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# Human Factors

**THE ATTENTIONAL DEMAND OF AUTOMOBILE DRIVING  
REVISITED –  
Occlusion distance as a function of task-relevant event  
density in realistic driving scenarios**

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## VISUAL DEMAND OF DRIVING REVISITED

1

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9

10 THE ATTENTIONAL DEMAND OF AUTOMOBILE DRIVING REVISITED –

11 Occlusion distance as a function of task-relevant event density in realistic driving scenarios

12

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18

19 Précis: Visual occlusion technique is an established method for assessing visual demands of

20 driving. In this paper, we present support for our hypothesis of the utility of occlusion

21 distance as a function of task-relevant event density in realistic traffic scenarios with driver-

22 controlled speed and occlusion times.

23

24 Keywords: driver, task demands, visual occlusion, event rate, event density, distraction,

25 inattention, driving experience, expectancy

26

1 **Abstract**

2 **(a) Objective** We studied the utility of occlusion distance as a function of task-relevant event  
3 density in realistic traffic scenarios with self-controlled speed. **(b) Background** The visual  
4 occlusion technique is an established method for assessing visual demands of driving.  
5 However, occlusion time is not a highly informative measure of environmental task-relevant  
6 event density in self-paced driving scenarios because it partials out the effects of changes in  
7 driving speed. **(c) Method** Self-determined occlusion times and distances of 97 drivers with  
8 varying backgrounds were analyzed in driving scenarios simulating real Finnish suburban  
9 and highway traffic environments with self-determined vehicle speed. **(d) Results** Occlusion  
10 distances varied systematically with the expected environmental demands of the manipulated  
11 driving scenarios whereas the distributions of occlusion times remained more static across the  
12 scenarios. Systematic individual differences in the preferred occlusion distances were  
13 observed. More experienced drivers achieved better lane-keeping accuracy than  
14 inexperienced drivers with similar occlusion distances, however, driving experience was  
15 unexpectedly not a major factor for the preferred occlusion distances. **(e) Conclusion**  
16 Occlusion distance seems to be an informative measure for assessing task-relevant event  
17 density in realistic traffic scenarios with self-controlled speed. Occlusion time measures the  
18 visual demand of driving as the task-relevant event rate in time intervals, whereas occlusion  
19 distance measures the experienced task-relevant event density in distance intervals. **(f)**  
20 **Application** The findings can be utilized in context-aware distraction mitigation systems,  
21 human - automated vehicle interaction, road speed prediction and design, and in the testing of  
22 visual in-vehicle tasks for inappropriate in-vehicle glancing behaviors in any dynamic traffic  
23 scenario for which appropriate individual occlusion distances can be defined.

1           THE ATTENTIONAL DEMAND OF AUTOMOBILE DRIVING REVISITED –  
2       Occlusion distance as a function of task-relevant event density in realistic driving scenarios  
3  
4       A novel taxonomy defines driver inattention as “*insufficient, or no attention, to activities*  
5       *critical for safe driving*” (Regan, Hallet & Gordon, 2011, p. 1775). Even if the taxonomy is a  
6       highly valuable effort to standardize the use and operationalization of the construct, Regan et  
7       al. (2011) admit that the definition remains open-ended because it does not define the critical  
8       activities for safe driving. The difficulties in coming up with a standard definition pinpoints  
9       the problem that in spite of over 40 years of research, we do not yet understand the demands  
10      of the driving task itself at the level that we would be able to inclusively define what is  
11      inattentive driving.

12           Even if there are certainly other types of task demands involved, automobile driving  
13      is first and foremost a visual-manual task requiring visual information. There is compelling  
14      evidence indicating a statistical relationship between individual off-road glance durations and  
15      the risk of safety-critical incidents in real traffic (Liang, Lee, & Yekhshatyan, 2012). The  
16      percentage of over-2-second off-road glances during in-car task completion is one of the  
17      limiting criteria for acceptable visual sampling behaviors in the verification guidelines for the  
18      visual-manual in-vehicle electronic devices of the National Highway Traffic Safety  
19      Administration (2013). However, already a 1-second glance away from the road could be an  
20      occurrence of visual inattention in some driving environments. In the terminology of the  
21      driver inattention taxonomy as posed by Regan et al. (2011): How much visual attention is  
22      required in order to sufficiently process the safety-relevant targets in different driving  
23      conditions at a given moment, at what frequency, and what are those targets? What are these  
24      visual demands of driving in a certain situation for different drivers?

## VISUAL DEMAND OF DRIVING REVISITED

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1           Seminal work of Senders, Kristofferson, Levison, Dietrich and Ward (1967) on an  
2 interstate road and on a racetrack utilized the visual occlusion technique to intermittently  
3 occlude the visual field of the driver with an occlusion visor in order to acquire an  
4 understanding of the visual demands of driving. In four experiments, Senders et al. (1967)  
5 systematically varied either the vehicle velocity or the length of the occlusion interval  
6 (occlusion time, OT) in order to get a quantitative description of the relationship between  
7 vehicle speed and OT (Experiments 1 & 2: I-495), as well as road curvature and OT  
8 (Experiments 3 & 4: Motorsport park). They found that on a particular road OT and vehicle  
9 speed are inversely related if one of these and all other factors are controlled (Senders et al.,  
10 1967). Five hundred milliseconds seemed to be a sufficient visual sampling time (visor open)  
11 in between occluded periods for an experienced driver to keep the control of the vehicle in  
12 the studied driving environments.

13           Concerning the qualitative questions of what and where do drivers require visual  
14 information while driving, Mourant and Rockwell (1970, 1972) conducted pioneering work  
15 with eye tracking on real roads. Mourant and Rockwell found the effects of road familiarity  
16 (1970) and driving experience (1972) on the on-road fixation targets. Both of the factors  
17 seemed to move fixations from the right-hand side of the road towards the vehicle's distant  
18 field of travel but also free visual resources to inspect other safety-relevant targets such as  
19 mirrors.

20           Later in a driving simulator, Tsimhoni and Green (1999, 2001) utilized the occlusion  
21 technique in order to study visual demand of driving curves repeating the findings of Senders  
22 et al. (1967). Tsimhoni and Green (2001) have also applied the technique in an effort to  
23 determine how secondary in-vehicle activities affect visual sampling behavior while driving.

24           After Senders et al. (1967) and Wortelen, Baumann and Lüdtkke (2013), we define the  
25 visual demand of the driving task as the event rate at which the driver has to update the focus

1 of visual attention in order to decrease uncertainty of the task-relevant event states in the  
2 immediate field of view to a preferred level. In line with the framework of Wortelen et al.  
3 (2013), a task-relevant event state in driving is a source of visual information such that when  
4 its value is changed significantly, a response is required from the driver in order to achieve a  
5 subgoal in the driving task, for instance, to keep the vehicle in the lane. The task-relevant  
6 event states in driving can include, for example, lane position, headway distance, visibility of  
7 obstacles, signs or cues, as well as object trajectories, including one's own vehicle. The  
8 significance of the change depends on the particular goals of the driving task but the safety-  
9 related goals can be assumed to be fairly general across drivers and drives. In occlusion  
10 experiments, the expected rate of the significant task-relevant events in time (expectancies by  
11 Wickens, Helleberg, Goh, Xu, & Horrey, 2001) is in inverse relationship to OT.

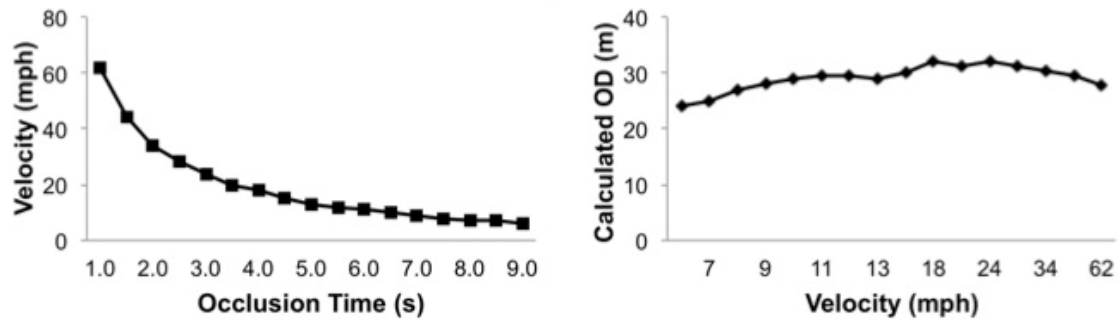
12 We argue that a limitation of OT is that it is a function of the event rate only in the  
13 time domain, and cannot by itself (without considering speed) specify the density of task-  
14 relevant events in the spatial scenario. Because of the limitations of OT when applied to  
15 realistic driving scenarios with voluntary speed control, we propose a new measure of visual  
16 demand of driving environments, occlusion distance (OD). OD refers to the distance a driver  
17 feels comfortable driving with his or her eyes shut when the driver is fully concentrating on  
18 the driving task.

19 In order to illustrate the difference, Figure 1 shows the calculated ODs and vehicle  
20 speeds on predefined OTs after Senders et al. (1967) data for participant J.W.S. Given all the  
21 situational factors other than the speed are the same, the OD for this particular interstate road  
22 and driver seems fairly constant across different speeds. OD tells us simply that this  
23 particular driver can drive on average 30 meters on this particular road without visual  
24 information, regardless of speed. OT, on the other hand, describes the level of visual demand

## VISUAL DEMAND OF DRIVING REVISITED

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1 of driving with various speeds on the road as a function of the task-relevant event rate in  
 2 time. With the same OT but at a higher speed, more OD is traveled blind.



3

4 *Figure 1.* Calculated velocity points by occlusion time and the corresponding occlusion

5 distances (OD) by velocity for the participant J.W.S. in Senders et al. (1967) Experiment 1 (I-  
 6 495)

7 In this paper, we present support for our theoretical model of visual demand in driving  
 8 and the utility of occlusion distance as a function of task-relevant event density in realistic  
 9 traffic scenarios with driver-controlled speed and occlusion times.

