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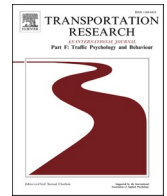
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## Spare visual capacity and driver inattention in dynamic car following scenarios

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### ABSTRACT

Drivers often look away from the forward roadway. However, this does not necessarily mean that they are inattentive, as they might be utilizing their spare visual capacity (SVC). Because of the safety-critical risks associated with inattentive driving, it is imperative to analyze how much visual capacity a driver can afford to use for secondary activities while avoiding the possibility of an accident. This study aimed to define and identify driver inattention in a car following task based on an estimate of the driver's situational SVC. A mathematical model of SVC in car following was created based on the possible but unlikely worst-case scenario in any situation. The model generates situation-specific marginal values of the minimum time that can lead to a possible collision when a driver looks away from the lead car. A classification algorithm was developed to define and identify inattention based on the model's estimates. The model reveals that SVC in car following varies significantly from situation to situation, depending on relevant situational, technical, and cognitive factors. A driving simulator study ( $N = 32$ ) indicated that drivers are often willing to occlude themselves in car following when there is a chance of a rear-end collision and that this behavior becomes more likely with higher speeds. A strong linear association between distance headway and brake response time was also found. Quantifying SVC in driving helps in determining driver inattention against a valid baseline based on what is possible. The proposed modeling approach can be utilized for the development of improved safety guidelines and effective context-sensitive (in)attention monitoring systems.

### 1. Introduction

First coining the term in 1971, Safford conceptualized spare visual capacity (SVC) in driving as redundant visual sampling of the forward roadway that is unnecessary for safe driving. That is, SVC equates to the amount of time a driver can spend safely sampling for items that are nonessential for succeeding in the driving task, such as looking at the smartphone, the in-vehicle infotainment system, or outside scenery. Safford (1971) hypothesized that car drivers possess SVC with respect to their visual sampling ability. To prove this, he conducted a series of experiments in which he used the method of voluntary visual occlusion to measure the *percentage of time* a driver managed to keep their eyes closed during a specific driving task without a collision. Later research has shown that SVC in driving is highly situational and that it varies with the driver and the specific attentional demands of the driving situation (Kujala et al., 2021). This finding generates the need to study the relevant variabilities in SVC from a normative perspective, that is, to assess how long a driver can afford to look away from the traffic in any specific situation to avoid safety-critical events, such as a possible collision. In

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this study, a more precise and situationally dependent measurement of a driver's SVC in a specific safety-critical driving task, car following, is defined. Based on this novel measurement, visual inattention can be effectively defined and identified. According to naturalistic studies, rear-end crashes in car following are associated with the highest impact of visual distraction on safety-critical events in traffic (Bálint et al., 2020; Victor et al., 2015).

Driver (in)attention monitoring systems (Fredriksson et al., 2021) require a better understanding of the situational SVC in driving to avoid false positives and to be effective. Empirical evidence of SVC questions the common notion of labeling a driver as inattentive each time the driver looks away from the forward roadway (Ahlström, Georgoulas, et al., 2021; Kircher & Ahlstrom, 2017; Kujala et al., 2021). There are already implementations of distraction warning algorithms that allow a buffer of a couple of seconds before warning the driver to look back on the road (Ahlstrom et al., 2013; Donmez et al., 2007; Kujala et al., 2016; Victor, 2010), and it has been recently suggested that these thresholds should be sensitive to the road type or driving scenario (Ahlström, Georgoulas, et al., 2021; Han et al., 2023; Kujala et al., 2024). However, in the definition of safety-critical thresholds for alerting drivers about inattention, more emphasis should be placed on what is possible in a situation as opposed to what is probable based on odds ratios calculated across variable situations.

For instance, the popular 2 s threshold as an acceptance limit for off-forward glance durations was derived based on odds ratios in near-crash and crash statistics collected in a naturalistic study as a gross measure over a variety of situations and drivers (Klauer et al., 2006). There is no internal logic as to why a 2 s off-forward glance duration or any other static threshold would be sufficient for a driver to be categorized as attentive or inattentive across all possible variable situations in traffic. In some situations, 2 s may be too restrictive (e.g., empty roads, good visibility, straight roads with no crossings ahead). In other situations, 2 s could be too allowing (e.g., following a car, a short time headway [THW], poor visibility, crossing traffic ahead). A valid static threshold for inattention identification cannot be generalized for every situation, as many environmental, mechanical, and cognitive factors are associated with driving, and they vary from situation to situation. Furthermore, time-to-collision (TTC) formulations and safety guidelines for THWs are estimated for situations in which the lead car and the following car continue driving at the same speed (e.g., Hayward, 1972; Vogel, 2003). While this is often what happens in a fluent traffic flow, the traffic system on crowded roads is full of turbulence, and there can be many variabilities in the relative speeds of cars in car following scenarios.

This study aims to develop a mathematical model that can be used to predict a situational collision-critical threshold of SVC in car following while incorporating all the related situationally variable environmental, mechanical, and cognitive factors. It is argued that given the safety-critical nature of inattention classification, we should prioritize possibility over probability in the definition of thresholds. Therefore, parameter estimates focus on the ends of relevant probability distributions, and worst-case scenarios are used in the analysis. As opposed to existing car following models that aim to predict how drivers behave in car following (e.g., Chen et al., 2012; Hamdar et al., 2015; Sheu & Wu, 2015), this new model is normative; that is, it indicates how drivers should distribute their limited attention in car following situations in order to be safe. Such a mathematical model could be utilized to develop improved safety guidelines, driver monitoring and inattention warning systems, or training apparatus concerning situational SVC in driving.

The rest of the paper is structured as follows. First, the model is introduced. Second, analytical findings from applying the model to the definition of SVC in typical car following scenarios are reported. Next, empirical findings from a driving simulator study illustrate the usefulness of the model for classifying driver attentive or inattentive. Finally, the model, its limitations, and the findings are discussed in relation to the state of the art.

## 2. Model

Each instance a driver voluntarily takes eyes off the road, that is, occludes oneself during a car following task, is treated separately because every single instance is important from the safety perspective and differs from others contextually. We define  $OT^{(i)}$  (i.e., occlusion time for the  $i^{th}$  instance,  $i = 1, 2, \dots$ ) as the period for which a given driver voluntarily occludes one's vision from the road for the  $i^{th}$  time during a car following task. The main interest is in finding the minimum threshold value of  $OT^{(i)}$  that can lead to a possible collision (hereafter  $OT_{min\_pc}^{(i)}$ ). In other words, it is the time threshold before which a bounded-rational driver should return their eyes back on the lead car in order to avoid a possible rear-end crash in any situation, given the driver's limited knowledge about the status of the lead car during the occlusion.

The method is a form of counterfactual (what-if) reasoning (e.g., Bärghman et al., 2017; Gerstenberg et al., 2021; Sui et al., 2021) – although not relying on what has happened in the past but on what is logically possible to happen in a predefined situation – as opposed to counterfactual simulations on existing data (e.g., Bärghman et al., 2017). According to Gerstenberg et al. (2021), counterfactual reasoning enables humans to make causal judgments. Note that the model has similarities to threat-assessment algorithms (e.g., Brännström et al., 2010), but the purpose of the current model is to enable the classification of drivers as attentive or inattentive in car following.

To determine a safety-critical measure like  $OT_{min\_pc}^{(i)}$ , that is, the critical absolute and minimum threshold value, it is imperative to consider driving under extreme (i.e., worst possible) conditions to make sure any unlikely yet possible situation is not left out. The following worst-case scenario is analyzed to consider the extreme but possible scenario that can emerge when a following car's driver voluntarily occludes oneself at any given point during a car following task: the lead car's driver brakes hard because of an emergency at the same moment the following car's driver occludes oneself.

