# Visual Complexity of Head-Up Display in Automobiles Modulates Attentional Tunneling

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**Objective:** To investigate how the visual complexity of head-up displays (HUDs) influence the allocation of driver's attention in two separate visual domains (near and far domains).

**Background:** The types and amount of information displayed on automobile HUDs have increased. With limited human attention capacity, increased visual complexity in the near domain may lead to interference in the effective processing of information in the far domain.

**Method:** Near-domain and far-domain vision were separately tested using a dual-task paradigm. In a simulated road environment, 62 participants were to control the speed of the vehicle (SMT; near domain) and manually respond to probes (PDT; far domain) simultaneously. Five HUD complexity levels including a HUD-absent condition were presented block-wise.

**Results:** Near domain performance was not modulated by the HUD complexity levels. However, the far domain detection accuracies were impaired as the HUD complexity level increased, with greater accuracy differences observed between central and peripheral probes.

**Conclusion:** Increased HUD visual complexity leads to a biased deployment of driver attention toward the central visual field. Therefore, the formulation of HUD designs must be preceded by an in-depth investigation of the dynamics of human cognition.

**Application:** To ensure driving safety, HUD designs should be rendered with minimal visual complexity by incorporating only essential information relevant to driving and removing driving-irrelevant or additional visual details.

**Keywords:** attentional tunneling, driving simulation, head-up display, visual complexity

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## INTRODUCTION

A head-up display (HUD) is a transparent display originally utilized in aviation, providing pilots with primary flight, navigation, and other guidance information on a flat piece of glass called a combiner (Hillebrand et al., 2012). It has recently been introduced in the field of automotive technology and emerged as a critical research area. Automotive HUDs superimpose driving-related information into the driver's front field of view on the windshield of the vehicle, allowing drivers to maintain their gaze on the roadway ahead. HUDs have been shown to enhance driver performance and safety by reducing the need to divert attention away from the primary task of driving or by reducing the cost (i.e., time) for information access (Charissis et al., 2008; Horrey & Wickens, 2004). It has been suggested that the use of HUDs effectively minimizes the time and cognitive demands needed to search for appropriate visual information away from the road compared to conventional in-vehicle information systems, such as head-down displays (HDDs), which require drivers to re-accommodate their gaze back to the front view (Hillebrand et al., 2012; Ward & Parkes, 1994).

Recent technological advances in the automobile industry have spurred the widespread use of automotive HUDs. Automobile manufacturers have diversified the HUD layouts by increasing the types of information displayed, ranging from driving assistance, communication, and even entertainment (Park & Im, 2020). Critically, a growing body of research has adopted the visual complexity of HUDs as one major determinant used to evaluate their usability (Burnett & Donkor, 2012; Currano et al., 2021; Park & Im, 2020) and suggested that increased HUD visual complexity significantly overloads a driver's perceptual processing. This is detrimental to effective attention allocation for driving-related information at any moment (Palmer, 1994; Ward & Parkes, 1994).

Inappropriate attention allocation while driving has been studied with a concept called *attentional tunneling* (Mackworth, 1965; Fadden et al., 2000; Martin-Emerson & Wickens, 1997), which describes the narrowing of visual attention due to excessive attentional resources devoted to the central visual field at the expense of the peripheral visual field (Burnett & Donkor, 2012). Wolfe et al. (2019) emphasized that the detection rate of road-related information decreased as the eccentricity of the information increased from the point of gaze. Van Winsum (2018) also showed that the sensitivity of the peripheral visual field decreased as a function of visual load, which indicates that visual load is a possible modulator of tunnel vision. These findings suggest that when driving, the visual load on central vision is negatively correlated with the sensitivity of peripheral detection. Critically, tunnel vision is highly related to the use of HUDs; Liu (2003) found that responses to external, on-road objects were impaired when driver's attention was initially allocated to a HUD, indicating difficulties in attentional disengagement from HUDs. Liu attributed such impairment in performance to "cognitive capture" by HUDs, which arises from the "salient effect" generated by the nonconformal, asynchronous perceptual characteristics of the HUD (Wickens & Long, 1995). Such nonconformal characteristics result from the disparate contrast, transparency, and artificiality of HUD images compared to the scene beyond the windshield. Taken together, the degree of attentional tunneling is possibly dependent on the visual complexity of the HUD images, thus increasing the attentional resources allocated to the central HUD area compared to the outer environment as the visual load of HUD images increases.