10

### Theoretical Model of Visual Demand in Driving

11 We define the visual demand of the driving task as the event rate at which the driver has to  
 12 update the focus of visual attention in order to decrease uncertainty of the task-relevant event  
 13 states in the immediate field of view to a preferred level. We specifically note that the event  
 14 rate can be either in the time domain *or* in the space domain. That is, the updating may occur  
 15 at specific time intervals, or at specific distance intervals. In the special case of constant  
 16 speed, these two will be perfectly correlated.

17 In the following, we assume a driver (a cognitive agent)  $k$  with a perfect expectancy  
 18 evaluation skill who pushes occlusion time to a constant maximum level of tolerated  
 19 uncertainty in all scenarios.

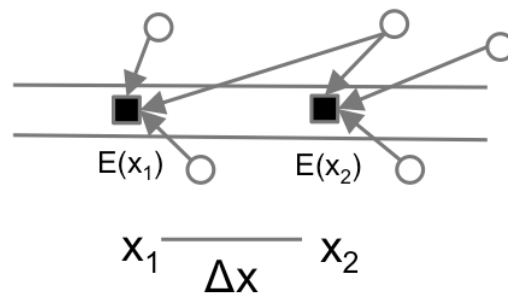
20 After Wortelen et al. (2013), a task-relevant event  $e(g, t)$  occurs if at time  $t$   
 21 visual information, which is relevant for a goal  $g$  is used by the cognitive agent  $k$  to



1 achieve  $g$ . That is, event  $e(g,t)$  occurs, if at time  $t$  a production rule is fired for goal  $g$  and  
2 thus, the visual information is used by the cognitive agent. A production can process  
3 perceived visual information from the environment, such as the headway distance, or features  
4 of a stored dynamic visuospatial mental representation of the environment, such as the  
5 imagined lane position of the vehicle. A production that processes visual information can also  
6 fire without producing a motor response. This would correspond to a real-world behavior of a  
7 driver perceiving something task-relevant in the environment such as a headway distance and  
8 making a judgment that the current headway distance is sufficient and no response is needed.

9 By our definition, the visual demand of a driving scenario is a function of the total  
10 number of events in the scenario per time or distance unit. With a perfect cognitive model of  
11 driving (similar to, e.g., Salvucci, 2006), the visual demand, that is, the number of events in  
12 the scenario per time or distance unit would correspond directly to the number of productions  
13 firing, in which visual information is used.

14 For the cognitive agent  $k$ , the field of view at a point  $x_i$  induces  $E(x_i)$  task-relevant  
15 events. When the driver  $k$  moves along the road a distance  $\Delta x$ , the total number of processed  
16 events is  $\sum_i E(x_i)$ . In Figure 2,  $\sum_i E(x_i) = E(x_1) + E(x_2) = 6$ . The circles represent driving  
17 task relevant targets (i.e., event states) in the road environment, such as a traffic sign or an  
18 approaching car from the right at an intersection ahead. Each arrow represents task-relevant  
19 visual information for an event that is processed by the driver, such as the observed speed of  
20 the approaching car. Note that visual information of a single physical target can be processed  
21 in multiple events.



1

2 *Figure 2.* Illustration of task-relevant events at two points on the road ( $x_1$  and  $x_2$ ). Each circle  
 3 represents a task-relevant source of visual information (i.e., event state) in the road  
 4 environment.

5 The temporal event rate,  $\sum_i E(x_i) / \Delta t$ , is the time-based function that is traditionally studied

6 in occlusion experiments. In general, the event rate in time is a function of both the number

7 of events per distance,  $\sum_i E(x_i) / \Delta x$ , and the speed of the car,  $\Delta x / \Delta t$ . We can write this as

8 an equation

$$9 \quad \frac{\sum_i E(x_i)}{\Delta t} \approx \frac{\sum_i E(x_i)}{\Delta x} \frac{\Delta x}{\Delta t} \approx D(x)V(x) \quad (1)$$

10 which is exact when  $\Delta t$  is very small.  $V(x)$  is then the momentary velocity of the car. We

11 denote  $D(x)$  as the event density. It is the discrete version of the information density of the

12 road (“*events per mile*” rather than “*bits per mile*”) as defined by Senders et al. (1967). The

13 driver can adjust the event rate by scanning freely ahead and adjust speed so that a

14 comfortable event rate is not exceeded. This is the key task in theoretical models of driving

15 such as Fuller (2005) and Summala (2007).

16 However, the occlusion method makes the mathematical interpretation more complex

17 compared to unoccluded driving. It is necessary to consider a new parameter: the driver’s

18 uncertainty  $U(x)_k$  of the task-relevant event states during occlusion (Senders et al., 1967).

1 The uncertainty is hypothesized to be a function of the number of task-relevant events  
 2 induced by the field of view. Increases in the observed event density in the field of view adds  
 3 to the complexity of the stored dynamic visuospatial mental representation of the scenario  
 4 that must be processed during the following occlusion. The more events that have to be  
 5 processed while occluded, the faster the build-up of uncertainty.

6 Thus, uncertainty builds up in this model as a function of events, not time, as in the  
 7 work of Senders et al. (1967). We make the simplifying assumption that the uncertainty of  
 8 the task-relevant event states is linearly related to the number of processed (i.e., expected)  
 9 events during the occlusion:  $U(x)_k = \Delta x D(x)$ , that is,  $U(x)_k = \sum_i E(x_i)$  (see Eq. 1).

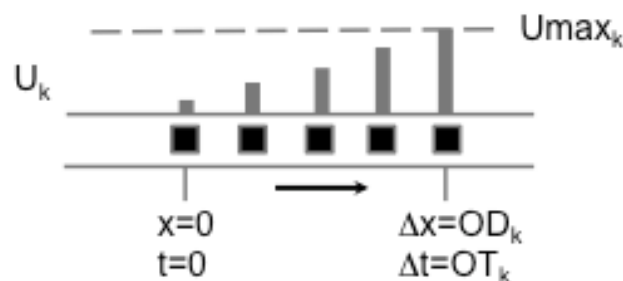
10 The driver  $k$  will ask for additional visual information as soon as the driver's  
 11 uncertainty of the task-relevant event states during the occlusion has reached the driver's  
 12 maximum level of uncertainty tolerated,  $U(x)_k = Umax_k$ . For our perfect cognitive agent  $k$   
 13 the constant  $Umax_k$  would correspond to the maximum processing capacity of the human  
 14 visual memory for moving scenes (Thomson, 1983). For any real driver,  $Umax_k$  could be  
 15 affected by other personal factors, such as tolerance of ambiguity (Furnham & Marks, 2013)  
 16 and risk tolerance. The driver will thus end the occlusion when  $U(x)_k = Umax_k$ . Then, for a  
 17 constant speed  $V(x)$ , we have the equation

$$18 \quad U(x)_k = D(x)V(x)OT(x)_k = Umax_k \quad (2)$$

19 In this paper, we are interested in estimating  $D(x)$ . In most occlusion studies so far  
 20 (Senders et al., 1967: Experiments 1 and 3; Tsimhoni & Green, 1999; 2001), the situation has  
 21 been simplified considerably by holding the drivers to a constant speed. The driver can  
 22 control occlusion time  $OT$  so that the event rate is kept within the limits of preferred  
 23 uncertainty. In this special case of constant speed  $OT$  can be used to estimate  $D(x)$ .

1            However, these results would be limited, for example, to visual demand of negotiating  
 2 a curve with a constant speed. Driving on a road with realistic curvature with a forced static  
 3 speed is fundamentally a different task than driving the same road with a voluntary speed  
 4 control, at the operational level as well as from the perspective of visual demands. As an  
 5 example, in our upcoming data speed is strongly dependent on the curvature of the road,  
 6 since drivers decelerate when they enter a curve.

7            On the other hand, if both  $V$  and  $OT$  can vary, then  $OT$  can not be used to estimate  
 8  $D(x)$  without considering changes in speed. For these cases, however, we can define a new  
 9 function that has not been used in earlier research: the occlusion distance  $OD(x)_k$ , defined as  
 10 the distance the driver drives during an occlusion (see Figure 3). This is very close to  
 11  $OT(x)_k * V(x)_k$ , but the relationship is not exact because the driver may accelerate or  
 12 decelerate during the occlusion (i.e., react according to the preceding unoccluded field of  
 13 view).



14  
 15 *Figure 3.* The relationships between  $U_k$ ,  $U_{max_k}$ ,  $OD_k$ , and  $OT_k$ . Driver  $k$ 's uncertainty ( $U_k$ )  
 16 reaches  $k$ 's maximum level of uncertainty tolerated ( $U_{max_k}$ ) when the distance  $\Delta x$  traveled  
 17 equals  $OD_k$  and the time  $\Delta t$  traveled equals  $OT_k$ .

18 The occlusion distance combines the two driver-controlled variables in this setup into one:

$$19 \quad U_{max_k} = D(x)OD(x)_k \quad (3)$$

20 and allows a prediction for driver behavior to be made:

$$1 \quad OD(x)_k = \frac{Umax_k}{D(x)} \quad (4)$$

2        We call the  $Umax_k$  factor as the subjective uncertainty acceptance threshold that  
3 should be fairly static for driver  $k$  across different traffic scenarios. It describes the threshold  
4 at which the driver feels that the comfortable safety margins have been crossed (Summala,  
5 2007). That is, the driver  $k$  is capable of processing (or willing to process) at most  $Umax_k$   
6 events per  $OD(x)_k$ .  $Umax_k$  of a given driver can be estimated in a visual occlusion experiment  
7 with a sufficient sample of drivers.

8        Both OT and OD are imperfect measures for visual demand, but each has its own  
9 strengths. OT varies with the inverse of the task-relevant event rate in the time domain (i.e.,  
10 dynamic visual demands of driving), but cannot determine whether the changes are due to  
11 changes in speed or to changes in the number of events in the scenario. OD varies with the  
12 inverse of the event density in the space domain from one unoccluded view to another (i.e.,  
13 static visual demands of the driving environment), but does not give information on how the  
14 driver is processing information in the time domain.

