50*]} \cdot [Speed*50*](t) + \beta_{LowSpeed}^{[50]} \cdot [LowSpeed50](t) \\
& + \beta_{Acc}^{[*70*,*50*]} \cdot [Acc*70*,*50*](t) + \beta_{RelSpeed}^{[*70*]} \cdot [RelSpeed*70*](t) + \beta_{NoLead}^{[*70*]} \cdot [NoLead*70*](t) \\
& + \beta_{pEyesOnRoad}^{[*70*]} \cdot [pEyesOnRoad*70*](t) \\
& + \beta_{DistNextGan} \cdot DistNextGan(t) + \beta_{Nlanes}^{[*50*]} \cdot Nlanes(t) + \varepsilon_n^C(t)
\end{aligned} \tag{4}
$$

$$NC_n(t) = 0 + \varepsilon_n^{NC}(t) \tag{5}$$

where $\alpha^{[*70*]}, \alpha^{[*50*]}$ and $\alpha^{[50]}$ are the constants associated with each gantry, $\beta^{[*70*]}$, $\beta^{[*50*]}$, and $\beta^{[50]}$ are vectors of parameters related to the explanatory variables presented in Table 5, and $\varepsilon^C(t)$ and $\varepsilon^{NC}(t)$ are logistic-distributed error terms. Due to the relatively small sample size (201 events), we have included a few parameters that are statistically significant at the 10 % level. However, most parameters are statistically significant at the 5% level.

The constants associated with each VSL differ in their impact on compliance. The negative constant associated with the 70-flashing VSL indicates that, everything else being equal, drivers are unlikely to comply. The positive constant associated with the 50-flashing VSL indicates that, everything else being equal, drivers are likely to comply. The constant associated with the 50 VSL does not have a significant

Table 5
Estimation results of the logistic regression model. Compliance with the VSLs is assessed 200 m after the gantry. The driver behaviour characteristics and the glance behaviour metrics are measured as mean values in the interval 200-300 m before the gantry. The distance to the next gantry and the number of lanes are measured in correspondence of each gantry.

Variable	Description	Parameters	Estimate	t-stat.	p-value
–	Constant	$\alpha^{[*70*]}$	−0.832	−4.19	< 0.0005
–	Constant	$\alpha^{[*50*]}$	0.339	2.10	0.036
–	Constant	$\alpha^{[50]}$	0.367	1.27	0.205
Speed	Speed of the subject vehicle before the *70* gantry in km/h	$\beta_{Speed}^{[*70*]}$	−0.0994	−6.46	< 0.0005
Speed	Speed of the subject vehicle before the *50* gantry in km/h	$\beta_{Speed}^{[*50*]}$	−0.0623	−5.15	< 0.0005
LowSpeed	Binary variable equal to one when the speed of the subject vehicle before the 50 gantry is lower than 56 km/h	$\beta_{LowSpeed}^{[50]}$	0.730	2.10	0.036
Acc	Acceleration of the subject vehicle before the *70* and *50* gantry in m/s^2	$\beta_{Acc}^{[*70*, *50*]}$	−1.47	−3.67	< 0.0005
RelSpeed	Relative speed (leader speed - subject vehicle speed) before the *70* gantry in km/h	$\beta_{RelSpeed}^{[*70*]}$	−0.0443	−1.71	0.087
NoLead	Binary variable equal to one when there is no lead vehicle before the *70* gantry	$\beta_{NoLead}^{[*70*]}$	0.0712	0.08	0.932
pEyesOnRoad	Proportion of time with eyes-on-road before the *70* gantry	$\beta_{pEyesOnRoad}^{[*70*]}$	1.82	1.71	0.087
DistNextGan	Distance to the next gantry in m	$\beta_{DistNextGan}$	−0.00253	−3.07	0.002
Nlanes	Number of lanes at the location of the *50* gantry	$\beta_{Nlanes}^{[*50*]}$	−0.522	−2.73	0.006

impact on compliance.

Several driver behaviour characteristics of the subject vehicle before each gantry have a significant impact on compliance afterwards. Drivers are more likely to comply at lower speeds. The impact of speed on compliance is significantly higher after the 70-flashing VSL than after the 50-flashing VSL. Drivers are more likely to comply after the 50 VSL when their speed is lower than the speed limit. Speed included as a linear predictor did not have a significant impact on compliance. Drivers are more likely to comply after the 70- and the 50-flashing VSLs when their acceleration is low. The effect of acceleration on compliance does not differ significantly between the 70- and the 50-flashing VSLs. Acceleration did not have a significant impact on compliance after the 50 VSL. Drivers are more likely to comply after the 70-flashing VSL when they are approaching a slower leader (p-value = 0.087). The relative speed did not have a significant effect on compliance after the 50-flashing and the 50 VSLs. The time headway did not have a significant impact on compliance. Lane changes did not influence compliance significantly.