Burnett and Donker (2012) used a dual-task paradigm to separately examine the effect of HUD visual complexity on central perception within the HUD (responding to driving-relevant items on the HUD; HUD task) and the peripheral perception outside the HUD (detecting changes of two-dimensional shape targets; peripheral detection task, PDT). They found that increasing HUD complexity, in terms of the number of items presented on the display, elicited a linear increase in reaction time and a decrease in response accuracy in both the HUD task and PDT. It is noteworthy, however, that several questions remain regarding whether the study properly investigated attentional tunneling. First, the two tasks used in the study were based on the perception of items in a unitary visual domain (near domain) which did not require the detection of on-road events outside the vehicle (far domain). According to Wickens and Long (1995), the near domain refers to the displayed imagery superimposed on the windshield or HUD, whereas the far domain refers to the world beyond the windshield (Fadden et al., 1998). Wickens and Long stressed the importance of detection tasks in measuring the detection sensitivity of events in the far domain, which is critically related to driving safety. However, in Burnett and Donkor's experiment the PDT targets were two-dimensional shapes fixed on the screen which belonged to the near domain as HUD images. Therefore, their findings leave the effect of HUD visual complexity on the detection of far domain objects untested.

Additionally, their results regarding PDT performance only imply a decreased sensitivity in peripheral vision, which is conceptually distinct from attentional tunneling. Importantly, according to the "selective filter theory" proposed by Broadbent (1958), human attention has a limited capacity that requires selection to process multiple items. Since attentional tunneling is also a phenomenon due to limited attention capacity, examining the amount of attention allocation directed to the central relative to peripheral fields is necessary. Therefore, PDT performance in Burnett and Donkor's (2012) experiment does not in itself imply attentional tunneling; a comparison between the performances of the central and peripheral detection tasks is necessary (Ringer et al., 2016). Indeed, the central visual field (HUD task) performance was also impaired by HUD complexity in their experiment, thus leaving the tunneling effect even more in question.

Another limitation in previous studies showing the effects of HUD complexity is that rendering a plausible driving scene has been prioritized over strictly controlling the visual components. For instance, in Park and Im's (2020) experiment where an increase of latency in identifying HUD information was observed as a function of the number of HUD items, the background images differed across trials due to the implementation of a realistic driving environment. Visual complexity has been shown to be affected by various features such as the distribution of objects (Schnur et al., 2018), number of items, color variability, and symmetry (Miniukovich & De Angeli, 2014). Therefore, adopting diverse road environments in an experimental setting could have rendered the results vulnerable to the confounding effects of the overall perceived visual complexity apart from the HUD. Considering the delicate nature of visual complexity, visual elements must be carefully selected in the scene and the visual complexity of elements controlled aside from the HUD.

The goal of the present study was to investigate how the use of visually complex HUD modulates attentional tunneling in the far-domain vision of drivers. Defining visual complexity as the number of distinct symbols or items within the display (Burnett & Donkor, 2012; Park & Im, 2020), the level of HUD visual complexity was arranged into five levels as a function of the number of items, including the HUD-absent condition and four different levels of HUD visual complexity. The effects of HUD visual complexity on the near and far domains were examined using a dual-task paradigm. The speed monitoring task (SMT), which required participants to adjust the speed of the vehicle within the speed limit, measured the effect of HUD complexity on the utilization of the task-relevant information (i.e., the current speed of the participant's vehicle and the speed limit) from a HUD (i.e., near domain). The secondary task was the probe detection task (PDT), where participants were required to report sudden changes in stimuli (i.e., road-edge lights) residing in far domain road environments. In the PDT, central and peripheral probes were presented, and the comparison of the detection sensitivities of these probes was conducted to investigate the presence and magnitude of attentional tunneling in the far-domain vision of the drivers.

The experiment was conducted with the expectation that the influence of HUD complexity would be independently reflected in the speed monitoring and probe detection task data. The hypotheses for the two tasks were as follows. [H1] In the SMT, the presence of a HUD would improve participants' ability to continuously monitor and control vehicle speed, which replicates the effectiveness of HUDs observed in previous studies (e.g., Charissis et al., 2008; Liu & Wen, 2004; Smith et al., 2016; Sojourner & Antin, 1990). [H2] Moreover, the SMT performance would not be influenced by HUD visual complexity since attention would be primarily allocated to the current speed display due to task demands. Importantly, however, the performance of the PDT would be significantly modulated by HUD visual complexity, which is the primary interest of the present study. Specifically, the detection accuracy of central probes would remain constant or increase as HUD visual complexity increases. In contrast, the detection of peripheral probes would suffer as the level of visual complexity increases due to the deprivation of attentional resources required for detecting the probes. [H3] Consequently, the current study hypothesizes that the relative difference between the detection accuracies for the central and peripheral probes, which indexes the amount of attentional tunneling, would increase as a function of visual complexity.