15        In the following, we seek to demonstrate that the three specific hypotheses supporting  
16 our theoretical model are justified by the data set collected in two driving simulator  
17 experiments with intersection, suburban, and highway scenarios:

18 H1. With self-determined speed and OT, median ODs will increase across environments of  
19 progressively reduced event density from intersections to suburban to highway scenarios  
20 whereas OTs will vary significantly less. Highways have larger built-in safety margins (e.g.,  
21 less curvature, no crossings, wider one-way lanes) to enable safe driving at higher speeds  
22 than suburbs. Intersections have more task-relevant targets to scan for than the other two  
23 scenarios, such as signs, lights, crossing roads, crosswalks, and lanes to select. H1 would  
24 support the model of OD as a function of task-relevant event density in space and OT as a  
25 function of the preferred task-relevant event rate. It would support the idea that drivers try to

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12

1 keep the visual demands of driving (i.e., event rate) at a general comfortable range across  
2 scenarios of varying event density.

3 H2. OD varies systematically with a nearly constant individual factor for the same driver  
4 across driving scenarios. The finding would give support for the consistency of the subjective  
5 uncertainty acceptance threshold  $U_{max_k}$  within a driver and for the generalizability of OD  
6 across driving scenarios.

7 H3. Curvature of the road ahead has a significant inverse relation to OD. The specific  
8 environmental demands of road curvature should have an effect on OD if OD is a measure of  
9 the task-relevant event density of the environment.

10 By validating these three hypotheses, we can demonstrate that OD can be effectively used to  
11 define the environmental and driver-specific task-relevant event density with a generalizable  
12 metric over a wide variety of drivers and dynamic real-world scenarios.

### 13 **Occlusion in Simulated Realistic Driving Scenarios**

14 Because nowadays ethical research boards will not approve on-road occlusion studies, and  
15 with good reason, we used a motion-platform driving simulator to mimic Finnish suburban  
16 and highway driving as realistically as possible.

### 17 **Research Method**

18 **Participants.** A total of 130 volunteers were recruited by contacting private and  
19 public sector employees in Central Finland, the University of Jyväskylä student mailing lists,  
20 and vehicle inspection stations in the city of Jyväskylä. Driving schools in Jyväskylä, as well  
21 as the Central Finland educational consortium, were contacted in order to reach novice  
22 drivers. Motion sickness was monitored during the experiments with the Simulator Sickness  
23 Questionnaire (SSQ, Kennedy, 1993). Thirty-three participants withdrew from the study or  
24 had to be excluded from the data because of simulator sickness symptoms, or as outliers  
25 (driving at least 30% of the time the scene was constantly unoccluded). The final sample

1 included 40 women and 57 men between the ages of 18 and 61 ( $M=30.8$ ;  $SD=9.9$ ). They all  
2 had a valid driving license and lifetime driving experience from 0 to 43 years ( $M=13.0$ ;  
3  $SD=9.9$ ). Participants drove weekly from 0 to 2,500 kilometers ( $M=237$ ;  $SD=432$ ) and in a  
4 year from 50 to 130,000 kilometers ( $M=14,262$ ;  $SD=19,322$ ). All the participants had a  
5 normal or corrected to normal vision. The experiments were conducted in Finnish with fluent  
6 Finnish-speakers. All the participants were rewarded with a movie ticket.

7       **Environment and tools.** The motion-base medium-fidelity driving simulator is  
8 located at the driving simulator laboratory of the Department of Computer Science and  
9 Information Systems in University of Jyväskylä (see Figure 4). The CKAS Mechatronics  
10 2DOF motion platform provided movements for the simulator, simulating accelerations and  
11 decelerations of the vehicle in order to make the maintenance of speed more natural and less  
12 visually demanding by minimizing the need to observe the speedometer to keep the speed  
13 constant. The virtual driving scene was displayed on three 40" (95.6 cm x 57.4 cm) LED  
14 displays with a resolution of 1440 x 900 pixels. The simulator was equipped with a Logitech  
15 G27 force feedback steering wheel, accelerator, and brake. A right side paddle shifter in the  
16 steering wheel was used for unoccluding the driving scene for 500 ms for each press.

17



1

2 *Figure 4.* The motion-base medium-fidelity driving simulator

3 The driving simulation software was provided by Eepsoft ([www.eepsoft.fi](http://www.eepsoft.fi)). The experiments  
4 were driven in a virtual environment simulating real-life Finnish suburban and highway  
5 traffic environments in Martinlaakso, Vantaa (see Figure 5). The virtual environment  
6 included Head-Up-Display (HUD) speedometer, RPM gauge, and a rear-view and side  
7 mirrors. The virtual car's transmission was set to automatic. Driving log data were logged  
8 and saved at 10 Hz. Additional research equipment included a head-mounted Dikablis eye-  
9 tracking system with a 50 Hz sampling rate (eye-tracking data not reported here).





1

2 *Figure 5.* Examples of 6 simulated locations (numbered) compared to real ones (below). 1:  
 3 intersection with traffic; 2: junction to highway; 3, 4, 5: suburban roads; 6: intersection with  
 4 traffic lights.

5 **Procedure.** After the collection of demographic data, all the participants completed a  
 6 practice session followed by three experiments in different environments. The practice  
 7 session was driven in an urban environment until the participant felt comfortable, on an  
 8 average about 10 minutes per practice, first unoccluded and then occluded. After the  
 9 practices, the participant first drove a Suburban experiment for approximately 25 minutes,  
 10 after a break a 15 minute Highway experiment, and finally 5 minute suburban experiment in  
 11 snowfall conditions (snowfall results not reported here). The driving scene was occluded by  
 12 default and participants were able to unocclude the scene for 500 milliseconds by pressing  
 13 the right-hand paddle behind the steering wheel. To keep the scene continuously unoccluded  
 14 the paddle had to be repeatedly pressed.

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1           A speed limit of 60 km/h was instructed for the Suburban experiment and 80 km/h or  
2           120 km/h for two different types of road in the Highway experiment. Driving directions were  
3           provided by Finnish voice guidance at predetermined points on the tracks. The instructions  
4           were given two times before each street corner or junction and the participant had the  
5           possibility to ask the experimenter to repeat the instructions. In order to make the participants  
6           focus on the driving task but still to try to maximize the comfortable occlusion time, they  
7           were informed that the 30 most accurate participants in the driving task and with the least  
8           unoccluded time would be rewarded with another movie ticket. Driving task accuracy was  
9           defined by the number of lane excursions that were scored in real-time by the experimenter.  
10          The accuracy of lane keeping was assessed by how many times the HUD speedometer  
11          (Figure 4) crossed a white lane marking, but this was not explicitly stressed in order to avoid  
12          unnatural visual demand for an experienced driver through fixating on the lane markings.

13           In this setup, lane-keeping accuracy could be determined independently from the OD  
14          because lane excursions were monitored covertly. Although it is not a direct measure of safe  
15          driving as such, the lane-keeping accuracy differed dramatically from driver to driver (from 2  
16          to 120 excursions). The accuracy parameter was thus defined as  $(120 - \text{number of excursions}) / 120$ , being normalized between 0 and 1. Participants were also instructed to obey  
17          traffic rules, to choose their preferred driving speed, beware of unexpected events and react  
18          as in real situations. No completion time limits were given. Participants were told that they  
19          could withdraw from the experiment whenever they wish.

21           **Data set.** The final data set consisted of 97 drivers who drove through the Suburban  
22          and Highway experiments. Four other drivers finished both experiments, but were found to  
23          have often (at least 30% of the time) clicked the unocclusion paddle at intervals that were less  
24          than 500 milliseconds, meaning the scene was constantly unoccluded. The other drivers did  
25          not indicate such behavior or only 1-2% of the time, so the four outliers were easily identified

## VISUAL DEMAND OF DRIVING REVISITED

17

1 and excluded from the analysis. The sample size in the following statistical tests varies  
2 between 93, 95, and 97 because of missing data due to technical problems with four  
3 participants. For the Suburban and Highway experiments  $N=95$ .

4       The data set consisted of two types of scenarios (Suburban and Highway, see Table  
5 1). The tracks, that is, road segments, were divided into separate segments by defining trigger  
6 points on the road at points where the user was instructed to turn at an intersection. Another  
7 trigger point was set where the driver had cleared the intersection. The tracks were thus  
8 defined as segments between the last trigger line marking the end of an intersection and the  
9 first trigger line of the consecutive intersection. The drivers accelerated at the beginning of  
10 each track in order to reach a velocity preferred by the driver. In total, there were 13 tracks  
11 that were long enough to be usable to estimate the average behavior of drivers over the  
12 tracks. Nine of these were Suburban (60 km/h speed limit) and four were Highway (80 or 120  
13 km/h) tracks. In addition, 19 of the intersections were studied. These varied considerably, but  
14 all contained an instruction for the driver to turn at an intersection. Driver behavior was  
15 highly variable. Some stopped at some intersections, while others never did. This  
16 confounding behavior could not be modeled. Therefore, the intersection data for speeds over  
17 2 m/s were used for the OT-OD comparison, but not for a close-up analysis of the occlusion  
18 data. For the Intersection data  $N=97$ .