Various characteristics of the road segment significantly influenced compliance. Drivers complied more often when the distance between gantries was shorter. This effect did not differ significantly between VSLs. Drivers were more likely to comply after the 50-flashing VSL when the number of lanes in the road section was smaller. In contrast, the number of lanes did not have a significant impact on compliance after the 70-flashing and after the 50 VSLs. The presence of an electronic speed control system did not have a significant impact on compliance. Exiting the motorway after the 50 VSL did not influence significantly compliance.

The glance behaviour of the driver had a significant impact on compliance after the 70-flashing VSL. Drivers are more likely to comply when the proportion of time with eyes-on-road is larger (p-value = 0.087). However, the proportion of long glances off road and count of switches between on and off-road glances did not have a significant impact on compliance. Glance behaviour did not have a significant impact on compliance with the 50-flashing and with the 50 VSLs. The proportion of time when the gantry was visible and when the gantry was visible and active did not have a significant impact on compliance.

The gender and the age of the driver did not have a significant impact on compliance. In addition, we tested a driver-specific error term and an event-specific error term. Both resulted to be non-significant and therefore were not included in the final specification of the model.

To analyse the effect of changes in the explanatory variables on the probability to comply, the probability to comply was calculated 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 90.05 km/h before the 70-flashing VSL, decreasing to 79.18 km/h before the 50-flashing VSL, and to 42.55 km/h before the 50 VSL. The acceleration was equal to -0.251 m/s^2 and the relative speed was -1.54 km/h. The distance to the next portal was equal to 295 m and the number of lanes in the road section was equal to 3. The proportion of time with eyes-on-road was 87.5 %. The characteristics of the baseline condition were chosen based on the mean values in the sample. The probability to comply after the 50 VSL is equal to 59 % when the speed is higher than 56 km/h (vs. 75 % in the baseline observation). Fig. 3 presents the results for the continuous variables, which are all consistent with previous discussions. Visual inspection suggests that low speeds and low accelerations have the strongest impact on compliance after the 70- and the 50-flashing VSLs. The other variables have a medium to moderate effect on compliance.

3.4. Validation analysis

A validation analysis was performed in which the final model in Table 5 was compared to a logistic regression model that has only a constant. The aim of this analysis is to evaluate the final model ability to forecast the responses of drivers not comprised in the estimation sample.