## METHOD

### Participants

All participants had normal or corrected-to-normal visual acuity and a valid driver's license, and self-reported to be skilled at driving. Participants with prior experience of using HUDs were excluded to minimize confounding effects from

HUD preferences and familiarity. A total of 66 participants (49 males, mean age = 24.56 years) were recruited and provided their informed consent. A payment of KRW 15,000 (approximately USD 12) was provided for their participation. This research complied with the American Psychological Association Code of Ethics and was approved by the Institutional Review Board at Korea University (KUIRB-2021-0312-01).

## Apparatus

The experiment was conducted in a dimly lit chamber. The virtual environment, stimuli, and responses were controlled using a Unity 2020.3.21f1 (Unity Technologies, San Francisco, CA, USA). Visual stimuli were presented on a 49-inch UHD TV (Samsung, Seoul, Korea). Responses were made using Logitech G29 Driving Force Racing Wheel and Pedals (Logitech International S.A., Lausanne, Switzerland). Engine sound was provided through headphones for an immersive experience in the simulated environment. The participant's sagittal midline, steering wheel, and pedals were aligned to the HDD and HUD, which were positioned on the left side of the screen equivalent to the driver's seat in a typical vehicle. The distance of the accelerator pedal was adjusted for each participant. The viewing distance was approximately 60 cm (Figure 1).

*Figure 1.* An image of the experimental setup. The steering wheel and the accelerator pedals were aligned to the center lines of the HUD and HDD in the display.

## Stimuli

The stimuli for the PDT were road-edge lights, which were installed regularly at 50 m intervals on the left and right sides of the road. The road-edge lights were all turned on in yellow by default (R = 255, G = 255, B = 113) and were specified as probes when turned off (R = 31, G = 31, B = 31). The size of the road-edge lights was 30 $cm^3$ in the virtual environment, which was 0.44° × 0.34° by visual angle on the screen when being turned off.

## Driving environment

The virtual road was 22 m wide and approximately 1.3 km long in the practice block and 6 km long in the main experiment blocks (Figure 2). To minimize confounding effects that arise from the driving scenery's variability, on-road objects and surrounding environments were removed except for streetlights and speed-limit signs. The vehicle followed a predetermined route along the midpoint of the road without the participants' control of the steering wheel, which ensured equally controlled visual angles of the stimuli (i.e., road-edge lights) for all participants. This "steering assistant" setting is comparable to the steering system in Level 3 autonomous driving where vehicles can steer without human input.

## Head-down display (HDD)

Current vehicle speed was displayed by the speedometer indicator position which reflected the amount of pressure on the accelerator pedal. The HDD was rendered by using an open-source three-dimensional sport utility vehicle (SUV) model. The HDD included a speedometer, a tachometer, an engine temperature, and a fuel gauge. The indicators of the speedometer and tachometer were programmed to reflect the amount of pressure on the accelerator pedal. The HDD speedometer was the sole source of information for the current speed of the vehicle in HUD-absent condition.


*Figure 2.* An example image of the experimental display.