19

## VISUAL DEMAND OF DRIVING REVISITED

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## 1 Table 1

## 2 Scenarios per Track [values are median, mean, (SD)].

Experiment 1 – Suburban scenarios (N=95)								
Track ID	Length m	Winding (W) m/m	Speed m/s	Occlusion Time (OT) s	Occl. Distance (OD) m	Median OT * Median Speed	Traffic	Type
M02	395	0.11 0.12 (0.06)	10.0 10.0 (2.4)	0.86 0.99 (0.64)	7.5 8.6 (5.8)	8.6	None	Suburban, almost straight, 60 km/h
M04	396	0.32 0.32 (0.15)	10.5 10.5 (2.3)	0.74 0.92 (0.67)	6.8 8.4 (6.4)	7.8	One approaching	Suburban, 60 km/h
M10	1059	0.012 0.020 (0.02)	13.0 12.7 (2.5)	0.97 1.20 (0.87)	10.7 14.1 (11.7)	12.6	High*	Suburban, almost straight, 60 km/h
M12	1039	0.038 0.039 (0.008)	12.3 12.4 (2.5)	0.90 1.10 (0.79)	9.9 12.6 (10.1)	11.1	Approaching	Suburban, almost straight, 60 km/h
M22	355	0.18 0.15 (0.05)	10.9 10.9 (2.1)	0.85 1.01 (0.71)	7.9 9.6 (7.5)	9.3	None	Suburban, 60 km/h
M28	423	0.34 0.33 (0.07)	9.7 9.5 (1.9)	0.60 0.74 (0.54)	4.8 6.1 (4.9)	5.8	High*	Suburban, narrow road, 60 km/h
M33	704	0.15 0.15 (0.04)	12.8 13.0 (2.6)	0.80 0.97 (0.70)	9.2 11.6 (8.8)	10.2	One approaching	Suburban, 60 km/h
M46	850	0.063 0.066 (0.016)	12.6 12.6 (2.5)	0.80 0.97 (0.70)	8.9 11.1 (8.6)	10.1	Approaching	Suburban, 60 km/h
M54	571	0.18 0.23 (0.14)	10.5 10.6 (2.8)	0.69 0.88 (0.67)	5.8 8.0 (7.1)	7.2	High*	Suburban, 60 km/h
Experiment 2 – Highway scenarios (N=95)								
M64	1208	0.041 0.037 (0.010)	21.0 20.5 (2.8)	0.51 0.64 (0.48)	8.4 10.7 (8.7)	10.7	High*	Highway, 80 km/h
M66	1015	0.028 0.027 (0.005)	21.2 21.2 (2.3)	0.81 0.97 (0.74)	14.2 17.6 (14.3)	17.2	None	Highway, 80 km/h
M71	1182	0.030 0.029 (0.007)	28.1 27.9 (3.9)	0.56 0.71 (0.54)	12.3 16.6 (14.2)	15.7	High*	Highway, 120 km/h
M73	1135	0.011 0.019 (0.014)	26.5 26.0 (4.7)	0.65 0.81 (0.65)	12.9 16.7 (15.2)	17.2	None	Highway, 120 km/h

1 *Note.* \*: In cases of high traffic, cars with artificial intelligence driving in the same direction drove at the  
2 nominal maximum speeds, and thus usually outran drivers. Most tracks in fact were in practice empty  
3 except for the approaching cars.

4 The study closest to ours, Tsimhoni and Green (1999), had the following restrictions: a  
5 simple predefined road with a radius of curvature measured at just a few points, constant  
6 speed, no other cars, and the participant only varying the occlusion time. The level of visual  
7 demand was defined as  $0.5/(0.5+OT)$ , and a linear model of visual demand with a radius of  
8 curvature and age was determined by averaging values over all drivers for the four well-  
9 defined curvature points.

10 In contrast, in our experiments the driver drove on simulated real-world roads that  
11 were not designed to prove any hypotheses and the driver was able to vary vehicle speed  
12 (only a nominal maximum for the road was defined) as well as the occlusion time.  
13 Furthermore, the driver was told to drive carefully and to obey traffic regulations.  
14 Additionally, other traffic in the form of cars controlled by artificial intelligence algorithms  
15 (AI cars) could move in the same or opposite direction (Figure 5: 1, 2) and there were  
16 intersections with potential traffic (Fig. 5: 1, 6), traffic lights (Fig. 5: 6), and various other  
17 signage (Fig. 5: 1, 2). The downside of this naturalistic driving simulation was that it  
18 introduced variables that could not be modeled. We suspect that intersections, zebra  
19 crossings, and road signs, in particular, may have caused highly variable effects, since the  
20 drivers were asked to be vigilant of crossing traffic and pedestrians.

21 **Calculation of Winding.** The calculation of road curvature for real-world roads is a  
22 numerically unstable parameter, a fact that could be ignored in Tsimhoni and Green (1999)  
23 where the simulated road was designed specifically for the purpose of the analyses of  
24 curvature on occlusion time. In addition, they only measured road curvature at four points,  
25 whereas we needed to measure it continuously.

1           The radius of curvature  $R$  of a natural road is not constant, but rather is constantly  
2 varying as the driver moves in and out of a curve. To improve measurements, we defined a  
3 related parameter we coined Winding, denoted by  $W$ . It is a measure of how much the driver  
4 needs to turn the steering wheel while driving along the track.

5           We suggest that the number of task-relevant events on a winding road is related to the  
6 amount of steering a driver anticipates as being required ahead. The Winding is related to the  
7 radius of curvature  $R$ , but is dimensionless and numerically more stable. For any infinitesimal  
8 distance  $dx$ , the dimensionless lateral deflection is  $dx/R(x)$ . The total lateral deflection over a  
9 long distance  $L$  is then given by:

$$10 \quad W = \frac{1}{L} \int_0^L \frac{dx}{R(x)} \quad (5)$$

11           The integral is divided by  $L$  in order to make  $W$  dimensionless and independent of the  
12 chosen value of  $L$ . The distance  $L$  must be defined empirically, but we found 100 meters to  
13 be practical. This is also consistent with the result of Tsimhoni and Green (1999), by which  
14 the closest 100 meters ahead before a curve included 70 % of the locations of the maximum  
15 visual demand. A value of 0.1 means that the road is on average deflected 10 cm per every  
16 meter driven. For the roads in our simulation the typical values of  $W$  were less than 0.2; only  
17 in the tightest corners did it exceed 0.4.

18            $W$  is dimensionless but can be defined as (meters deflection)/(meters distance).  
19 Qualitatively, it describes how many meters the path is deflected per each meter that is  
20 traveled forward.

21           **Effects of other cars.** The effect of AI cars on driver behavior could not be  
22 meaningfully evaluated. Some of the tracks had AI traffic going in the same or opposite  
23 direction as the driver, but this had no practical effect on the results. The lead cars drove at  
24 the nominal speed limit of the scenario, while test subjects almost always drove at lower

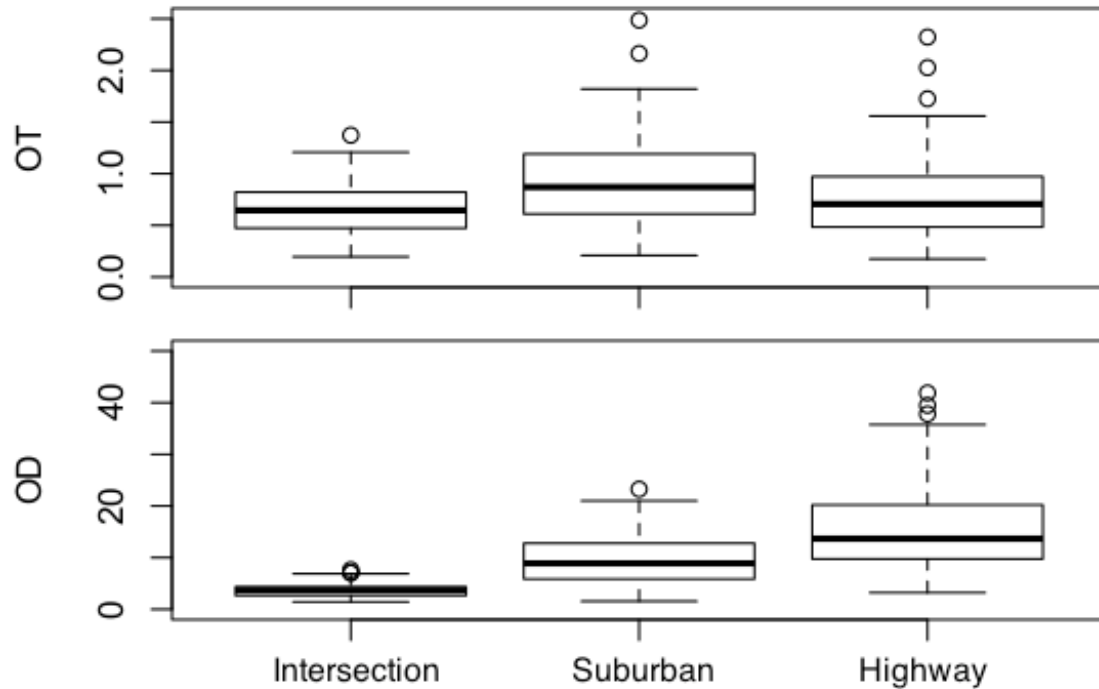
1 speeds. Thus, unexpectedly, there was little to no interaction with the AI traffic, and the AI  
2 traffic was ignored in this study.

### 3 **Results**

4 **H1. With self-determined speed and OT, median ODs will increase across environments**  
5 **of progressively reduced event density from intersections to suburban to highway**  
6 **scenarios whereas OTs will vary significantly less.** Median and mean OTs, ODs, and  
7 speeds per track are listed in Table 1. Over all the drivers, median ODs seem to vary in a  
8 similar systematic fashion between the tracks in Table 1 as median OT \* median speed  
9 (Pearson's  $r(11)=.98, p<.001$ ). This suggests that it is sufficient to approximate that  
10  $OD(x)=V(x)*OT(x)$  although the exact distance travelled during OT is then somewhat under-  
11 or overestimated. It is, however, more interesting to look at the underlying distributions.  
12 Figure 6 shows the individual median OTs and ODs per scenario for the three different  
13 scenarios.

14

1



2

3 *Figure 6.* Tukey box-plots with medians and quartiles of individual median OT (s, top) and  
 4 OD (m, bottom) for the Intersection ( $N=97$ ), Suburban ( $N=95$ ), and Highway ( $N=95$ )  
 5 scenarios.

6 Analysis on the effects of the scenario (Intersection, Suburban, Highway) with one-way  
 7 repeated measures ANOVA indicates significant differences between the scenarios in both  
 8 mean OD,  $F(2,184)=208.619$ ,  $p<.001$ , *partial*  $\eta^2=.694$ , as well as in mean OT,  
 9  $F(2,184)=56.388$ ,  $p<.001$ , *partial*  $\eta^2=.380$ . However, Table 2 and Figure 6 indicate that the  
 10 mean OD increases considerably from Intersection to Suburban to Highway scenarios  
 11 whereas mean OTs stay within a range between .67 to .95 seconds.