### 2.1. Definitions

All the relevant situational, technical, and cognitive parameters of interest need to be considered to develop a mathematical model for estimating  $OT_{min-pc}^{(i)}$ . These factors and their definitions are provided in the following:

- Initial distance headway (DHW) between the lead car and the following car: When the following car’s driver occludes oneself, the DHW, which is measured as the bumper-to-bumper distance between the lead car and the following car, plays a significant role in the possible worst-case scenario. This is a situational variable and is denoted as  $DHW_T^{(i)}$ .
- Initial speed of the lead car: This is the speed of the lead car at the moment the following car’s driver occludes one’s vision from the road. This is a situational variable and is denoted as  $S_L^{(i)}$ . This is also the last speed of the lead car that the following car’s driver was able to observe before taking eyes off forward. It defines the braking distance of the lead car from the point the following car’s driver occluded oneself, together with other relevant factors reviewed below.
- Initial speed of the following car: This is the speed of the following car at the moment the following car’s driver occludes oneself. This is also a situational variable and is referred to as  $S_F^{(i)}$ . Here, it is assumed that the following car maintains a uniform speed (i.e., the  $S_F^{(i)}$ ) until the last point after which the brake response of the following car is initiated, that is, when the following car’s driver has reverted vision back to the lead car and has decided to apply the brakes after understanding the emergency.
- Braking distance of the lead car: This is the distance traveled by the lead car before finally stopping after the braking response of the car has been initiated. Hereafter, this braking distance is referred to as  $BD_L^{(i)}$ . Aside from the initial speed of the car ( $S_L^{(i)}$  in this case), this parameter depends on the deceleration rate (hereafter  $a_L^{(i)}$ ) produced by the car. In estimating  $OT_{min-pc}^{(i)}$ , it is assumed that the lead car’s driver brakes with the maximum achievable mean deceleration rate for a driver during an emergency. Thereby,  $a_L^{(i)}$  is assumed to be a constant parameter. The formula to derive the value of  $BD_L^{(i)}$  can be selected from the many formulas available in the literature. Factors such as grade, crown, and surface of the road could influence these formulations (Transportation Officials, 2011).
- Brake response time (BRT) of the following driver: This is the time that the following car’s driver would require to revert their vision back to the road and for glance dwell, to understand the dynamics of the roadway and recognize the emergency ahead that necessitates braking (i.e., mental processing time), to perform the required muscle movement, and, finally, to apply the brakes (i.e., movement time). Hereafter, this parameter is denoted as  $BRT_F^{(i)}$ . This variable depends on the driver’s individual perceptual, cognitive, and motor skills. Furthermore, the BRT has been shown to depend on the urgency of the situation (Markkula et al., 2016). As guessing or predicting the response time a particular driver would generate in the case of emergency is challenging, it is best to consider and estimate this variable from the worst-case scenario to derive the safest possible estimate of  $OT_{min-pc}^{(i)}$ . That is, to determine what is the maximum possible time a driver can take to react and act in the face of an unexpected emergency. This variable should be adjusted based on the driver and the observed urgency of the situation. It is important to note that during the BRT of the driver, the car is assumed to maintain its initial speed (i.e.,  $S_F^{(i)}$ ).
- Braking distance of the following car: This is the distance traveled by the following car before finally stopping after the braking response of the car has been initiated. Hereafter, it is referred to as  $BD_F^{(i)}$ . Aside from the initial speed of the car ( $S_F^{(i)}$  in this case), this parameter depends on the deceleration rate (hereafter  $a_F^{(i)}$ ) produced by the car. It is assumed that the same maximum (mean) deceleration rate for the lead car’s driver is also possible for the following car’s driver, thanks to the same level of observed urgency of the event (Markkula et al., 2016). The factors affecting braking distance, such as grade, crown, and surface of the road, between the two cars traveling on the same road can likewise be considered equal. As it is assumed that both the lead car and the following car will achieve the same braking deceleration rate,  $a_F^{(i)}$  is assumed to be a constant parameter and is equal to  $a_L^{(i)}$ .

### 2.2. General equations

Coming back to the extreme scenario conceptualization, modeling the entire event based on the response of the following car’s driver in a given  $i^{th}$  self-occlusion instance (where  $i = 1, 2, \dots$ ) during a car following task is possible by using the terminal (or final) DHW (hereafter  $DHW_T^{(i)}$ ) between the lead car and the following car. This will be a function of the above-mentioned parameters and the corresponding  $OT^{(i)}$ , that is, the period during which the following car’s driver occluded their vision from the road in that instance. This mathematical equation can be presented as follows:

$$DHW_T^{(i)} = DHW_T^{(i)} + BD_L^{(i)} - S_F^{(i)} \bullet BRT_F^{(i)} - BD_F^{(i)} - OD^{(i)}, \tag{1}$$

where  $OD^{(i)}$  refers to the distance traveled by the following car during the period the driver was occluded in that given  $i^{th}$  instance during a car following task (i.e.,  $OD^{(i)} = OT^{(i)} \times S_F^{(i)}$ ).

Now,  $OD_{min-pc}^{(i)}$ , that is, the minimum occlusion distance that can lead to a possible collision, can be determined by defining the value of  $DHW_T^{(i)}$  as zero because at the moment a crash happens, the DHW (i.e., the bumper-to-bumper distance) between the two cars

becomes zero. Therefore, by defining  $DHW_T^{(i)} = 0$ , Eq. (1) can be rewritten as:

$$OD_{min\_pc}^{(i)} = DHW_L^{(i)} + BD_L^{(i)} - S_F^{(i)} \bullet BRT_F^{(i)} - BD_F^{(i)}. \tag{2}$$

To translate the distance units into time units,  $OT_{min\_pc}^{(i)}$  can then be defined as:

$$OT_{min\_pc}^{(i)} = (DHW_L^{(i)} + BD_L^{(i)} - S_F^{(i)} \bullet BRT_F^{(i)} - BD_F^{(i)})/S_F^{(i)}. \tag{3}$$

By selecting appropriate values for  $BRT_F^{(i)}$ ,  $a_L^{(i)}$ , and  $a_F^{(i)}$ ,  $OT_{min\_pc}^{(i)}$  can be estimated using Eq. (3) for any given self-occlusion instance of the following car’s driver and for different values of  $DHW_L^{(i)}$ ,  $S_L^{(i)}$ , and  $S_F^{(i)}$ .

### 2.3. Identification and classification of inattention based on $OT_{min\_pc}^{(i)}$

Now,  $OT_{min\_pc}^{(i)}$ , which can be estimated for any given following car’s driver at the specific time point where the driver occludes oneself, can be interpreted and compared with the driver’s actual  $OT^{(i)}$  in the following way:

- If  $OT_{min\_pc}^{(i)} > OT^{(i)}$ , then the following car’s driver can be considered attentive (visually, i.e., there is still SVC available in that instance).
- Otherwise, if  $OT_{min\_pc}^{(i)} \leq OT^{(i)}$ , then the driver became inattentive or distracted (i.e., the driver used all the SVC available) and could have possibly collided, and, as a special case of being inattentive,
- if  $OT_{min\_pc}^{(i)} \leq 0$ , then the driver should not have occluded at all and could have possibly collided; that is, there was no SVC available to occlude oneself.

Note that  $OT_{min\_pc}^{(i)}$  reaches the breakeven point, that is, it becomes zero when

$$(DHW_L^{(i)} + BD_L^{(i)} - S_F^{(i)} \bullet BRT_F^{(i)} - BD_F^{(i)})/S_F^{(i)} = 0, \text{ i.e.,}$$

$$DHW_L^{(i)} = BD_F^{(i)} + S_F^{(i)} \bullet BRT_F^{(i)} - BD_L^{(i)}. \tag{4}$$

Therefore, as long as  $DHW_L^{(i)} > BD_F^{(i)} + S_F^{(i)} \bullet BRT_F^{(i)} - BD_L^{(i)}$ , some SVC is available.

For the special case in which both vehicles travel at the same speed ( $S_L^{(i)} = S_F^{(i)}$ ) and have the same deceleration rate ( $a_L^{(i)} = a_F^{(i)}$ ),  $BD_F^{(i)} = BD_L^{(i)}$ . In this case, the breakeven point from Eq. (4) is reached when

$$DHW_L^{(i)} = S_F^{(i)} \bullet BRT_F^{(i)}, \text{ i.e., when } THW_L^{(i)} = BRT_F^{(i)}. \tag{5}$$

In this condition, once the initial time headway between the lead car and the following car from rear to front ( $THW_L^{(i)}$ ), measured at the moment the following car’s driver occludes oneself, matches the BRT of the following car’s driver, SVC ceases to exist. Therefore, in the case of equal car speeds and deceleration rates, a driver – to be attentive – should only occlude oneself when maintaining a THW from the lead car that is considerably larger than their BRT. Furthermore, with equal car speeds and deceleration rates, a driver can be classified as driving unsafe if, at any time, the THW is less than the driver’s BRT. Appendix 1 presents a look-up table of the critical DHWs, for equal lead and following car speeds and deceleration rates, at or below which driving in the worst-case scenario of a lead car braking suddenly hard is unsafe, on the basis of the driver’s BRT.