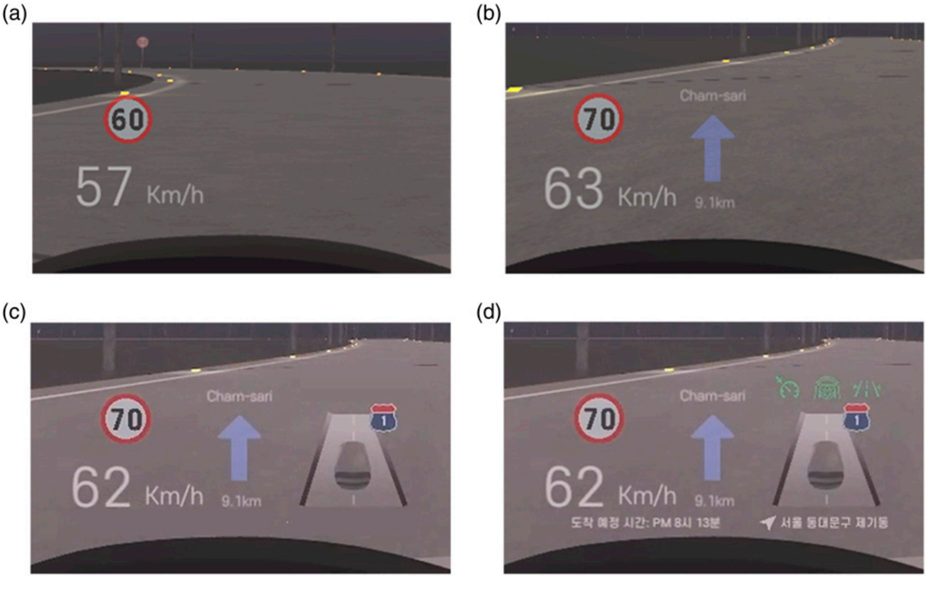


*Figure 3.* Layouts of items in HUD. HUD Level 1 displayed current speed and speed limit information in fixed positions (A). HUD Level 2 displayed navigational information along with the items in HUD Level 1 (B). A road image was added in HUD Level 3 (C). HUD Level 4 added miscellaneous icons and detailed navigational information in letters (D).

## Head-up display (HUD)

The HUD visual complexity was manipulated and categorized into four levels based on the number of items presented in the HUD area (Figure 3). HUD Level 1, the simplest among the HUDs, contained two task-relevant items: current speed limit and current vehicle speed. Notably, the items added in HUD Levels 2, 3, and 4 were all task-irrelevant, hence were not required to process any task-relevant information. The HUD was displayed above the

HDD, with the distance between the lower edge of the HUD (based on HUD Level 4) and the upper edge of the HDD speedometer panel being approximately 2°. The optical distance of HUD was fixed throughout the experiment without collimation, to control the location of HUD. The size of the HUD was approximately 8° × 4° by visual angle, based on HUD Level 4. The position of each item in the display was arranged based on HUD layouts that are currently commercialized by automobile manufacturers (Cho, 2015).

### Procedure

The experiment employed a dual-task paradigm where participants performed the SMT and PDT simultaneously. For the SMT (primary task), participants had to maintain vehicle's speed under the speed limit using the accelerator pedal. Vehicle speed was controlled by the amount of pressure placed on the pedal which was directly reflected in the HUD display and the speedometer in the HDD. Two types (60 km/h or 70 km/h) of speed limits were presented in a block, with an equal length of speed limit zones (sequentially 60, 70, 60, and 70 km/h). Current speed limit was notified by a speed-limit sign (HUD-absent and HUD-present conditions) and on the HUD (HUD-present condition). Participants were instructed to maintain their vehicle speed between 51 km/h and 60 km/h in 60 km/h speed-limit zones, and between 61 km/h and 70 km/h in 70 km/h speed-limit zones.

For the PDT (secondary task), participants had to respond to probe locations. Each pair of left and right road-edge lights was considered as a trial and was planted with virtually equal distance between trials. As participants performed the SMT, the road-edge lights approached closer, and at the moment when the left and right road-edge lights reached approximately 4° to the left and 19° to the right from the driver's midline, respectively, either one, both, or no lights were turned off, indicating a probe. Participants had to respond to the probes as quickly as possible by pressing the corresponding buttons on the steering wheel. For example, when the left road-edge light was turned off, participants had to press the left button with their left hand. Both buttons had to be pressed when both lights were turned off. Critically, the probes on the left side of the road (i.e., left road-edge lights turned off) were considered central probes, because these probes resided within the central visual field of the participant (within 4° in visual angle to one side, Wolfe et al., 2017) close to both the HDD and HUD. Detection of the central probes did not require a shift of gaze nor a shift of attention while performing SMT simultaneously. In contrast, the probes on the right side of the road (i.e., right road-edge lights turned off) were considered peripheral probes because these probes resided in the peripheral vision of the driver, located far from both the HDD and HUD. Detection of the peripheral probes required participants to shift their focus of attention (covert attention; Carrasco, 2011) while keeping their gaze fixed to the HUD to perform SMT. As stated above, a trial could contain either a central probe, a peripheral probe, both probes, or no probes.

Participants were instructed to hold the steering wheel with both hands. The practice block contained two conditions: HDD and HUD Level 1. Each practice block consisted of 60 trials. The experiment consisted of five blocks of 120 trials with each block presented in one of the HUD complexity conditions (HUD-absent, HUD Levels 1, 2, 3, and 4). Each block consisted of 40 central probe trials, 40 peripheral probe trials, 20 both probe trials, and 20 no probe trials, presented in a pseudorandom order. The sequence of the conditions was counterbalanced by adopting a Latin square design. A 60 s break period was provided between blocks.

## DATA ANALYSES

Among the 66 participants, 4 were excluded from the analyses; two participants did not exceed the chance level of accuracy (50%) on PDT, and two others did not follow instructions. After the removal of these participants, the number of participants allocated to each Latin square sequence condition was 12 or 13.