12



## VISUAL DEMAND OF DRIVING REVISITED

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1 Table 2

2 *Mean OD and Mean OT per Scenario (SD).*

	<u>Intersection</u>	<u>Suburban</u>	<u>Highway</u>	<u>Mean Difference</u> <u>Sub-Int</u>	<u>Mean Difference</u> <u>High-Int</u>	<u>Mean Difference</u> <u>High-Sub</u>
OD (m)	3.76 (1.40)	9.86 (4.78)	15.53 (8.38)	6.10***	11.77***	5.67***
OT (s)	.67 (.25)	.95 (.44)	.74 (.39)	.27***	.07*	-.20***

3 *Note.* \*\*\*:  $p < .001$ , \*:  $p < .05$ . Int=Intersection ( $N=97$ ), Sub=Subway ( $N=95$ ), High=Highway ( $N=95$ ).

4 The mean difference in OT between Suburban and Highway scenarios is only .27  
5 seconds, and the difference is to an opposite direction than in OD. The mean difference in OT  
6 between the Intersection and Highway scenarios is only .07 seconds. These findings suggest  
7 that even if OT is able to differentiate the high Intersection demands, OT varies as a function  
8 of task-relevant event rate in time and is not able to differentiate the spatial task-relevant  
9 event density between the Suburban and Highway environments that are built to allow safe  
10 driving at significantly different speeds. On the other hand, OD can indicate the differences  
11 in the expected spatial demands between the scenarios. However, OD cannot indicate that the  
12 visual demand of driving near the nominal speed limits in Suburban and Highway scenarios  
13 are nearly at the same level, with slightly higher demands on Highway driving and  
14 approaching the demands of the Intersection scenarios. Hence the two measures provide  
15 complementary information.

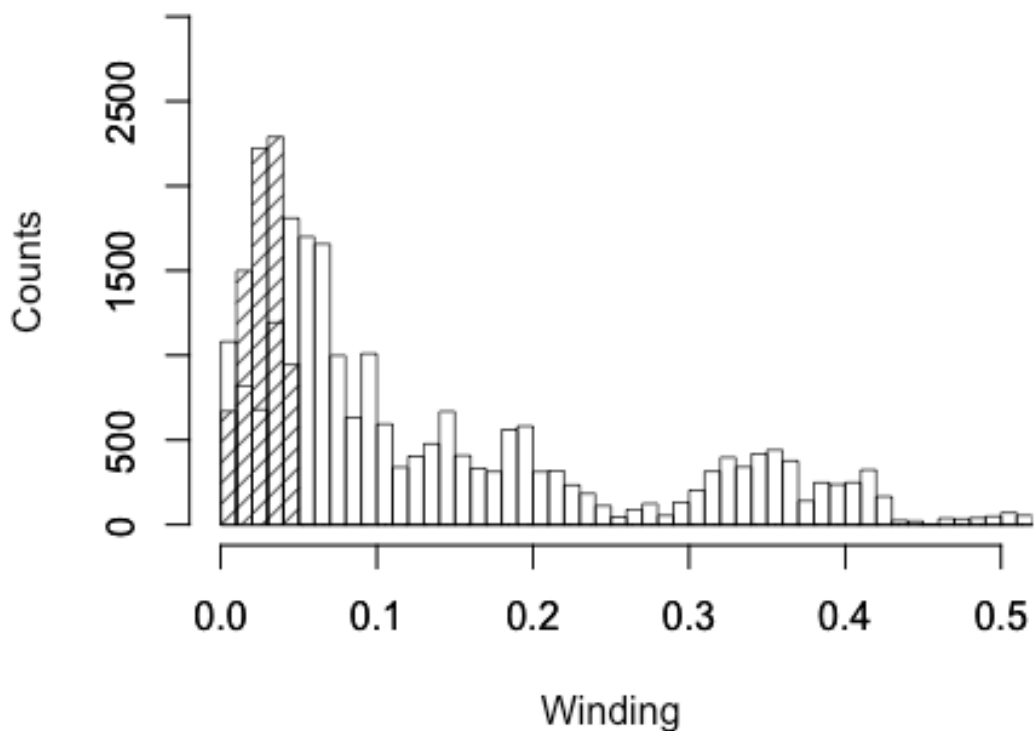
16 These findings support H1 and thus support the model of OD as a function of task-  
17 relevant event density in space whereas OT seems to be a function of preferred task-relevant  
18 event rate in time. The findings suggest, as expected, that by controlling speed according to  
19 the experienced event density, the drivers tend to keep the occlusion times on a similar  
20 comfortable range of approximately .50 to 1.00 seconds across different driving scenarios.  
21 The data and our theoretical model can provide an explanation why drivers' preferred range

1 of off-road glance durations seem to reside within this time frame across driving scenarios  
2 (Wierwille, 1993). The task-relevant event densities of constructed real-world road  
3 environments are in a linear relationship with the drivers' preferred speeds in these  
4 environments such that the preferred off-road glance durations (a function of the task-  
5 relevant event rate) rarely exceed 2.00 seconds.

6 **H2. OD varies systematically with a nearly constant individual factor for the**  
7 **same driver between driving scenarios.** The Highway scenario differed from the others in  
8 that the Winding is extremely low (see Figure 7), there were no intersections to worry about,  
9 and driving was not affected by AI cars because in almost all cases the AI lead cars drove  
10 much faster than the participants. The within-scenario visual demand is thus for all practical  
11 purposes near constant. Any variations in the highway scenario should be due to individual  
12 differences. To eliminate issues with possible AI lead cars, we removed the first 200 meters  
13 of the highway tracks from the analysis. Therefore, in all except a few cases the lead cars had  
14 driven off, and do not confound the analysis of the visual demand.

15

1

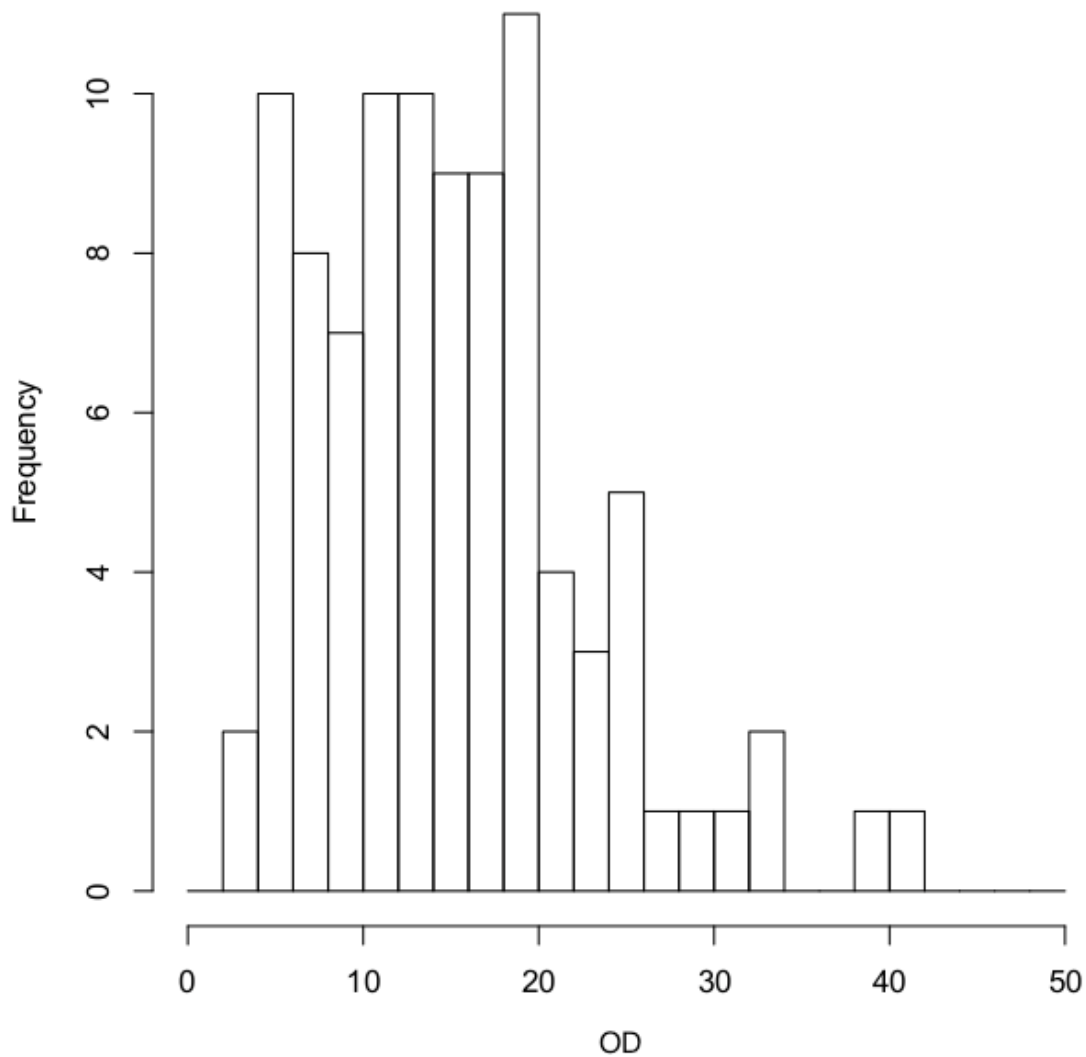


2

3 *Figure 7.* Winding (m/m) on the Highway track samples (lined) compared to the Suburban  
 4 track samples (blank).

5 The median highway OD was 13.7 m, and the 15th and 85th percentiles were 7.1 and 23.4 m  
 6 (see Figure 8). The median OT was .71 s, and the 15th and 85th percentiles were .36 and 1.10  
 7 s. The median OD (as well as OT) can thus vary by up to a factor of three between drivers.  
 8 Since the drivers in the highway scenario did not modulate the speed rapidly (i.e. did not  
 9 apply brakes sharply), the OD and OT are closely correlated ( $r(91)=.95, p<.001$ ).