Now,  $OT_{min\_pc}^{(i)} \leq 0$  also means that even if the driver is visually observing the lead car, a collision is still possible with the lead car in the worst-case scenario, in which the lead car suddenly brakes hard. Therefore, Eq. (4), also provides a critical threshold value of the DHW that, if maintained at or below, can lead to a possible collision in the worst-case scenario in the form of:

$$DHW_{pc} = BD_F + S_F \bullet BRT_F - BD_L. \tag{6}$$

Now, at a given time point t,

- if  $DHW_{pc}^{(t)} < DHW^{(t)}$ , then the driver is maintaining a sufficient DHW, and some SVC is available.
- Otherwise, if,  $DHW_{pc}^{(t)} \geq DHW^{(t)}$ , then the driver is maintaining an unsafe DHW, and no SVC is available.

### 2.4. Additional assumptions

There are three additional assumptions behind the model:

- Whenever a driver has eyes off the forward roadway in real traffic, it is possible the driver can still gather visual information through peripheral vision (e.g., of a looming lead car; Svärd et al., 2021). This possibility is omitted from the model, and the driver

is considered fully occluded from observing the lead car. This can also be viewed as the worst-case scenario, which is the target of the modeling.

- In all modern cars with brake assist systems (BAS), the brakes engage almost instantly as soon as the brake pedal is pressed swiftly. Thus, for the model, we omit the possibility of any brake engagement time, which Green (2000) defined as the additional time required for the pedal to depress and for the brakes to engage.
- It is assumed that the driver cannot swerve to avoid hitting the lead car. This is also a worst-case scenario and is possible if there are cars or other obstacles on the adjacent lanes or on the side of the road.

### 3. Analytical results

Here,  $OT_{min\_pc}^{(i)}$  values emerging from the model for different car following scenarios are defined and illustrated. To do so, the values of  $BD_L^{(i)}$ ,  $BRT_F^{(i)}$ , and  $BD_F^{(i)}$  need to be determined:

- $BD_L^{(i)}$ : To compute the braking distance of the lead car, the following formula from the American Association of State Highway and Transportation Officials (AASHTO) Green Book (Transportation Officials, 2011, pp. 111) is considered:

$$BD_L^{(i)} = 0.039 \frac{(S_L^{(i)})^2}{a_L^{(i)}}$$

where  $S_L$  (km/h) is the initial speed of the lead car with which it is moving until the brake response of the car is initiated, and  $a_L^{(i)}$  ( $m/s^2$ ) is the mean deceleration rate of the lead car during braking. Now, as per the previous conceptualization, the value of  $a_L^{(i)}$  is a constant across instances, and it approximates the maximum achievable mean deceleration rate for the driver during an emergency. For estimation purposes,  $6 m/s^2$  is the value of  $a_L^{(i)}$  that is assumed, as this is close to 0.61 g, the maximum observed (mean) deceleration rate among 64 drivers when braking for a surprising inflatable barricade in the track study by Fitch, Blanco, Morgan, and Wharton (2010). Peak deceleration rates of over 1 g have been observed in crash events in naturalistic driving data (SHRP2 data; Bärghman et al., 2023), but Markkula et al. (2016), for instance, showed that these peak deceleration rates are not constant even in these critical events; nevertheless, there is some jerk and a mean deceleration rate in such events could also be close to 0.6 g. Based on these studies, it is assumed that a driver adapts the braking response and thus the deceleration rate based on the observed kinematics and criticality of the situation but that the maximum mean deceleration rate for the duration of the braking event in a worst-case scenario is close to  $6 m/s^2$ .

- $BRT_F^{(i)}$ : For the analytical model, considering the possible variability in drivers' BRTs in a worst-case scenario is meaningful. Estimates for the plausible minimum and maximum BRTs can be taken from the AASHTO Green Book (Transportation Officials, 2011, p. 111). Based on these estimates, most drivers' BRTs in an unexpected event range from 1.0 to 4.0 s. Thus, the following car's driver is assumed to have the shortest BRT of 1.0 s and the largest BRT of 4.0 s. The variation in  $OT_{min\_pc}^{(i)}$  between these is then modeled.

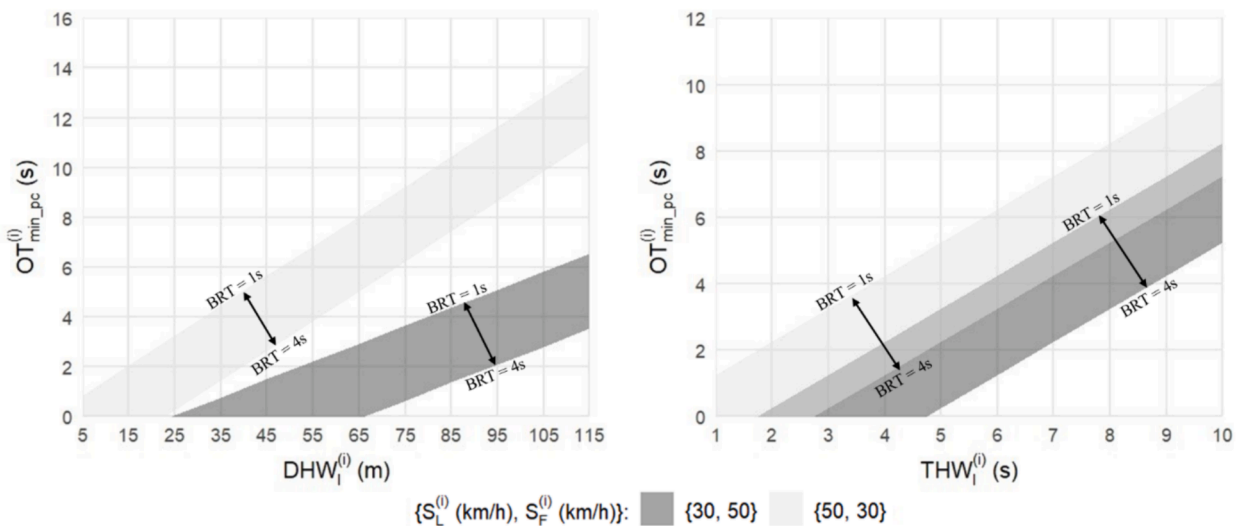


Fig. 1. Effects of the distance headway ( $DHW_i^{(i)}$ , m) and the time headway ( $THW_i^{(i)}$ , s) on  $OT_{min\_pc}^{(i)}$  at two pairs of fixed speed values, {30,50} and {50,30}, across various BRTs ranging from 1 to 4 s.

- $BD_F^{(i)}$ : Again, to compute the braking distance of the following car, the following formula from [Transportation Officials \(2001, pp. 111\)](#) is used:

$$BD_F^{(i)} = 0.039 \frac{(S_F^{(i)})^2}{a_F^{(i)}}$$

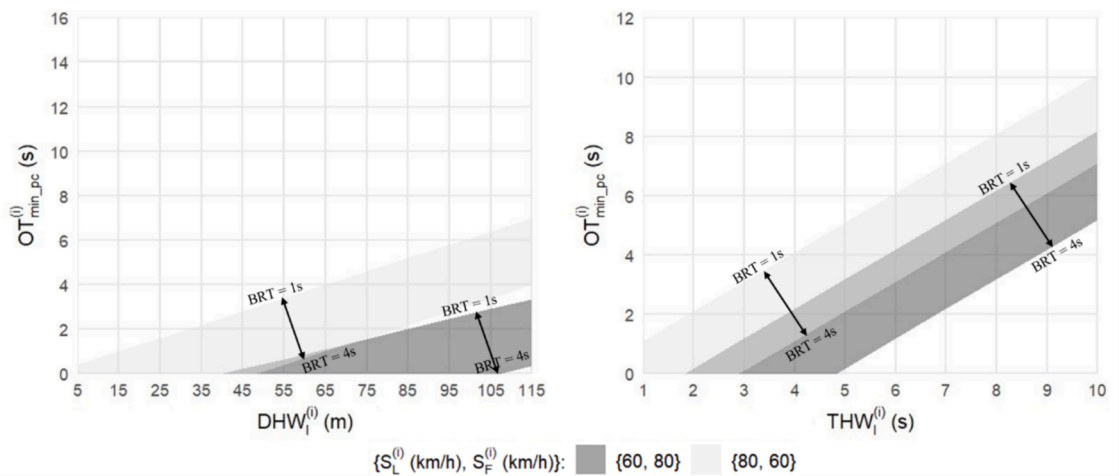
where  $S_F$  (km/h) is the initial speed of the following car with which it is moving until the last point after which the brake response of the car is initiated, and  $a_F^{(i)}$  ( $m/s^2$ ) is the deceleration rate produced by the following car. Now, as per the present conceptualization, the value of  $a_F^{(i)}$  is a constant across instances. It is the maximum possible (mean) deceleration rate that can be achieved by the following car’s driver. Here, it is assumed that the following car’s driver can decelerate at the same rate as that of the lead car’s driver in an emergency because of the same level of observed criticality ([Markkula et al., 2016](#)) and the assumed equal friction between the tires and the road surface between the two cars. Therefore,  $6 m/s^2$  is also used as an estimate for  $a_F^{(i)}$ .