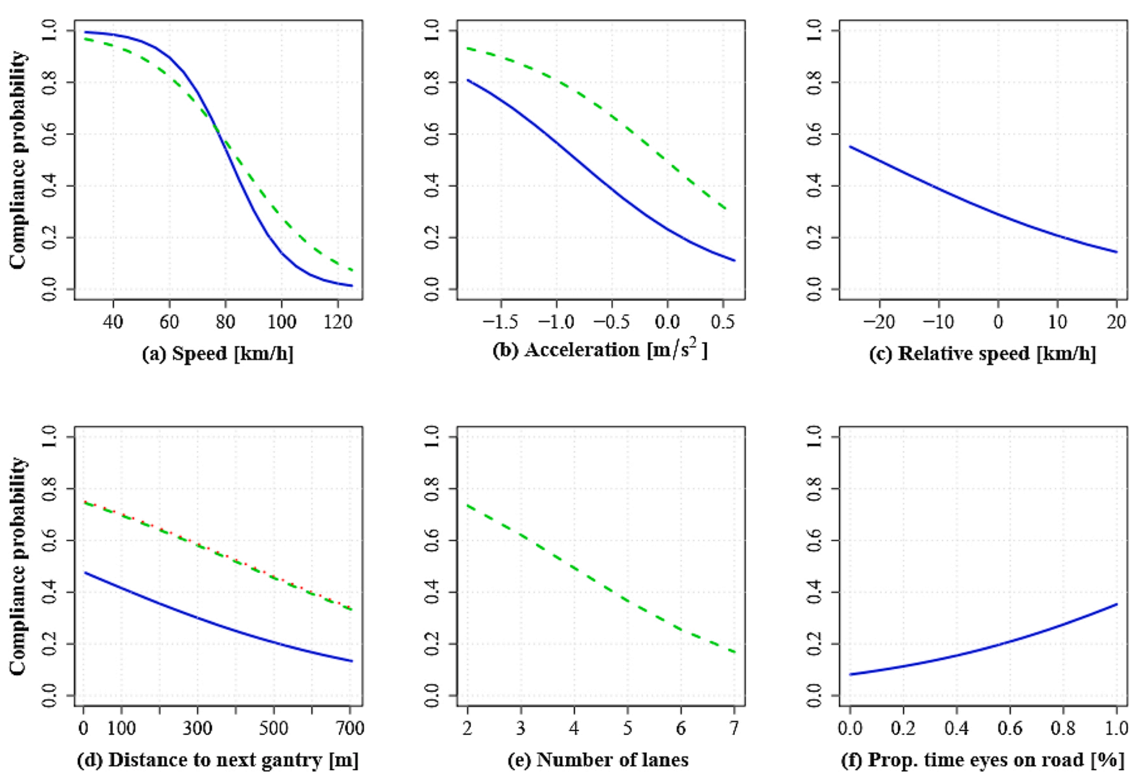

Fig. 3. Impact of the explanatory variables included in the model on the probability to comply after the 70-flashing VSL (blue solid line), 50-flashing VSL (green dashed line) and 50 VSL (red dotted line). The variables are listed as follows: (a) speed; (b) acceleration; (c) relative speed; (d) distance to the next gantry; (e) number of lanes in the road section; (f) proportion of time with eyes-on-road (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

Ideally, the final model should be applied to other databases to understand its predictive ability. Given that we do not have other comparable databases at the time of writing, we performed an out-of-sample validation approach. A five-fold cross validation method was preferred because of the small number of drivers available (Hastie et al., 2009). We randomly divided the drivers into five groups, estimated the models based on the observations of four groups (80 % of the drivers), and validated the models based on the observations of the group not comprised in the estimation sample (20 % of the drivers). The validation procedure was repeated five times. The final log likelihood of the models on the validation subsamples was chosen as an evaluation metric to compare the model performances. This metric allows us to identify which model has the highest prediction ability out of sample. The smaller the log likelihood, the higher the accuracy reached.

Table 6 presents the final log likelihood values of the models on the validation subsamples. The last column shows the improvement in accuracy. The findings show that the final model has higher prediction accuracy than the constant model on all validation subsamples. The final model shows the smallest accuracy improvement when it is validated on group two, meaning that some drivers in this group behaved differently than the other drivers did. These differences might be explained by heterogeneity in personality traits or driving styles that are not captured in the final model. This analysis suggests that the final model is suitable to predict the responses of individual drivers not comprised in the estimation sample.

4. Discussion and conclusions

This study investigated the main factors associated with driver compliance with variable speed limits (VSLs). The variable speed limit database of Rijkswaterstaat was integrated into the Dutch passenger car data in the UDRIVE naturalistic driving database. The video data were manually annotated and the resulting dataset was analysed in a logistic regression model. This model allowed us to investigate the link between multiple explanatory variables and the observed behaviour of drivers. Caution must be applied in the interpretation of the results due to the relatively small number of observations available, the sample of participants, and the type of AID system. The findings are relevant to the development of driving assistance system and to the assessment of the impacts on traffic operations.

4.1. Main findings

The speed and the acceleration of the subject vehicle observed before the gantry are the main factors influencing compliance with the 70- and the 50-flashing VSLs. These findings are consistent with those of Lee and Abdel-Aty (2008) and Conran and Abbas (2018) who showed that compliance is high when the speed change implied by the VSL is small. We can conclude that drivers are more likely to comply when they start to reduce their speed early. The initial speed has a larger effect on compliance after the 70-flashing than after the 50-flashing VSL. A possible explanation could be that drivers are more constrained by the surrounding traffic conditions as they approach congestion. Drivers are also more likely to comply with the 70-flashing VSL when approaching a slower leader. This result indicates that they are influenced by the responses of the drivers downstream in medium-dense traffic conditions.

Table 6
Five-fold cross validation of the logistic regression model. C denotes the model that has only a constant and $\widehat{\beta}$ indicates the final model in Table 5.

Validation subsample	Drivers	Observations	Constant log likelihood L(c)	Final log likelihood $L(\widehat{\beta})$	$\frac{L(c) - L(\widehat{\beta})}{L(c)}$
1	6	123	−78.6	−69.9	0.1107
2	6	117	−78.9	−72.7	0.0794
3	5	123	−82.0	−69.2	0.1556
4	5	120	−74.6	−61.4	0.1778
5	5	120	−74.3	−63.5	0.1450
M	5.4	121	−77.7	−67.3	0.1337
SD	0.55	2.51	3.23	4.72	0.0388

Glance behaviour is moderately associated with compliance with the VSLs. Drivers are more likely to comply with the 70-flashing VSL when the proportion of time with eyes-on-road is larger. This result reflects those of Peng et al. (2013) who found that eyes-off-road have a negative impact on lane keeping performance. The finding suggests that compliance increases with awareness of the traffic situation downstream. Further analysis is needed to link glance behaviour to the visibility of the VSLs on the gantries and to engagement in secondary tasks.