10



1

2 *Figure 8.* Distribution of median OD (m) of each driver in the Highway scenarios ( $N=95$ ).

3 The scenario-dependent visual demand in all the Highway scenarios was assumed to be

4 constant, and the significant variations seen in OD thus show differences in the drivers'

5 perceptions of the task-relevant event density, which are in fact not present in the objective

6 distribution of the events in the external scenario. Based on our theoretical framework, we

7 interpret these differences to describe the subjective uncertainty acceptance threshold  $U_{max_k}$ ,8 so that for any individual driver  $k$  on the Highway scenario  $OD(x, highway)_k = U_{max_k} * 13.7$ .9 H2 suggests that across scenarios  $OD(x)$  varies systematically (because the event10 density varies with the distance  $x$ ), and that across subjects  $U_{max_k}$  varies systematically. Let

1  $h_m = 13.7$  m be the median OD of the sample for the Highway scenarios and  $s_m = 8.9$  m the  
 2 median OD of the sample for the Suburban scenarios. Then the normalized values of  
 3  $OD(x, highway)_k$  and  $OD(x, suburban)_k$  for the driver  $k$  are:

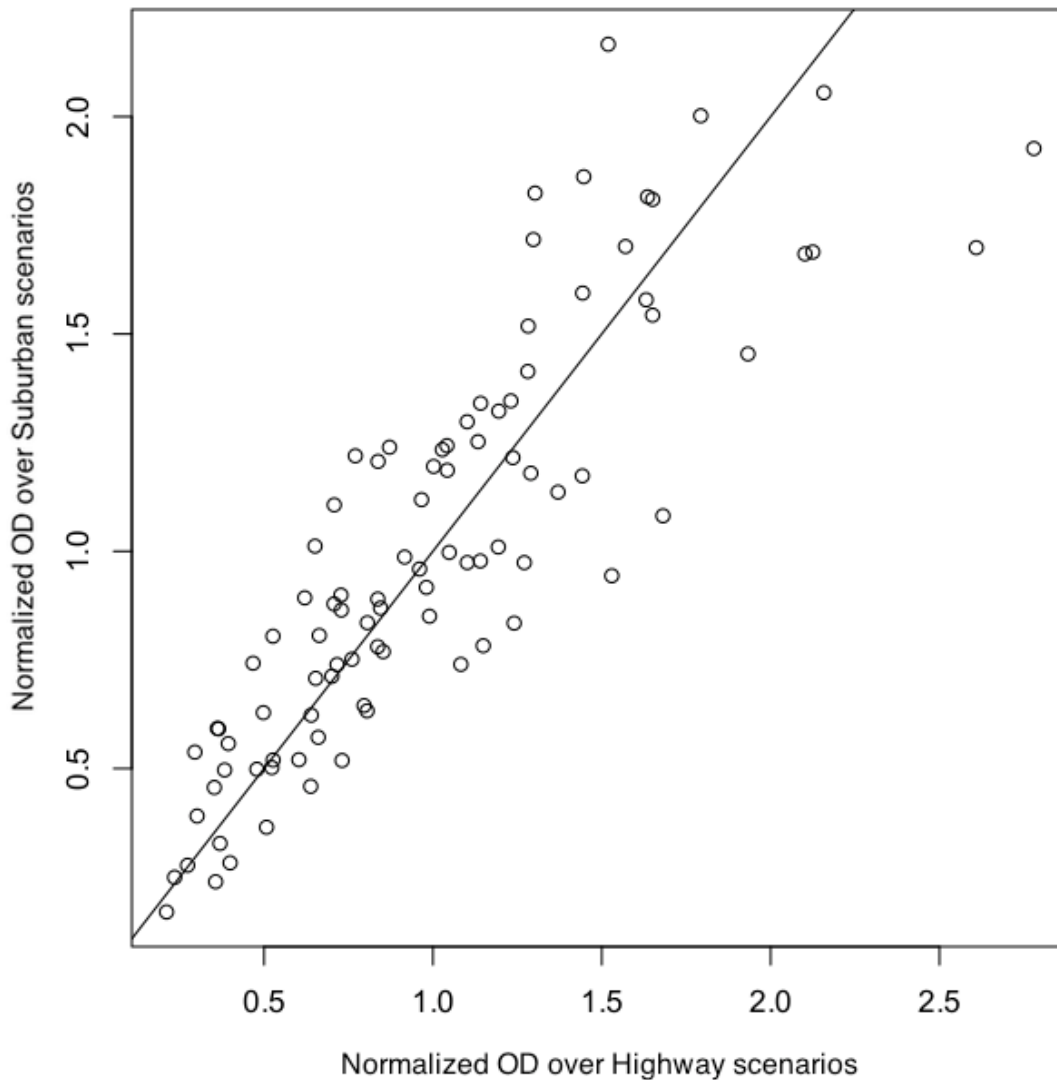
$$4 \quad \frac{OD(x, highway)_k}{h_m} = Umax_k \quad (6)$$

$$5 \quad \frac{OD(x, suburban)_k}{s_m} = Umax_k \quad (7)$$

6 Then we can rewrite  $OD(x, suburban)_k$  as a linear function of  $OD(x, highway)_k$  using the  
 7 above equations:

$$8 \quad OD(x, suburban)_k = \frac{s_m}{h_m} OD(x, highway)_k \quad (8)$$

9 Now we can show that for any individual driver, the value of  $Umax_k$  remains almost constant  
 10 across all scenarios. Figure 9 shows a scatter plot of the per-driver relative values for the two  
 11 scenarios (Highway and Suburban). The data points are normalized to the median OD for all  
 12 drivers in the scenario. It is seen that a driver with a low OD on the Highway tracks will also  
 13 have a low OD on the Suburban tracks ( $r(91)=.85$ ,  $p<.001$ ). The correlation between  
 14 Highway and Intersection tracks is slightly lower ( $r(93)=.71$ ,  $p<.001$ ). However, we can state  
 15 that the measured value of  $Umax_k$  for a given driver will be relatively constant over different  
 16 scenarios.



1

2 *Figure 9.* Normalized OD (m) for each driver, Suburban vs. Highway scenarios ( $N=93$ ).

3 Note that the correlations are approximately the same for OT across scenarios as they  
 4 were for OD ( $r(91)=.82$ ,  $p<.001$  and  $r(93)=.71$ ,  $p<.001$  respectively). There are also  
 5 statistically significant correlations between median speeds ( $r(91)=.48$ ,  $p<.001$  for Highway  
 6 vs. Suburban, and  $r(93)=.29$ ,  $p=.003$  for Highway vs. Intersection), although these  
 7 correlations are much lower than for OT and OD. Nevertheless, fast drivers seemed to drive  
 8 fast in all scenarios: high-occlusion-time drivers had high occlusion times across all  
 9 scenarios.

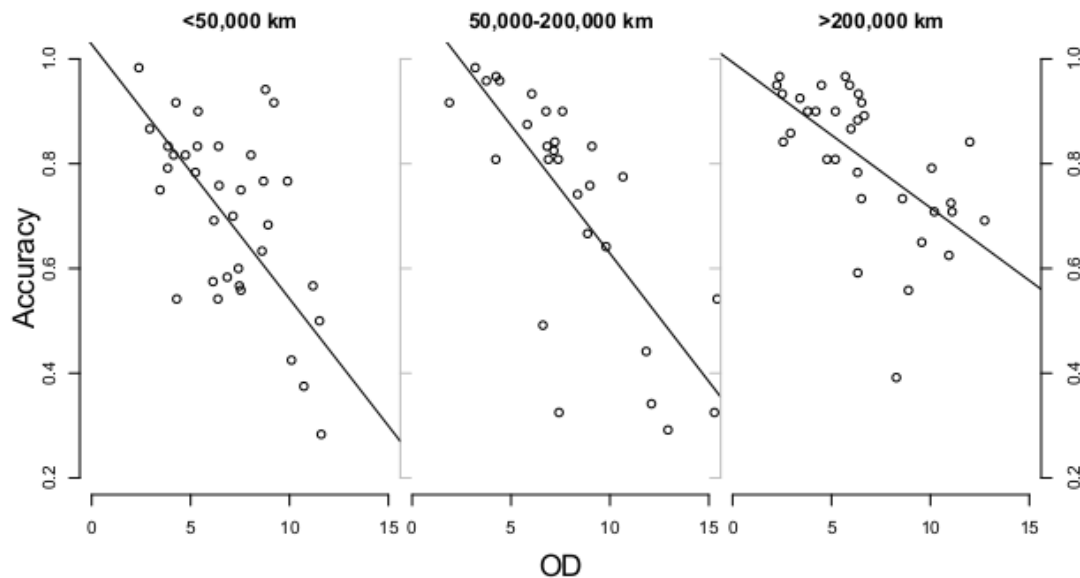
1           However, high-OT drivers may not be high-speed drivers. For both the Highway data  
2 and the Suburban data, the correlation of OT and speed is statistically insignificant  
3 (Highway:  $r(93)=-.03$ ,  $p=.740$ ; Suburban: ( $r(93)=-.08$ ,  $p=.420$ ). For the Intersections the  
4 calculation of median speed and the correlative analysis is not appropriate due to the much  
5 stronger and highly variable acceleration and deceleration behaviors compared to the  
6 Highway and Suburban scenarios.

7           Based on earlier research, it was expected that driving experience would affect the  
8 choice of OD (and OT), since novice drivers require more frequent updates of focal visual  
9 attention for lane keeping than experienced drivers (Mourant & Rockwell, 1972; Summala,  
10 Nieminen, & Punto, 1996). The analysis was made for the Suburban scenarios. The  
11 participants were divided into three classes according to self-reported lifetime driving  
12 experience: under 50,000 km ( $n=36$ , median OD=7.0), 50,000-200,000 km ( $n=28$ , median  
13 OD=7.3), and over 200,000 km ( $n=33$ , median OD=6.3). In addition, we studied the effects  
14 of gender and age on drivers' median ODs in the Suburban scenarios ( $N=95$ ). One-way  
15 between-subjects ANOVAs were conducted for analyzing the effects of driving experience  
16 (<50,000 km; 50,000-200,000 km; >200,000 km) and gender (male; female).