Next, by using the above-described values in Eq. (3), some example values of  $OT_{min\_pc}^{(i)}$  are presented for different conditions and varying values of  $DHW_I^{(i)}$ ,  $S_L^{(i)}$ ,  $S_F^{(i)}$ , and  $BRT_F^{(i)}$ . The conditions are based on speed limits (50 km/h: ca. 31 mph and 80 km/h: ca. 50 mph) and typical DHW and speed variabilities on Finnish urban and main roads (<https://vayla.fi/vaylista/aineistot/digiroad>).

### 3.1. Effects of $DHW_I^{(i)}$ , speed variability, and brake response time on $OT_{min\_pc}^{(i)}$ at lower and higher speeds

[Fig. 1](#) (left) illustrates the  $OT_{min\_pc}^{(i)}$  for different values of  $DHW_I^{(i)}$  (in meters) considering two pairs of fixed values of  $\{S_L^{(i)}, S_F^{(i)}\}$  (in km/h), which are {30,50} and {50,30}. Fifty kilometers per hour is a common speed limit on Finnish urban and suburban roads outside city centers.  $OT_{min\_pc}^{(i)}$  represents the safety-critical threshold of SVC in a specific situation. At zero  $OT_{min\_pc}^{(i)}$ , no SVC is available. For comparison, [Fig. 1](#) (right) illustrates the  $OT_{min\_pc}^{(i)}$  for different values of THW,  $THW_I^{(i)}$  (in seconds), considering the same pairs of fixed values of speed. Note that  $THW_I^{(i)}$  is defined here from the rear of the lead car to the front of the following car (to still avoid a crash, i.e., time gap), compared to, for instance, the front of the lead car to the front of the following car, which is the THW definition provided by the Society of Automotive Engineers ([Green, 2013](#)).

Accordingly, [Fig. 2](#) illustrates the  $OT_{min\_pc}^{(i)}$  for different values of  $DHW_I^{(i)}$  (in meters, left) and  $THW_I^{(i)}$  (in seconds, right), considering two pairs of fixed values of  $\{S_L^{(i)}, S_F^{(i)}\}$  (in km/h), which are {60,80} and {80,60}. Eighty kilometers per hour is a typical speed limit on Finnish main roads. [Fig. 3](#) illustrates the effect of the time headway ( $THW_I^{(i)}$ , s) on the  $OT_{min\_pc}^{(i)}$  for conditions, where the two cars have the same speed and equal possible deceleration rate (Eq. (5)).



**Fig. 2.** Effects of the distance headway ( $DHW_I^{(i)}$ , m) and the time headway ( $THW_I^{(i)}$ , s) on  $OT_{min\_pc}^{(i)}$  at two pairs of fixed speed values, {60,80} and {80,60}, across various BRTs ranging from 1 to 4 s.

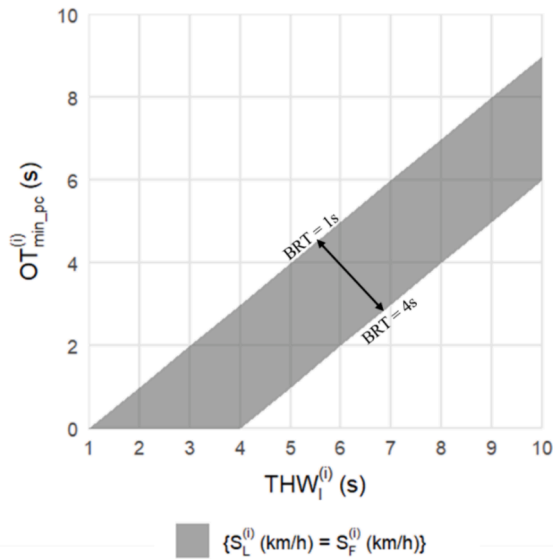


Fig. 3. Effects of the time headway ( $THW_i^{(i)}$ , s) on  $OT_{min\_pc}^{(i)}$  in equal speed and deceleration rate conditions, across various BRTs ranging from 1 to 4 s.

#### 4. Empirical results

##### 4.1. Materials and methods

A driving simulator experiment was conducted to evaluate how human drivers perform vis-a-vis the critical  $OT_{min\_pc}^{(i)}$  values computed based on Eq. (3) in dynamic car following scenarios. The experiment was carried out at the driving simulator laboratory of the University of Jyväskylä using a medium-fidelity driving simulator comprising a Logitech G25 steering wheel and pedals (including automatic shifting), an adjustable driver’s seat, a motion platform (CKAS T2s 2DOF), and three 40” Samsung LED displays (4,320 ×



Fig. 4. The simulated driving environment.



900) presenting the driving environment generated by Eepsoft driving simulation software (<https://www.eepsoft.fi/>, Fig. 4). The driving log data were saved at 10 Hz.

Thirty-two participants (M: 23, F: 9; university staff and students) with driving licenses were recruited for the experiment, and they were compensated with a 20 EUR gift certificate. Before participation, they filled out informed consent forms. Table 1 provides the relevant demographic information of the participants.

A three-lane highway road was designed for the study. The participant's car was placed in the middle lane with a car moving in front of the participant, as well as multiple cars moving in the adjacent lanes but in the same direction; lane change was prohibited.

The experiment was divided into two parts (Fig. 5). In the first trial of the first part (BRT1), the lead car, which drove at a static speed of 80 km/h, was programmed in such a way that it would suddenly brake hard (at  $6 \text{ m/s}^2$ ) after 2 min of driving, creating an emergency for the participants to react to and thus allowing us to estimate their BRTs for an unexpected event. The instructions for the participants were to stay in their lane and to try to maintain a minimum DHW to the lead car that they perceived as still safe. For the course of the trial, cruise control was set up and active in the participant's car at 80 km/h, but they were allowed to use the brake and the gas pedals as per their convenience in order to keep their car at their preferred safe minimum DHWs. The BRT trial was repeated three times to assess whether the participants would adjust their DHWs and BRTs after the first trial in which the braking event was unexpected. In the latter two trials, the lead car braked suddenly after 1.5 (BRT2) and 1 min (BRT3) of driving.

In the second part of the experiment, a voluntary occlusion feature – following the study by Safford (1971) – was introduced in which the participants could occlude themselves (i.e., the screens in front of them turned black) at their own will using a lever placed behind the steering wheel. This part of the study consisted of two 5 min counterbalanced driving sessions using the dynamic conditions described in Table 2. The lead car was programmed to vary its speed from 40 to 60 km/h or from 70 to 90 km/h, depending on the trial (low speed or high speed). This meant that its distance from the participant's car varied, but it was ensured that if the participant kept driving at the cruise control speed, the cars would not crash. However, the participants did not know this

The participants were instructed to stay in their lane and encouraged to maximize the time driven occluded while avoiding collision with the lead car, an approach that is line with the study design of Safford (1971). They were advised that they could brake if they felt that the DHW was too short but that the car would speed up automatically to the speed set for cruise control after braking. The participants were instructed to try to avoid adjusting their headways unless necessary because we were interested in knowing whether they chose to occlude themselves even when the headway was not safe. However, the variance of the DHWs shows that they adjusted them (Table 4). On average, in 59.5 % (SD = 31.3 %) and 17.1 % (SD = 27.5 %) of the trial duration in the low- and high-speed conditions, respectively, there was SVC available for the driver, corresponding to about 3 min and 51 s, respectively. Therefore, there were many occasions in both conditions in which the participants could have occluded themselves without being labeled as inattentive.

## 4.2. Results

Tables 3–5 present the relevant descriptive statistics on the participants' BRTs in the BRT trials, the DHWs throughout the experiment, and the voluntary occlusion counts and durations in the occlusion trials.