For the SMT, the area under the curve (AUC) of the speed responses was calculated

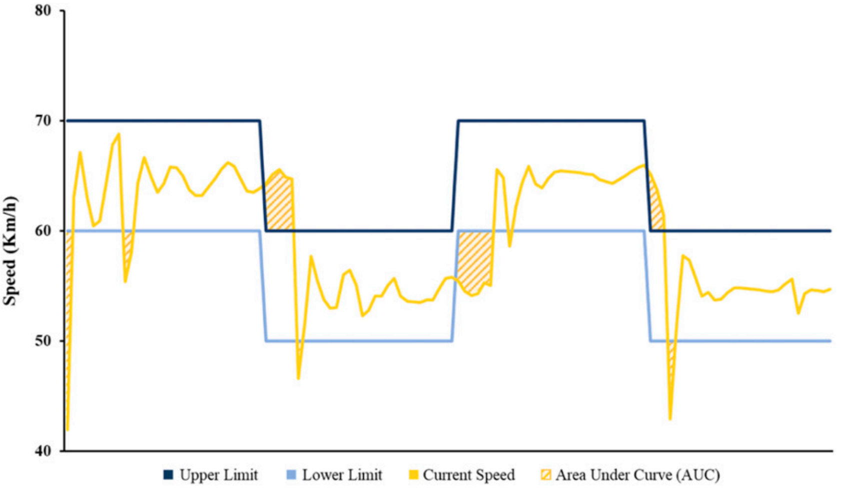


*Figure 4.* Example plot of upper speed limit, lower speed limit, current speed, and area under the curve (AUC; shaded in yellow) based on individual speed monitoring task response.

for each block condition. The AUC was calculated as the degree of deviation of the current speed from the valid speed limit range; a large AUC value indicates an ineffective perception of driving-relevant information (e.g., current speed) in the near domain (Figure 4). The mean AUC was calculated for each participant as a function of HUD complexity (HUD-absent, HUD Levels 1, 2, 3, or 4). One-way repeated-measures analysis of variance (ANOVA) was conducted on the mean AUC to investigate the effect of HUD complexity. Additionally, another one-way repeated-measures ANOVA was conducted using mean AUC data collapsed across the four complexity conditions into a single condition (i.e., HUD-present), to examine whether the presence of HUD benefits the monitoring of the current speed.

For the PDT, response times (RTs) and accuracies of the manual responses were measured. RT was defined as the elapsed time from probe onset (when the light was turned off) to the corresponding button press. Trials that exceeded the valid speed range in SMT were removed from the analyses of PDT performance to ensure participants' concurrent engagement in the dual task (Hibberd et al., 2013; Strobach et al., 2015). Trials with incorrect or no response were marked invalid trials.

The mean correct RT and accuracy were calculated for each participant as a function of probe location (central vs. peripheral), HUD complexity (HUD-absent, HUD Levels 1, 2, 3, and 4), and speed limit (60 km/h vs. 70 km/h). Three-way repeated-measures ANOVAs were conducted on the mean correct RT and accuracy data, using those variables as within-subject factors.

## RESULTS

### Speed Monitoring Task

*Area Under the Curve.* The overall mean AUC was 6.82. The main effect of HUD complexity was not significant, $F$ (4, 244) = 1.946, $p$ = .115, indicating that the performance in the SMT was not affected by HUD complexity (Table 1, Figure 5). Additional analyses comparing the HUD-absent condition and the collapsed data of HUD-present conditions revealed a smaller AUC in HUD-present condition ($M$ = 6.52) compared to the HUD-absent condition ($M$ = 7.99), $F\,(1, 61) = 4.36$, $p = .041$, $\eta_p^2 = .067$, Cohen's $d$ = .265, indicating improved performance with HUD usage.

**TABLE 1:** Mean Area Under the Curve (AUC, With Standard Deviation in Parentheses) as a Function of Presence and Complexity of HUD in Speed Monitoring Task

| | HUD Absent | HUD Present | | | |
|---|---|---|---|---|---|
| | | Complexity Level 1 | Complexity Level 2 | Complexity Level 3 | Complexity Level 4 |
| AUC | 7.99 (5.51) | 6.77 (4.89) | 6.84 (4.70) | 6.44 (4.32) | 6.06 (3.83) |
| Average | | 6.52 (3.03) | | | |