17           The choice of OD level does not seem to be affected by driving experience  
18 ( $F(2,93)=1.31$ ,  $p=.270$ ) or gender ( $F(1,94)=.23$ ,  $p=.630$ ). Neither did age and OD correlate  
19 significantly,  $r(93)=-0.17$ ,  $p=.090$ .

20           In line with previous research, a Welch t-test shows a significantly lower median  
21 lane-keeping accuracy for the least experienced group than for the most experienced one (.69  
22 versus .81),  $t(61.793)=-2.9677$ ,  $p=.004$ , 95% CIs [-.21,-.04], two-tailed. The effect is still  
23 significant at  $p<.05$  but much smaller when the least experienced group is compared to all the  
24 others:  $t(67.184) = -2.1386$ ,  $p=.036$ , 95% CIs [-.17,-.005], two-tailed.

1 Interestingly, drivers' median OD and driver accuracy were significantly inversely  
 2 correlated ( $r(93)=-.64, p<.001$ ) in the Suburban scenarios. Figure 10 shows the OD-accuracy  
 3 relationship by experience category, together with the least-squares fits for each experience  
 4 category.



5  
 6 *Figure 10.* Lane-keeping accuracy in the Suburban scenarios by OD (m, median) and the  
 7 driving experience category.

8 As noted earlier, there was no direct correlation between driving experience and OD  
 9 (or OT). Based on our theoretical framework, we interpret this result to suggest that the  
 10 subjective uncertainty acceptance threshold  $U_{max_k}$  of a driver is not in a direct relationship  
 11 with driving experience. A higher OD seemed to systematically lead to a lower lane-keeping  
 12 accuracy regardless of the level of driving experience. However, higher level of driving  
 13 experience may result in better lane-keeping accuracy for a given OD value. No other  
 14 individual effects could be found.

15 H2 is supported by the data. The findings suggest that OD is a generalizable measure  
 16 across the studied driving scenarios and the consistency of the subjective uncertainty



1 acceptance threshold  $U_{max_k}$  over different driving scenarios is supported. This means that if  
 2 we know a driver's  $U_{max_k}$  value, we can make predictions of the driver's visual behavior in  
 3 road environments with known median OD values.

4 **H3. Curvature of the road ahead has a significant inverse relation to OD.** Next,  
 5 we modeled the dependence of OD on scenario parameters. This analysis was made with only  
 6 the Suburban tracks. To eliminate between-subject differences, ODs of the individual driver  $k$   
 7 were normalized by dividing by the median OD of the driver  $k$  for the Suburban scenarios:

$$8 \quad ODN(x, suburban)_k = OD(x, suburban)_k / median(OD(x, suburban)_k) \quad (9)$$

9 Thus, whether the driver is high-OD or low-OD, the normalized ODN for that driver will be  
 10 centered at a value of 1.

11 The tracks were digitized at ten-meter intervals. For each of the 10-meter intervals, an  
 12 average Winding  $W(x)$  was then calculated. The normalized OD values of all drivers were  
 13 also averaged, giving a single value

$$14 \quad OD(x, suburban) = \frac{1}{N} \sum_k ODN(x, suburban)_k \quad (10)$$

15 A least-squares fit gives  $OD(x, suburban) = 1.20 - 1.03 * W$ , with  $R^2 = .23$ . 95% CIs [1.17,  
 16 1.23] for the intercept, [-1.18, -0.87] for  $W$ . The median OD of all drivers over all suburban  
 17 tracks is 8.9 meters, so that this can be transformed into meters:  $OD(x, suburban) = 10.7 -$   
 18  $9.1 * W$ , 95% CIs [10.4, 11.0] for the intercept, [-10.5, -7.7] for  $W$ . This gives support for H3:  
 19 road winding has a significant effect on OD as it should if OD is a measure of task-relevant  
 20 event density of the environment. The finding shows that it is possible to estimate the task-  
 21 relevant event density of a driving environment by knowing its task-relevant environmental  
 22 parameters, such as road winding in this particular case.

## 1    **General Discussion**

2     In this paper, we studied the utility of occlusion distance as a function of task-relevant event  
3     density in realistic dynamic driving scenarios with driver-controlled speed and occlusion  
4     times by testing three hypotheses (H1-H3).

5           The fairly short range of mean OTs for the different driving scenarios (670-950  
6     milliseconds) is in the ballpark with the visual sampling model by Wierwille (1993).  
7     According to Wierwille, in most real world self-paced driving scenarios drivers try to keep  
8     off-road glances between 500 to 1,600 milliseconds. OT as well as OD indicated that the  
9     Intersection scenarios were the most demanding (Figure 6), although the mean difference in  
10    OT between the Intersection and Highway scenarios was only 70 milliseconds.

11           However, ODs as well as driving speeds varied considerably more than OTs between  
12    all the scenarios. According to OD, the Intersection scenarios had the highest event density,  
13    followed by Suburban, and then Highway scenarios (means 3.8-9.9-15.5 meters, Figure 6).  
14    These findings give support to our model of OD as a function of task-relevant event density  
15    in space and that by controlling speed according to the experienced event density, the drivers  
16    tend to keep the event rate in time on a similar comfortable range across different driving  
17    scenarios (H1 supported). Near the road speed limits, the OTs for the different scenarios will  
18    be close to each other either because of the built-in scalability of safety margins (and thus,  
19    task-relevant event densities) across different road environments to account for the  
20    corresponding design speeds (FTA, 2013; TRB, 2003) or because the majority of drivers tend  
21    to select a comfortable speed for each road (TRB, 2003; Recarte & Nunes, 2002).

22           The best linear model for OD in the Suburban scenarios proved to be  
23     $OD(x, suburban) = 10.7 - 9.1 * W$ , with  $R^2 = .23$ . The impact of Winding in our model (H3  
24    supported) can be explained by an effect observed by Lehtonen, Lappi, Kotkanen, and  
25    Summala (2013). Anticipatory look-ahead fixations to the winding road ahead seem to play a

1 major role in visual information gathering in curve driving besides tracking the tangent point  
2 of the curve, as in the earlier driving models (e.g., Salvucci, 2006). The more the road is  
3 winding ahead, the higher the event density, that is, the more visual targets have to be  
4 processed in order to ensure a safe path of travel and to track the variable tangent point for  
5 steering.

6 The objective task-relevant event density is not however the only factor behind the  
7 preferred OD level. The current data indicates that OD varies systematically with a nearly  
8 constant individual factor for the same driver across driving scenarios (Figure 9, H2  
9 supported). This finding gives support to the consistency of the subjective uncertainty  
10 acceptance threshold  $U_{max_k}$  in our theoretical model and thus, for the generalizability of OD  
11 across driving scenarios. A driver's maximum level of tolerated uncertainty of the task-  
12 relevant event states is defined by psychological factors.

13 The more experienced drivers were able to achieve more accurate lane-keeping  
14 performance with similar ODs than the least experienced drivers. The road familiarity effect  
15 observed by Mourant and Rockwell (1970) provides an example of learning the task-relevant  
16 event rates for a particular driving scenario with enough repetition (expectancy calibration by  
17 Horrey, Wickens & Consalus, 2006; predictions of system output by Chen and Milgram,  
18 2013). It is thought that novice drivers do not typically possess enough experience of  
19 different driving scenarios for proper evaluation of the situational event rates (Underwood et  
20 al., 2002; Wikman, Nieminen, & Summala, 1998).

21 However, unexpectedly the data did not support the idea of driving experience as a  
22 major factor on the preferred ODs. Better ability to evaluate the task-relevant event rate while  
23 occluded achieved with increasing driving experience can explain the improved lane-keeping  
24 accuracy with the same ODs, but it seems  $U_{max_k}$  cannot be explained fully by the  
25 expectancy evaluation skill. If that was the case, there should have been a more visible

1 difference in ODs between the least and the more experienced drivers according to previous  
2 research (e.g, Horrey et al., 2006). The findings suggest there might be individual differences  
3 in the level of uncertainty tolerated among both the least and the more experienced drivers.

4 Also the experienced high-OD drivers overestimated their capabilities if we assume  
5 that they tried to drive accurately: higher ODs led to lower lane keeping accuracy regardless  
6 of the level of experience (Figure 10). External motives and emotions, such as prizes for the  
7 most occluded drivers in our experiments, can push drivers towards risk-taking (Summala,  
8 1988; Näätänen & Summala, 1974). Only about 10% of the participants were able to drive  
9 with median ODs of 30 meters comparable to J.W.S.' in Senders et al. (1967) in the Highway  
10 scenarios (Figures 1 and 8, Table 2). The study left the question of other relevant individual  
11 factors open for further research.

12 We claim that OD is a function of the subjectively experienced task-relevant event  
13 density of the driving environment. OD does not refer to distance to hazards or headway  
14 distance but varies with the inverse of the spatial density of expected task-relevant events  
15 requiring processing from the driver in order to achieve one's current goals of driving, in  
16 accordance with Wortelen et al. (2013). From the safety point of view, OD is related to the  
17 construct of safety margin (Summala, 1988), but there are also other events that can be  
18 relevant for achieving a subgoal in the driving task, such as noticing the correct exit in order  
19 to find the way to a destination.

20 To summarize, the individual task-relevant event density in space is determined in the  
21 interaction of both environmental factors as well as psychological factors through the level of  
22 uncertainty the driver experiences and tolerates. For any given driver  $k$ , our Suburban model  
23 can be written as  $OD(x,suburban)_k = U_{max_k} * (10.7 - 9.1 * W)$ , where  $U_{max_k}$  is a driver-specific  
24 constant that we interpret here as the subjective uncertainty acceptance threshold.

1           Our tentative model so far focuses on the effects of the environmental factor of road  
2 winding. Even if Winding together with the  $U_{max_k}$ -factor could perhaps explain the observed  
3 differences between the scenarios, these differed in many other aspects as well. Further  
4 research should be done on the effects of relevant environmental factors such as visibility,  
5 weather, signs, and proximity of traffic as well as on building a more accurate model for  
6 predicting ODs in other road environments than Finnish suburban roads.