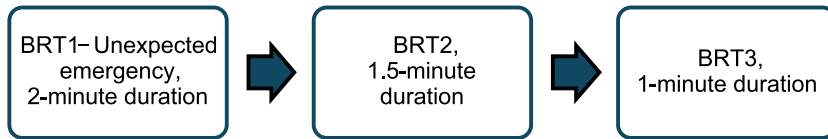
In the BRT trials, time-to-collision (TTC; Vogel, 2003) at the onset of the lead car braking in events where  $S_L^{(i)} \leq S_F^{(i)}$  (30 % of events) varied from 21.81 s to 627.78 s ( $M = 104.86 \text{ s}$ ,  $SD = 88.35 \text{ s}$ ). Naturally, TTCs rapidly decreased after the onset of braking. Nineteen of the 32 participants (59.4 %) collided with the lead car in the BRT1 trial (unexpected braking of the lead car), suggesting that the braking event was truly unexpected for them and that the minimum DHWs they thought were still safe were insufficient to avoid the crash (Table 6). In BRT1, the mean of the mean deceleration rates during emergency braking was  $6.21 \text{ m/s}^2$  ( $SD = 0.95$ ), while the maximum peak deceleration rate reached  $9.51 \text{ m/s}^2$  (as measured pre-crash). In BRT2 four (12.5 %) and BRT3 two (6.3 %) participants collided with the lead car.

Mixed-effects model for BRT across the three BRT trials indicates that the participants adapted their BRTs based on the DHWs at the onset of the sudden hard-braking event by the lead car (Table 7). The intraclass correlation coefficient (ICC) for the intercept-only model was 0.534, and therefore a multilevel model with a participant as a random effect seemed appropriate for the analyses. Strong BRT–headway correlations were observed in all three trials (BRT1:  $r = 0.87$ , BRT2:  $r = 0.92$ , BRT3:  $r = 0.75$ , Fig. 6), and the model indicates that, on average, the BRT increased by 0.03 s per 1 m of increase in DHW. However, there was an additive independent effect of the BRT trial number; the BRT decreased, on average, by 0.36 s from BRT1 to BRT3, suggesting that the surprise effect was gone in the third trial. After the fixed effects of DHW and BRT trial number were added, no significant variance in the participants' intercepts was observed ( $\sigma^2 < 0.001$ ). The random slope effect of DHW within participants was not significant either ( $\sigma^2 < 0.001$ ,  $p = 0.271$ ). This means that the effect of DHW on the BRT does not seem to vary significantly between the participants (see Appendix 2). However, the random slope effect of the trial within participants was significant ( $\sigma^2 < 0.145$ ,  $p < 0.001$ ). The ICC for this effect was

**Table 1**  
Demographics of the participants.

$N = 32$	Range	Mean	Median	Standard deviation
Age	21–57	32.1	31	8.9
Driving experience (in years)	2–44	12.8	10	9.4
Self-estimated driving experience per year (in km)	100–47,000	9,953.1	9,000	9,943.3
Self-estimated lifetime driving experience (in km)	5,000–650,000	123,613.5	100,000	153,346

**Part I: BRT trials**



**Part II: Voluntary occlusion trials**

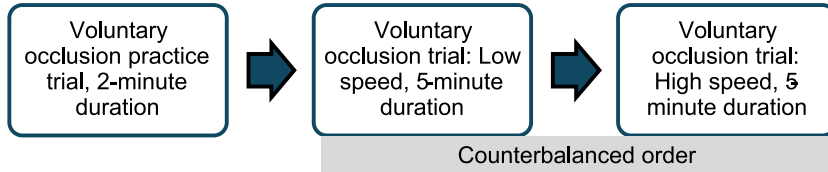


Fig. 5. Experimental design with the conditions in the two parts of the study.

**Table 2**

Speed conditions (km/h) for the voluntary occlusion trials.

Trial	Lead car speed range	Car cruise control speed set
Voluntary occlusion trial: Low speed	40–60	50
Voluntary occlusion trial: High speed	70–90	80

**Table 3**

Descriptive statistics of the brake response times per trial (s), *N* = 32.

Trial	Range	Mean	Median	Standard deviation
BRT1 – Unexpected emergency	0.82–3.40	1.90	1.70	0.82
BRT2	0.92–4.62	2.26	1.86	1.07
BRT3	0.61–4.61	1.98	1.60	1.03

**Table 4**

Descriptive statistics of the distance headways to the lead car (m), *N* = 32.

Trial	Range of minimum	Range of maximum	Mean	Standard deviation
BRT1 – Unexpected emergency*	4.3–37.0	16.7–96.6	31.0	15.6
BRT2*	3.9–71.5	24.5–148.1	44.1	27.9
BRT3*	10.8–103.9	18.9–140.0	41.7	26.8
Voluntary occlusion trial: Low speed**	4.5–29.2	24.4–160.2	31.7	11.6
Voluntary occlusion trial: High speed**	3.8–78.4	47.6–225.8	38.4	14.4

\* DHWs measured from reaching 80 km/h for the first time until the onset of the braking event.

\*\* DHWs measured at the start of each occlusion period.

**Table 5**

Descriptive statistics of the number of occlusions and occlusion durations (s), *N* = 32.

Trial	Range of occlusions	Mean		Standard deviation	
		Count	Duration	Count	Duration
Voluntary occlusion trial: Low speed	8–213	76	1.70	54.7	0.93
Voluntary occlusion trial: High speed	10–213	74	1.57	53.0	0.81

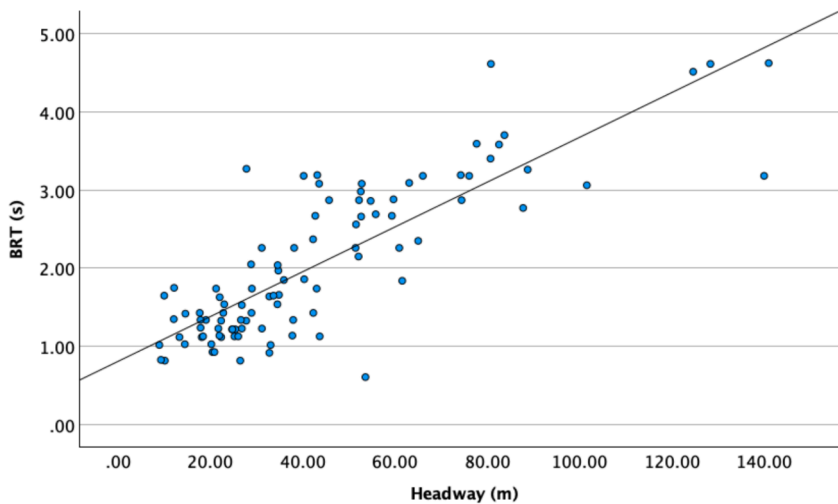
**Table 6**  
Mean brake response times (s) and distance headways (m) at the onset of braking event in crash events per BRT trial,  $N = 32$ .

Trial	BRT, s (range)	DHW, m (range)
BRT1 – Unexpected emergency (19 crashes)	2.03 (0.82–3.40)	30.76 (8.94–80.72)
BRT2 (4 crashes)	1.93 (1.34–3.19)	25.29 (17.70–43.17)
BRT3 (2 crashes)	2.15 (2.04–2.26)	32.87 (31.14–34.59)

**Table 7**  
Mixed-effects model for the brake response times (s),  $N = 32$ .

Fixed effects	Estimate	Standard error	$p$	95 % CI lower bound	95 % CI upper bound
Intercept	0.907	0.116	<0.001	0.678	1.137
Distance headway (per m)	0.031	0.002	<0.001	0.026	0.036
BRT1 – Unexpected emergency*	0				
BRT2	-0.217	0.133	0.107	-0.482	0.048
BRT3	-0.355	0.131	0.008	-0.615	-0.095
<b>Random effects</b>	$\sigma^2$	<b>Standard error</b>	<b><math>p</math></b>		
Trial (participant)	0.145	0.043	<0.001		
<b>Residual</b>	0.145				

\* The factors below are compared with the factor that obtains a value of zero.



**Fig. 6.** Strong linear association between distance headway (DHW) and brake response time (BRT) across the three trials (BRT1–BRT3),  $R^2 = 0.69$ . The association is strong even if the four datapoints with  $DHW > 120$  m were removed ( $R^2 = 0.64$ ).

0.50, suggesting that half of the residual variance can be attributed to the differences in the participants’ BRT behaviors based on the BRT trial. This variance was especially visible in the BRT3 trial. The final model fit (–2RLL) was 168.574, and the conditional pseudo- $R^2$  was 0.851 (IBM SPSS v29).

These findings stress the importance of considering the effect of the DHW on the driver’s BRT in our model. Fig. 7 illustrates the distribution of unsafe DHWs in the BRT trials as a percentage of the trial duration (10 Hz sampling rate). These are based on the sufficiency of the DHW if the lead car brakes hard (Eq. (6)), while the driver’s BRT is adjusted for the DHW at each time point based on Eq. (7) (where  $t_2$  is each time point of measurement, which is every 100 ms here). The DHW was labeled unsafe if it was below or at the critical DHW (Eq. (6)). Repeated measures ANOVA shows a significant effect of trial number on the percentage of driving with unsafe DHWs,  $F(2,62) = 6.384, p = 0.003, \eta_p^2 = 0.171$ . There was a significant decrease in unsafe DHWs from BRT1 to BRT2 ( $t(31) = 2.748, p = 0.010, d = 0.49$ ) and from BRT1 to BRT3 ( $t(31) = 2.818, p = 0.008, d = 0.50$ ) but not between BRT2 and BRT3 ( $p = 0.503$ ).