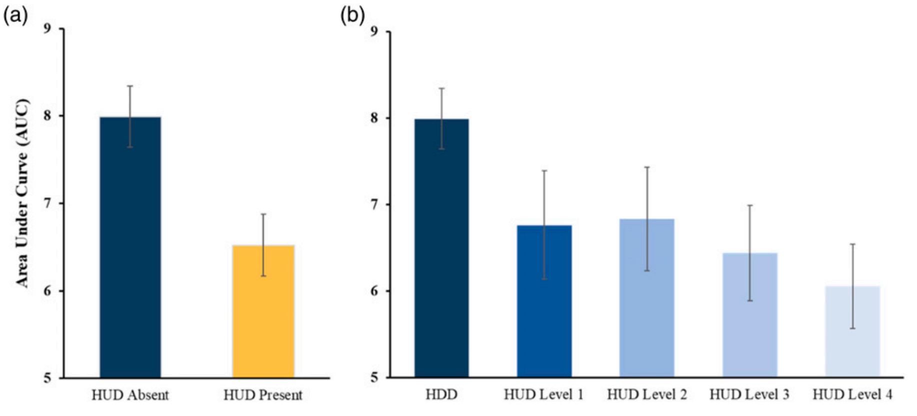


*Figure 5.* Mean area under the curve (AUC) plotted based on individual speed monitoring task response. Comparisons of mean AUC between HUD-absent and HUD-present conditions (A), and between each condition (B). Error bars show within-subjects standard error of the mean (Cousineau, 2005).

## Probe Detection Task

*Accuracy.* The overall accuracy was 91.7%. The main effect of probe location was significant, $F$ (1, 61) = 8.47, $p$ = .005, $\eta_p^2$ = .122, Cohen's $d$ = .368, indicating a higher detection accuracy for central ($M$ = 92.4%) compared to peripheral ($M$ = 91.0%) probes. The main effect of speed limits was significant, $F$ (1, 61) = 63.80, $p$ < .001, $\eta_p^2$ = .511, Cohen's $d$ = 1.014, with the accuracy rate higher in the 60 km/h speed limit zone ($M$ = 92.9%) than in the 70 km/h speed limit zone ($M$ = 90.5%). HUD complexity did not show a significant main effect, $F$ (4, 244) < 1. Importantly, the interaction between HUD complexity and probe location was significant, $F$ (4, 244) = 2.69, $p$ = .032, $\eta_p^2$ = .042, which demonstrates a decreasing trend of detection accuracy for peripheral probes and an increasing trend for central probes, as a function of HUD complexity (Figure 6). Other two-way interactions, or the three-way interaction between HUD complexity, probe location, and speed limit, were not significant.

To further explore the two-way interaction between HUD complexity and probe location, the difference in accuracy between central and peripheral probes (central-minus-peripheral accuracy) within each HUD complexity condition was examined. Pairwise $t$-tests revealed significant differences in all HUD complexity conditions (marginally significant in HUD Level 2) except HUD Level 1 (Table 2). The difference between the central and peripheral probes in HUD Level 1 (0.14%) was not significant, $t$ (61) = 0.27, $p$ = .789, indicating no performance difference between the central and peripheral detection accuracies when using the simplest HUD (see Supplementary Materials for the accuracy differences in HUD-absent condition and HUD Levels 2, 3, and 4).

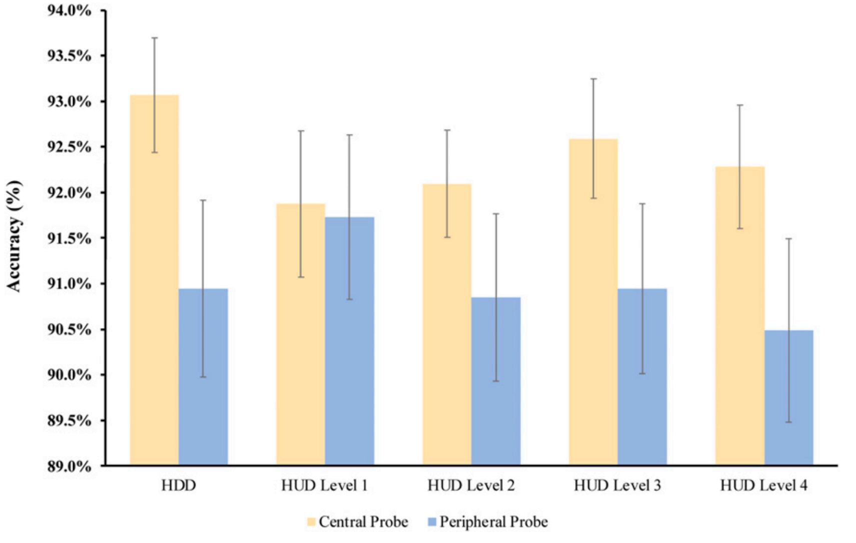


*Figure 6.* Mean accuracy plotted by probe location and HUD complexity in probe detection task. Error bars show within-subjects standard error of the mean (Cousineau, 2005).