7           A significant implication of our findings is that our theoretical model enables  
8 predictions. The median OD value of a given road environment can be predicted  
9 approximately, if its Winding is known. Even more importantly, it is possible to predict how  
10 an individual driver with a known uncertainty acceptance threshold  $U_{max_k}$  will respond to  
11 the road environment, and in terms of speed selection, in particular.

12           The other advantage of OD relates to experimental design. Only one drive per driver  
13 with self-determined speeds and OTs is required for mapping the experienced event density  
14 of a road environment for the driver. With this information collected from a large driver  
15 sample, for example, the populations' 85<sup>th</sup> percentile OTs for any speed on the road can be  
16 estimated.

17           This line of work can be utilized in the development of proactive distraction  
18 mitigation systems. The current findings indicate that because of the fairly static OT range  
19 across different driving scenarios, the general 2-second glance limit of acceptable in-vehicle  
20 glance duration (NHTSA, 2013) seems to make sense as the maximum limit for any situation.  
21 There seems to be also a correspondence to the risk limits of individual glance durations  
22 analyzed by Liang, Lee & Yekhshatyan (2012). However, for certain driving scenarios, such  
23 as intersections, two seconds can still be too much, depending on the speed of the car (Figure  
24 6).

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1           For a practical and acceptable proactive distraction warning application, we would  
2 want to define a warning threshold time (WT), that equals the time it takes to travel the  
3 longest distance the majority of drivers would choose to drive comfortably without vision  
4 when fully concentrating on the driving task in an occlusion experiment, that is,  $WT = OD /$   
5 speed. To determine WT, we should use the 85th percentile margin that is a common design  
6 standard in traffic engineering (TRB, 2003). The median OD for the 85th percentile driver for  
7 the Suburban tracks was 14.4 meters. This corresponds to a WT of .86 seconds at 60 km/h. It  
8 is important to note that this WT applies only for the specific scenario used for the  
9 calculation (empty roads, speed limit 60 km/h) and the effect of Winding should be taken into  
10 account.

11           Besides alerting purposes, dynamic WTs could be utilized as appropriate individual  
12 in-car glance limits for any given driving scenario and a driver with a known uncertainty  
13 acceptance threshold  $U_{max_k}$ . These would enable general verification criteria for in-vehicle  
14 infotainment and telematics systems for distracted glancing behaviors with in-car tasks. Other  
15 uses can be found in the domain of human - automated vehicle interactions (Wortelen et al.,  
16 2013), as well as highway and speed design.

17           Time is not the only factor that matters when the driver travels eyes off the road. The  
18 severity of a two second off-road glance depends on the velocity of the vehicle and the task-  
19 relevant event density of the road environment.

20

## 1 Key points

- 2 • Occlusion distance seems to be an informative measure for assessing task-relevant  
3 event density in realistic traffic scenarios with self-controlled speed and occlusion  
4 time.
- 5 • There are systematic differences in the preferred occlusion distances between  
6 individual drivers and driving scenarios.
- 7 • The more experienced drivers were able to achieve more accurate lane-keeping  
8 performance than the least experienced drivers with similar ODs. However, driving  
9 experience does not seem to be a major factor on the preferred ODs.
- 10 • Occlusion distance can be utilized in the development of context-aware distraction  
11 mitigation systems, human - automated vehicle -interaction, road speed design,  
12 prediction of driver speed selection, and in the testing of visual in-vehicle user  
13 interfaces.

14

## References

- 1
- 2 Chen, H.-Y.W. & Milgram, P. (2013). A framework for modelling and analysing variability
- 3 in visual occlusion experiments. *Proceedings of the Human Factors and Ergonomics*
- 4 *Society Annual Meeting 2013*. 1884-1888.
- 5 Finnish Transport Agency (2013). *Tien suuntauksen suunnittelu* (Liikenneviraston ohjeita
- 6 30/2013). Retrieved February 4, 2014, from
- 7 [http://www2.liikennevirasto.fi/julkaisut/pdf3/lo\\_2013-](http://www2.liikennevirasto.fi/julkaisut/pdf3/lo_2013-30_tien_suuntauksen_suunnittelu.pdf)
- 8 [30\\_tien\\_suuntauksen\\_suunnittelu.pdf](http://www2.liikennevirasto.fi/julkaisut/pdf3/lo_2013-30_tien_suuntauksen_suunnittelu.pdf)
- 9 Fuller, R. (2005). Towards a general theory of driver behaviour. *Accident Analysis and*
- 10 *Prevention*, 37, 461-72.
- 11 Furnham, A. & Marks, J. (2013). Tolerance of Ambiguity: A Review of the Recent
- 12 Literature. *Psychology*, 4, 717-728.
- 13 Horrey, W. J., Wickens, C. D., & Consalus, K. P. (2006). Modeling drivers' visual attention
- 14 allocation while interacting with in-vehicle technologies. *Journal of Experimental*
- 15 *Psychology: Applied*, 12, 67-78.
- 16 Kennedy R. S., Norman E. L., Berbaum, K. S & Lilienthal, M. G. (1993). Simulator sickness
- 17 questionnaire: An enhanced method for quantifying simulator sickness. *The*
- 18 *International Journal Of Aviation Psychology*, 3, 203-220.
- 19 Lehtonen, E., Lappi, O., Kotkanen, H., & Summala, H. (2013). Look-ahead fixations in curve
- 20 driving. *Ergonomics*, 56, 34-44.
- 21 Liang, Y., Lee, J.D., & Yekhshatyan, L. (2012). How dangerous is looking away from the
- 22 road? Algorithms predict crash risk from glance patterns in naturalistic driving.
- 23 *Human Factors*, 4, 1104-1116.
- 24 Mourant, R.R. & Rockwell, T.H. (1972). Strategies of visual search by novice and
- 25 experienced drivers. *Human Factors*, 14, 325-335.



- 1 Mourant, R.R. & Rockwell, T.H. (1970). Mapping Eye-Movement Patterns to the Visual  
2 Scene in Driving: An Exploratory Study. *Human Factors*, 12, 81-87.
- 3 National Highway Traffic Safety Administration (2013). *Visual-Manual NHTSA Driver*  
4 *Distraction Guidelines for In-Vehicle Electronic Devices* (NHTSA-2010-0053).
- 5 Näätänen, R. & Summala, H. (1974). A model for the role of motivational factors in drivers'  
6 decision-making. *Accident Analysis and Prevention* 6, 243-261.
- 7 Recarte, M.A. & Nunes, L. (2002). Mental load and loss of control over speed in real driving.  
8 Towards a theory of attentional speed control. *Transportation Research Part F*, 5,  
9 111-122.
- 10 Regan, M.A., Hallett, C., & Gordon, C.P. (2011). Driver distraction and driver inattention:  
11 Definition, relationship and taxonomy. *Accident Analysis & Prevention*, 43, 1771-  
12 1781.
- 13 Salvucci, D.D. (2006). Modeling driver behavior in a cognitive architecture. *Human Factors*,  
14 48, 362-380.
- 15 Senders, J. W., Kristofferson, A. B., Levison, W.H., Dietrich, C. W., & Ward, J. L. (1967).  
16 *The attentional demand of automobile driving. Highway Research Record, No. 195,*  
17 15-33.
- 18 Summala, H. (2007). Towards understanding motivational and emotional factors in driver  
19 behaviour: Comfort through satisficing. In C. Cacciabue (Ed.), *Modelling Driver*  
20 *Behaviour in Automotive Environments* (pp. 189-207). London: Springer.
- 21 Summala, H. (1988). Risk control is not risk adjustment – The zero-risk theory of driver  
22 behavior and its implications. *Ergonomics*, 31, 491-506.
- 23 Summala, H., Nieminen, T., & Punto, M. (1996). Maintaining lane position with peripheral  
24 vision during in-vehicle tasks. *Human Factors*, 38, 442-451.

## VISUAL DEMAND OF DRIVING REVISITED

40

- 1 Thomson, J. A. (1983). Is continuous visual monitoring necessary in visually guided  
2 locomotion? *Journal of Experimental Psychology: Human Perception and*  
3 *Performance*, 9, 427-443.
- 4 Transportation Research Board (2003). *Design Speed, Operating Speed, and Posted Speed*  
5 *Practices* (NCHRP Report 504).
- 6 Tsimhoni, O. and Green, P. (1999). Visual demand of driving curves determined by visual  
7 occlusion. *Proceedings of the Vision in Vehicles 8 Conference* (Boston, MA, August  
8 22-25).
- 9 Tsimhoni, O. and Green, P. (2001). Visual demand of driving and the execution of display-  
10 intensive in-vehicle tasks. *Proceedings of the Human Factors and Ergonomics*  
11 *Society Annual Meeting 2001*, 1586-1590.
- 12 Underwood, G., Chapman, P., Bowden, K., & Crundall, D. (2002). Visual search while  
13 driving: skill and awareness during inspection of the scene. *Transportation Research*  
14 *Part F*, 5, 87-97.
- 15 Wickens, C. D., Helleberg, J., Goh, J., Xu, X., & Horrey, W. J. (2001). *Pilot Task*  
16 *Management: Testing an Attentional Expected Value Model of Visual Scanning*  
17 (ARL-01-14/NASA-01-7). Savoy, IL: University of Illinois, Aviation Research Lab.
- 18 Wierwille, W. W. (1993). An initial model of visual sampling of in-car displays and controls.  
19 In A.G. Gale, I. D. Brown, C. M. Haslegrave, H. W. Kruysse, & S. P. Taylor (Eds.),  
20 *Vision in vehicles IV* (pp. 271-279). Amsterdam: Elsevier.
- 21 Wikman, A.S., Nieminen, T. & Summala, H. (1998). Driving experience and time-sharing  
22 during in-car tasks on roads of different width. *Ergonomics*, 41, 358-372.
- 23 Wortelen, B., Baumann, M., & Lüdtkke, A. (2013). Dynamic simulation and prediction of  
24 drivers' attention distribution. *Transportation Research Part F*, 21, 278-294.
- 25

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7

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