Because of the strong association between BRT and DHW, it also seems important to adjust the drivers’ situational BRTs based on the decreasing DHW in the worst-case event of a lead car braking hard at the onset of an occlusion. Therefore, the following computational algorithm is proposed to calculate the  $OT_{min\_pc}^{(i)}$  for the analyses of the empirical occlusion data and for similar measurements in general (also regarding in-car glancing). If a following car’s driver would occlude oneself for the  $i^{th}$  instance at any time

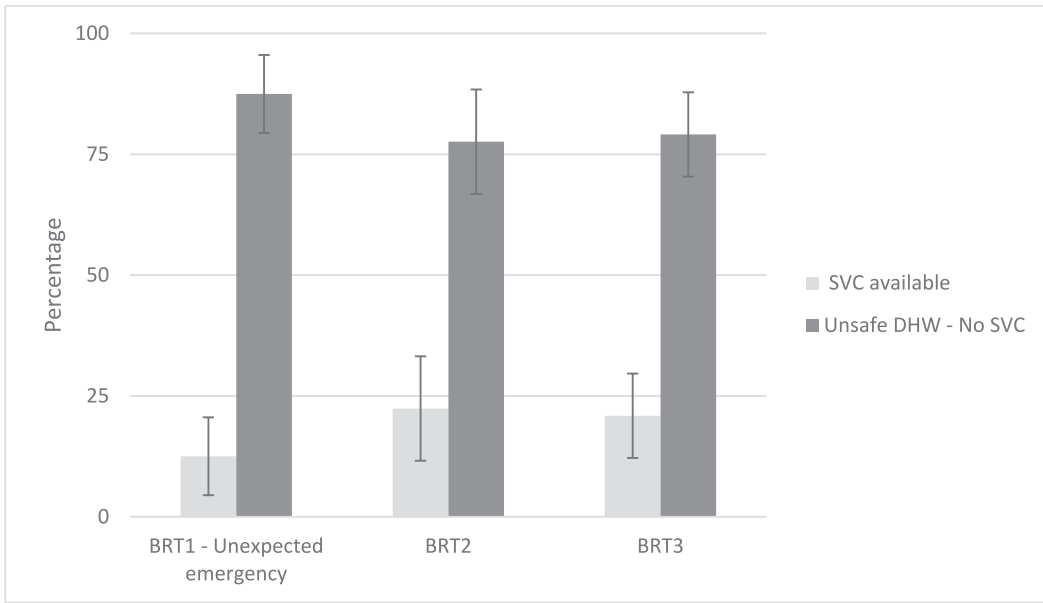


Fig. 7. Mean percentage of the BRT trial duration when the DHW was above (gray: SVC available) or at/below (dark gray: Unsafe DHW) the situational critical DHW (Eq. (6)). Errors bars: 95 % confidence interval for the means.

point  $t_1$  and if  $t_2$  is any future time point after that ( $t_2 > t_1$ ), then the DHW-corrected BRT should the driver decide to unocclude at  $t_2$  can be estimated as:

$$BRT_F^{(i)(t_2)} = BRT_F^{UE} + \{0.03 \bullet (DHW^{(i)(t_2)} - DHW^{UE})\}, \tag{7}$$

where  $BRT_F^{UE}$  is the BRT of the following driver in an unexpected emergency,  $DHW^{(UE)}$  is the DHW between the lead car and the following car for which  $BRT_F^{UE}$  is measured, and  $DHW^{(i)(t_2)}$  is the DHW between the lead car and the following car at  $t_2$ . The constant 0.03 is based on the linear model in Table 7. To estimate  $DHW^{(i)(t_2)}$ , the relative longitudinal position of the lead car that starts to brake at the onset of occlusion  $i$ ,  $y_L^{(i)(t_2)}$  at any time point  $t_2$ , can be derived as:

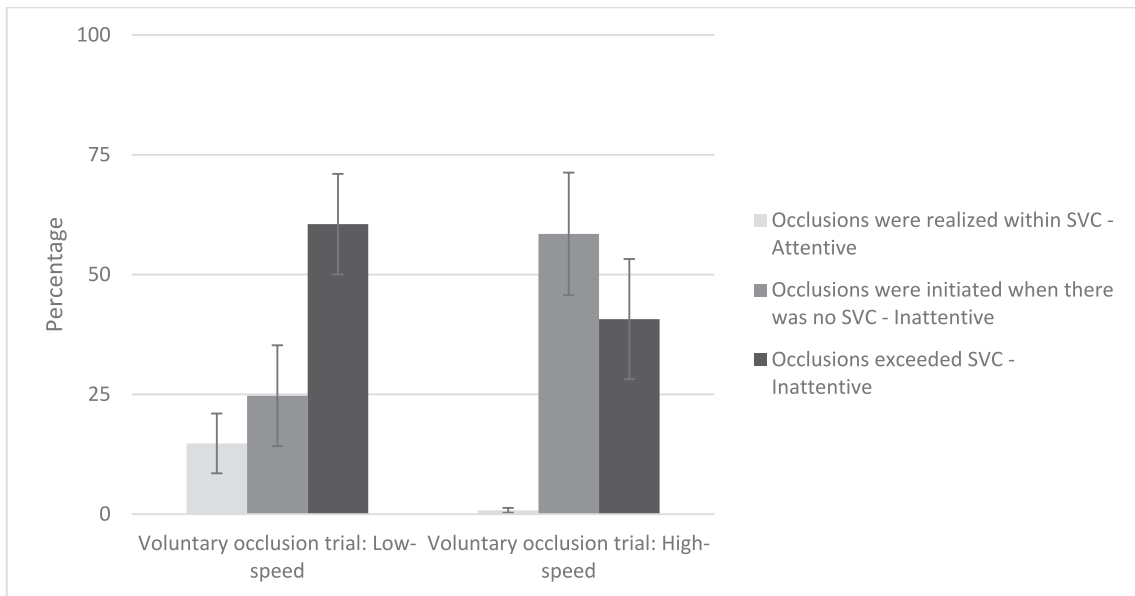


Fig. 8. Mean percentages of occlusions for which the driver was classified as attentive or inattentive based on SVC. Errors bars: 95 % confidence interval for the means.

$$y_L^{(i)(t_2)} = y_L^{(i)(t_1)} + \{ (S_L^{(i)(t_1)}) \bullet (t_2 - t_1)^{(i)} + (\frac{1}{2}) \bullet a \bullet (t_2 - t_1)^{(i)} \bullet (t_2 - t_1)^{(i)} \}, \quad (8)$$

with  $a = -6 \text{ m/s}^2$  as in Section 3. The relative longitudinal position of the following car at  $t_2$  is accordingly:

$$y_F^{(i)(t_2)} = y_F^{(i)(t_1)} + (S_F^{(i)(t_1)}) \bullet (t_2 - t_1)^{(i)}. \quad (9)$$

$DHW^{(i)(t_2)}$  for Eq. (7) can then be calculated as  $y_L^{(i)(t_2)} - y_F^{(i)(t_2)}$ . Now, the value of  $OT_{min\_pc}^{(i)}$  should the driver decide to unocclude at any time point  $t_2$  can be estimated as:

$$OT_{min\_pc}^{(i)(t_2-t_1)} = (DHW_1^{(i)} + BD_L^{(i)} - S_F^{(i)} \bullet BRT_F^{(i)(t_2)} - BD_F^{(i)}) / S_F^{(i)}. \quad (10)$$

As long as  $OT_{min\_pc}^{(i)(t_2-t_1)}$  is greater than  $(t_2 - t_1)$ , there is SVC, and at the moment  $OT_{min\_pc}^{(i)(t_2-t_1)}$  becomes less than or equal to  $(t_2 - t_1)$ , SVC ceases to exist. Furthermore, if  $OT_{min\_pc}^{(i)(t_2-t_1)} \leq 0$ , then SVC does not exist.

Based on Eqs. (7)–(10), the  $OT_{min\_pc}^{(i)(t_2-t_1)}$  for each occlusion in the empirical data was estimated. The participants' occlusion behaviors were then compared against these values in accordance with the classification rules presented in Section 2.3 in order to identify the driver as attentive and inattentive. Fig. 8 presents the distribution of the observed driver attentiveness and inattentiveness per occlusion and by trial.