**TABLE 2:** Mean Accuracy (in Percentage, With Standard Deviation in Parentheses) for Central and Peripheral Probes in Probe Detection Task as a Function of Presence and Complexity of HUD

| | | HUD Present | | | |
|---|---|---|---|---|---|
| | HUD Absent | Complexity Level 1 | Complexity Level 2 | Complexity Level 3 | Complexity Level 4 |
| Central probe | 93.07 (4.96) | 91.87 (6.32) | 92.10 (4.65) | 92.59 (5.16) | 92.28 (5.32) |
| Peripheral probe | 90.95 (7.63) | 91.73 (7.09) | 90.85 (7.22) | 90.95 (7.34) | 90.49 (7.94) |
| Difference | 2.12 (4.72) | 0.14 (4.23) | 1.25 (5.25) | 1.64 (5.75) | 1.80 (5.10) |

Next, the accuracy differences among the five HUD complexity conditions were compared to investigate how the differences changed as a function of HUD complexity. Pairwise $t$-tests revealed that the accuracy difference between central and peripheral probes in HUD Level 1 was smaller than those in the HUD-absent condition, $t$ (61) = 2.83, $p$ = .006, Cohen's $d$ = .359, HUD Level 3, $t$ (61) = 2.103, $p$ = .040, Cohen's $d$ = .267, and HUD Level 4, $t$ (61) = 2.423, $p$ = .018, Cohen's $d$ = .308. Although small in effect sizes, these significant pairwise comparisons of the accuracy differences demonstrate a sub-linear trend as a function of HUD complexity (Figure 7).

Pairwise comparisons between the detection accuracies of the central and peripheral probes within the both-probe condition also revealed a consistent pattern of results (see Supplementary Materials).

*Reaction time.* The overall mean RT was 924 ms. The main effect of the speed limits was significant, $F$ (1, 61) = 154.45, $p$ < .001, $\eta_p^2$ = .721, Cohen's $d$ = 1.594, showing that the mean RT in the 60 km/h speed limit zone ($M$ = 958 ms) was greater than in the 70 km/h zone ($M$ = 891 ms). There was a speed-accuracy tradeoff since the mean RT was longer with a higher accuracy rate in the 60 km/h speed limit zone, compared to a faster mean RT with a lower

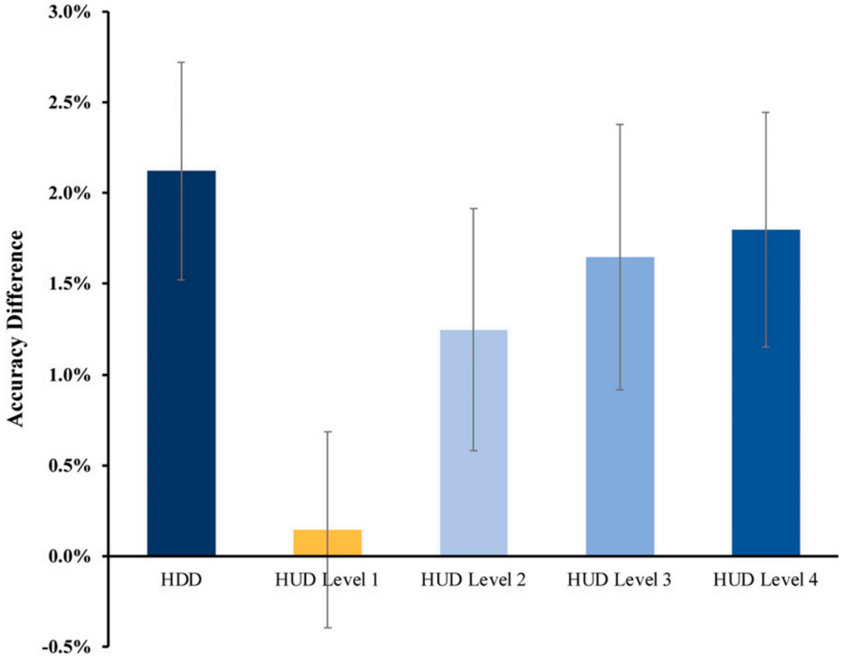


*Figure 7.* Mean accuracy difference between central and peripheral probes as a function of HUD complexity in probe detection task. Error bars show within-subjects standard error of the mean (Cousineau, 2005).

accuracy rate in the 70 km/h speed limit zone. The main effects of HUD complexity, $F$ (4, 244) < 1, and probe location, $F$ (1, 61) < 1, were not significant. Neither the two-way nor three-way interactions were significant in the RT data, $F$s < 1.51, $p$s > .2.