The characteristics of the road segment are significantly associated with compliance with the VSLs. Drivers are more likely to comply when the gantries are closer. A possible explanation could be that they can see multiple gantries at a time as the inter-gantry distance decreases. Further research is needed to investigate if drivers can indeed see multiple gantries simultaneously, or if this result can be explained by other characteristics of the road segment that are associated with the inter-gantry distance. Drivers comply less with the 50-flashing gantry when there are more lanes and the road is wider. A possible explanation could be that drivers were approaching a connection between motorway segments with distinct VSLs across the road section. Further research is needed to investigate the impact of road width on compliance after the 70-flashing and the 50 VSLs.

4.2. Recommendations for future research

The study analysed the main factors associated with driver compliance with the VSLs in an AID sequence on Dutch motorways, in situations during which the state of the VSLs did not change. The number of events available was limited to 201. Certain factors in this study (relative speed and proportion of time with eyes-on-road) were statistically significant at the 90 % confidence level but not at the 95 % confidence level. Future studies are suggested to investigate driver compliance with the AID system based on a larger sample of observations. The results are also influenced by the traffic conditions in which the Dutch AID system is activated. Further investigations are needed to generalize the results to other AID systems and to different traffic conditions (e.g., free-flow traffic).

The generalizability of the findings towards the general population of drivers is subject to certain limitations. The sample of participants was not representative of the general Dutch population of drivers in terms of age, years of driving experience, and gender. Furthermore, the sample size was relatively small (27 drivers). The validation analysis suggests that, to increase the prediction ability of the model, future studies should investigate the effect of driver characteristics on compliance with the VSLs. Finally, a single vehicle model (Renault Clio) was driven by all participants. Future studies are needed to understand the generalizability of the findings to other types of vehicles and to advanced driving assistance systems.

Engagement in secondary tasks was not analysed in this study because the measures derived from annotation showed low levels of inter-rater reliability. To evaluate the effect of secondary task engagement on compliance with the VSLs, further investigations using different annotation procedures may be required. In this study, engagement in secondary tasks was coded as 'true' when at least one of the secondary tasks defined in the UDRIVE codebook (Carsten et al., 2017) was observed. Hence, annotators had to memorize the definitions of a relatively large number of secondary tasks. Future studies might propose simpler definitions of engagement in secondary tasks and develop annotation procedures concentrating on individual secondary tasks (e.g., phone use, reading, smoking) as opposed to one global variable. Distinct buttons in the annotation panel for each type of secondary task can be introduced.

4.3. Recommendations for practice

Driver behaviour can be investigated in-depth in real traffic conditions by using the data collection techniques (variable speed limit database, naturalistic driving data and video data annotation) and the data analysis methods (logistic regression model) developed in this study. This advanced database allows us to gain insights that are unique and have a high level of validity. The results have practical implications for the development of intelligent transport systems and for the impact assessment of these systems on traffic operations.

Connected vehicle technologies and advanced driving assistance systems that account for the main factors identified in this study are required to replicate human driving style with VSLs. To increase the attention of the driver and elicit an early deceleration response while approaching the gantries, VMSs and VSLs could be also posted in in-vehicle devices (similar to the warning systems in Van Nes et al., 2010; Farah et al., 2012; Farah and Koutsopoulos, 2014) using infrastructure to vehicle communication systems. Based on these results, future studies should focus on developing systems as adaptive cruise control that gradually reduce the speed to comply with the VSLs while approaching the AID sequence. The driving assistance systems should account for within driver variability based on the driver state (proportion of eyes-on-road) and characteristics of the infrastructure (distance between gantries and number of lanes). Drivers are expected to adopt advanced driving assistance systems based on these insights in a wider variety of situations.

Traffic flow models that assess the effect of VSLs on traffic congestion may increase their accuracy by incorporating the main factors identified in this study. The results have shown that the traffic conditions, the driver state and the road characteristics explain part of the within driver variability in compliance with the VSLs. Most traffic simulation models currently available are not grounded on empirical results in naturalistic driving experiments. Based on the findings in this study, future work should develop advanced car-following models that describe driver compliance with the AID based on probabilistic decision rules, mimicking how drivers gradually reduce their speed and are influenced by the road characteristics (similar to the advanced car-following models incorporating driver distraction developed by Hoogendoorn et al., 2013; Saifuzzaman et al., 2015). Implementing this advanced car-following model into a microscopic traffic flow simulation, we will be able to forecast the effect of VSLs on traffic congestion realistically.

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 van Nes:** Conceptualization, Funding acquisition, Project administration, Writing - review & editing.

Declaration of Competing Interest

The authors reported no declarations of interest.

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