A paired samples  $t$ -test was conducted to examine whether there were statistically significant differences between the trials (i.e., low vs. high speed) across the three attention–inattention classification segments. The percentage of attentive occlusions decreased significantly with an increase in speed,  $d = 0.81$ ; the percentage of such occlusions that were initiated when there was no SVC increased with an increase in speed,  $d = 1.28$ ; and the percentage of occlusions that exceeded SVC increased with higher speeds,  $d = 0.62$  (Table 8).

## 5. Discussion

To the best of our knowledge, this study introduces the first mathematical, analytically derived, and driver- and situationally dependent measurement of SVC and definition of inattention in a driving task. The proposed definition of inattention based on SVC avoids the hindsight bias common to those definitions that rely on categorizing a driver as attentive or inattentive a posteriori based on what happened in a situation (Kircher & Ahlstrom, 2017; Regan et al., 2011). For driver (in)attention monitoring and alerting applications, we need to know a priori, before a crash or a lane excursion, whether the driver is attentive. The current definition is also fully in line with the conceptual definition by Regan et al. (2011, p. 1775) that inattention is “insufficient, or no attention, to activities critical for safe driving”.

The analytical results clearly indicate the insufficiency of static thresholds (e.g., 2 s) for SVC in dynamic car following scenarios. There is often SVC in car following, but this is highly dependent on the DHW, the following car's speed, the lead car's speed, and the BRT to avoid the possibility of a rear-end crash in an emergency braking scenario (i.e., what-if scenario). As the braking distances follow a quadratic growth function per initial driving speed, the higher the speed, the lower the SVC at similar DHWs or relative speeds. Even in a car following situation involving a static speed and equal deceleration rates, a 2 s THW does not allow for SVC unless the driver has a response time faster than 2 s (Eq. (5)). Response times to unexpected events can be easily lengthened by secondary tasks (Gao & Davis, 2017). Therefore, one should acquire this capacity by decelerating and/or increasing the DHW if looking away from the lead car.

The empirical findings suggest that drivers are willing to occlude themselves even if doing so is not safe based on the model and on their individual and situational BRTs. The study was conducted in a driving simulator, which may limit the generalizability of the results. However, before the occlusion measurements, all the participants had had an experience in the BRT trials that it is possible that the lead car brakes unexpectedly with force and in the first BRT trial (BRT1) more than a half (59.4 %) of them had crashed with it. The increase in DHWs and the associated increase in response times (Tables 3 and 4) in the two subsequent BRT trials indicate that the participants were better prepared for the possible braking event and thus more attentive, based on our new metric (Fig. 7). These findings and the decreased BRT by trial number when controlling for the DHW (Table 7) suggest that the braking event was truly unexpected in BRT1. Therefore, using the individual BRTs in BRT1 as the estimates for a response time in an unexpected hard braking event by the lead car was justifiable in the analyses of the following occlusion trials. In the case of occlusion (or after glancing away from the forward roadway), the sudden hard braking of the lead car can always be considered an unexpected event as the driver would probably not look away if expecting a lead car to brake.

It seems that drivers' ability to estimate whether occluding in a car following scenario is safe decreases with higher speeds. These results are in line with those of Risto and Martens (2011) that drivers' ability to correctly estimate the DHW decreases significantly with an increase in speed. Furthermore, it is known that the probability that drivers overestimate the TTC under occluded vision increases with an increase in the relative speed between the lead car and the following car (Kiefer et al., 2006). It is unlikely that the human brain could estimate the duration of time it is safe to look elsewhere other than at the lead car on the basis of something similar to the presented equations. Even if a driver is aware of their own speed, human perception is highly limited in speed and DHW or THW estimations (Taieb-Maimon & Shinar, 2001; Taieb-Maimon, 2007). These findings highlight the potential utility and effects of inattention warnings based on the presented model of SVC and inattention classification. However, the generalizability of the findings, equations, and assumptions should also be validated with real vehicles, either on a test track or in a natural driving environment.

**Table 8**Paired samples *t*-test for the differences in attentiveness/inattentiveness between the occlusion trials ( $\alpha = 0.05$ ),  $N = 32$ .

Voluntary occlusion trial: Low speed – High speed	Paired differences						
	Mean difference	SEM	95 % CI of the difference		<i>t</i>	df	<i>p</i> -value (2-tailed)
			Lower	Upper			
Occlusions were realized within SVC – Attentive	13.96	3.05	7.74	20.18	4.576	31	<0.001
Occlusions were initiated when there was no SVC –Inattentive	–33.77	4.66	–43.28	–24.27	–7.248	31	<0.001
Occlusions exceeded SVC – Inattentive	19.81	5.65	8.29	31.34	3.506	31	<0.001

Naturally, we cannot tell whether the driver is truly attentive to the lead car whenever they are looking elsewhere or even when they are looking at it (Ahlström, Kircher, et al., 2021). The model assumes that they are paying (internal) attention to the car following task for the occlusions that are within their situational SVC; therefore, these instances were labeled as *attentive*. At least, these occlusions can be regarded as safe from the perspective of the car following task, even if the driver's thoughts were elsewhere. Furthermore, the driver can be labeled *attentive* whenever they keep a safe headway to the lead car.

The modeling was started with a car following task as a highly safety-critical driving scenario, especially in terms of visual distraction (Bálint et al., 2020; Victor et al., 2015). A similar approach could also be applied to the measurement of SVC and the definition of inattention in other part-tasks of driving, such as lane keeping and visual sampling in crossings. For real-world (in) attention monitoring applications, a variety of combined SVC models per part-task that are applicable to all possible driving scenarios are needed. Furthermore, even in car following scenarios, additional contextual variables could be accommodated in the model, such as distances to cars on adjacent lanes, which have the possibility of making sudden lane changes in front of the driver. It should also be noted that the equations do not apply in situations in which the initial speed of the lead car is zero (i.e., a standstill) but the model could be modified to account for such situations too.

A few assumptions behind the model need to be discussed further. The equations are based on the notion of full occlusion, while the driver often has peripheral vision available while looking off forward (Wolfe et al., 2022). However, evidence suggests that drivers are not sensitive to peripheral information (e.g., lateral position of the car and brake lights) when conducting cognitively high-demanding in-car tasks (Grahn et al., 2023; Williams, 1982; Zhang et al., 2006). Again, the model applies to the worst-case scenario in which there is no peripheral information available or the driver is not able to utilize this. The model could also accommodate situations in which there are variable levels of occlusion, depending on, for instance, the in-car activity. In situations with good visibility ahead, with no traffic lights, or with no other drivers ahead of the lead car, a driver can anticipate and rely on the lead car not to brake hard or there could be noticeable room to swerve in the case of hard braking. Again, the equations apply to the worst-case scenario and define the absolute minimum SVC in a car following situation. However, expecting what is possible and not the unexpected in any driving situation, with the latter being impossible, is rational. Therefore, acceptable implementations of driver-alerting algorithms based on the equations might benefit from additional contextual information.

The model also assumes that the following car maintains a uniform speed during occlusion. Drivers might decrease their speeds when looking off forward, especially during in-car tasks (Jamson & Merat, 2005). Similar to adjusting the BRT based on the situational DHW, this behavior could be accommodated in the calculations. The same braking distance for both the lead car and the following car was also assumed. However, cars can differ in these aspects depending on their mechanical features, such as tires or BAS implementations, and drivers' ability to utilize BAS can also vary (Fitch, Blanco, Morgan, Rice, et al., 2010). Car- and driver-specific modifications of the constants would be useful in this regard. Obviously, the thresholds apply only to manual driving. Attempting to define the situational SVC for assisted driving would be interesting but would likely be more challenging than for manual driving part-tasks, as the reliability of the assistance system, given possible system failure in different scenarios, should also be determined (Bärgman & Victor, 2020).

The abilities of drivers could be estimated to define the optimal and perhaps most acceptable threshold for them. In the analysis of the experimental data, the BRT parameters were fitted for a specific driver. Because of the found strong linear association between BRT and DHW, adjusting the BRT estimate on the DHW is also important. This could likewise be done on the possible visual looming cues available for a driver in a situation (Markkula et al., 2016; Svård et al., 2021). The mixed-effects model for BRT (Table 7) supports the notion that drivers can adapt their BRTs based on the observed urgency of the situation (Markkula et al., 2016). With the same level of observed urgency, and if assisted by the car's BAS, the following car's driver can be assumed to produce similar response times and deceleration rates as those of the lead car's driver, although glancing elsewhere and missing the start of the braking event might lead to a delayed response similar to an unexpected event. There was not much variation between the individual BRTs when DHW is accounted for (see Appendix 2). This might suggest that any driver's BRT could be estimated based on the model in Table 7. Distance is something that can be more easily perceived by a driver than time gap (Taieb-Maimon & Shinar, 2001), which might explain the strong linear relationship between DHW and BRT. However, the model's reliability should be examined with a larger and more representative driver sample and in more realistic driving. For instance, the model assumes any driver can brake at  $-6 \text{ m/s}^2$  rate if needed but this ability may vary between drivers, even with BAS (Fitch, Blanco, Morgan, Rice, et al., 2010).

The parameter selections for the model are targeted at describing the situational thresholds for the absolute minimum SVC in car following. Appendix 1 shows the variability in critical DHWs that are unsafe in static-speed driving if the lead car's driver brakes hard suddenly, based on various response times. In the current experiment, the mean BRT for an unexpected event in BRT1 was 1.90 s (range: 0.82–3.40 s). Brake response times that are over 3 s can be considered relatively long, but all four participants with BRTs above

3 s also had relatively long DHWs at the onset of the braking event, ranging from 40.22 to 80.72 m. Observing a braking event at these distances in a simulator might be more challenging than in real traffic, aside from adapting the BRT to the criticality involved. However, in our simulator the expansion rates (range 0.0034–0.01) for the farthest DHWs at the onset of braking event with the observed speeds were above the 0.003 detection threshold reported for laboratory settings (Hoffman & Mortimer, 1996). On the other hand, our BRT estimates did not include glance transition times (Svärd et al., 2021). The analysis by Markkula et al. (2016) suggests that there is a looming threshold around 5 s TTC below which drivers seem to respond to lead car braking after an off-road glance very rapidly, in less than a second. From this point of view, the BRT of 0.907 s in our model (Table 7) for a hypothetical 0 m DHW might be too large but the relationships between DHWs, TTCs and BRTs in critical and non-critical braking events should be further clarified.

Interestingly, the common safety guideline of keeping a 2 s THW to a lead car in a static-speed car following scenario (e.g., <https://dmv.ny.gov/about-dmv/chapter-8-defensive-driving>) does not necessarily guarantee any SVC according to the worst-case scenario estimates (Figs. 1 and 2). It can be a safe THW for a situation in which the driver is fully attentive or can react within 2 s to a lead car braking, but the model suggests that in the worst-case scenario, a risk can be associated even with a brief glance off the forward roadway. It should be noted that it might be a very low risk based on statistics, and a responsive driver with peripheral vision available might easily have more SVC. However, the findings suggest that this common safety guideline might need a revision for *distracted driving*, that is, for situations in which the driver is multitasking behind the wheel. In some countries (e.g., Australia and Sweden), the guideline is 3 s, but this static threshold might also be insufficient based on the situational kinematics and the driver’s abilities (see Figs. 1 and 2). Adopting an attention monitoring system based on the current model might be useful to help train drivers early on to learn to adapt their headways in a safe manner to the situational parameters in either driving schools or during their first year of driving.

In future research, drivers’ speed adjustment, headway decisions, and in-car glances while multitasking in real traffic should be compared against the normative situational thresholds given by the model based on, for instance, the SHRP2 baseline data (<https://insight.shrp2nds.us/>). The equations can also be applied to classify a driver as attentive or inattentive to the DHW in car following scenarios even if the driver’s eyes are on the lead car (cf. Fig. 7). This approach would provide an estimate of how capable drivers are in ensuring safety – that is, whether they are playing with odds or with possibilities – and, thereby, how effective inattention warnings based on such thresholds could be in real traffic. The effects of various demographic variables, such as age, on the current metrics could be studied using larger and more representative samples. It would be interesting to study real-world crashes, such as in the SHRP2 data, by applying a hypothetical attention monitoring system based on the model to determine whether alerts on the thresholds would have helped avoid the crashes. Furthermore, the equations could be utilized as valid baselines for measuring the inattention potential of in-car tasks in simulated car following scenarios to test and benchmark, for instance, in-car user interfaces. As another example, it would be interesting to identify how much inattention the manual radio tuning task – the *norm* of acceptable distraction (e.g., Lee et al., 2018) – actually causes based on the inattention classification.

**CRedit authorship contribution statement**

**Tuomo Kujala:** Writing – review & editing, Writing – original draft, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization. **Abhishek Sarkar:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis.

**Data availability**

Data will be made available on request.

**Acknowledgment**

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**Appendix 1**

Table A1 shows the distribution of critical distance headways (DHWs; in meters) at and below which it is unsafe to drive if the lead car’s driver brakes hard suddenly and the lead car and the following car have the same initial speed and equal possible deceleration rate. In the table, the brake response time (s) equals the time headway from the rear of the lead car to the front of the following car.

**Table A1**

Critical distance headway (m) up to which it is unsafe to drive if the lead car’s driver brakes hard suddenly.

Speed (km/h)*	Brake Response Time (s) (=Time Headway)							
	0.5	1	1.5	2	2.5	3	3.5	4
30	4.17	8.33	12.50	16.67	20.83	25.00	29.17	33.33

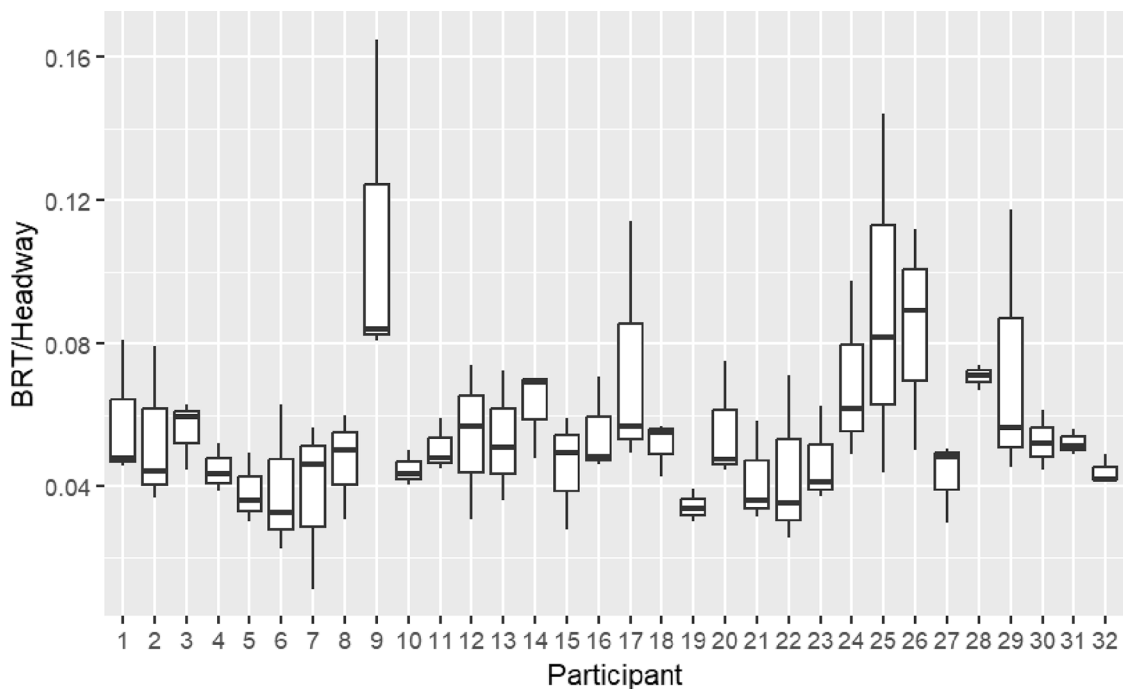
(continued on next page)

Table A1 (continued)

Speed (km/h)*	Brake Response Time (s) (=Time Headway)							
	0.5	1	1.5	2	2.5	3	3.5	4
40	5.56	11.11	16.67	22.22	27.78	33.33	38.89	44.44
50	6.94	13.89	20.83	27.78	34.72	41.67	48.61	55.56
60	8.33	16.67	25.00	33.33	41.67	50.00	58.33	66.67
70	9.72	19.44	29.17	38.89	48.61	58.33	68.06	77.78
80	11.11	22.22	33.33	44.44	55.56	66.67	77.78	88.89
90	12.50	25.00	37.50	50.00	62.50	75.00	87.50	100.00
100	13.89	27.78	41.67	55.56	69.44	83.33	97.22	111.11
110	15.28	30.56	45.83	61.11	76.39	91.67	106.94	122.22
120	16.67	33.33	50.00	66.67	83.33	100.00	116.67	133.33

\* Equal speeds and equal possible deceleration rates assumed for the lead car and the following car.

Appendix 2



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