## DISCUSSION

The present study investigated the effect of HUD visual complexity in modulating attention allocation between the central and peripheral visual fields. Specifically, the central probes showed greater detection accuracy than the peripheral probes, indicating an imbalance in attention allocation that was largely biased toward the visual field near HUD. Most importantly, such biased attention allocation, or attentional tunneling, was modulated by the degree of HUD complexity with the accuracy difference between the central and peripheral probes significant in all HUD complexity levels except HUD Level 1, and the amount of the difference increased numerically with visual complexity. These findings are consistent with previous psychophysiological studies demonstrating that visual fields with greater eccentricity were more susceptible to a reduction of sensitivity when foveal load increased (Harris & Fahle, 1996; Plainis et al., 2001; Williams, 1985).

Moreover, the benefit of using HUD over HDD was observed in both the near and far domains. In the SMT, a smaller AUC in the HUD-present compared with the HUD-absent condition indicated that the current speed displayed on the HUD helped drivers adjust their vehicle speed and reduced the gaze shift between the HDD (e.g., speedometer) and the far domain road environments, consistent with H1. In the PDT, the accuracy difference between the peripheral and central probes was also significantly reduced in the simplest HUD compared to the HUD-absent condition. However, the performance benefits of using HUD were offset in the most complex HUD condition, indicating the critical cost of visual complexity in the near domain HUD on far domain detection sensitivity. This cost is also in line with the findings from aviation research, where complex HUDs filled with nonconformal imagery have been found to impair the identification of far domain information by creating a physical and cognitive clutter that masks the far domain environment (Fadden et al., 2000; Martin-Emerson & Wickens, 1997; Ververs & Wickens, 1998). It is also important to note that the items presented on the HUD in the present study were nonconformal imagery, which refers to objects that are asynchronous to the spatial and perceptual characteristics of their far domain counterparts (Wickens & Long, 1995). (See Supplementary Materials for further discussions on "Speed-Accuracy Tradeoff," "Capacity-based Account or Time-shared Account of Attention?", and "Trade-offs of Ecological Validity and Statistical Power in Driving Tasks.")

## DISSOCIATED MODULATION OF NEAR DOMAIN AND FAR DOMAIN SENSITIVITIES

The influences of HUD visual complexity on near and far domain performance were segregated into two different tasks. In the SMT, the processing of task-relevant information within HUDs (i.e., vehicle speed) was not modulated by increased visual complexity, thus showing overall higher performance than provided with only HDD, which supported H2. Conversely, in the PDT, appropriate attentional distribution within far-domain vision was significantly impaired due to attentional tunneling, which accorded with H3. Such discrepant patterns of results imply that, in comparison with near domain visual processing, far domain visual processing is more vulnerable to disturbances in visual attention (Burnett & Donkor, 2012; Van Winsum, 2018), which disrupts adequate cognitive switching between the near and far domains (Prinzel III & Risser, 2004). The current study emphasizes the need to distinctively investigate these two domains of vision by adopting a dual-task paradigm.

## RAISING SAFETY CONCERNS OF USING COMPLEX HUDs

The present study critically implies that the visual complexity of HUDs is a crucial factor affecting driving safety. Attentional tunneling, which was shown to increase when using complex HUDs, draws the driver's attention to the central visual field and thus reduces the attentional resources allocated to the peripheral visual field. Critically, in real-world driving circumstances, a variety of expected (e.g., vehicles, brake lights) and unexpected (e.g., pedestrians, animals) on-road objects demand drivers to concurrently monitor and make rapid-and-adequate responses (Reyes & Lee, 2008). Since these objects usually emerge from the peripheral vision of the driver, the reduced detection sensitivity of peripheral vision implies impairment of such demands, impeding the immediate reactions necessary for the safety of both the driver and those outside the vehicle. Importantly, the current assessments of the attentional capacities as a function of HUD visual complexity were conducted under a completely controlled experimental setting which was free of vehicles, road signs, pedestrians, buildings, or any other objects that are commonly expected in real driving circumstances. Thus, we expect that the attentional modulation of the HUD complexities will be more severe in real driving, with higher burdens on the visual and attentional capacities of the drivers due to more complex environments and the multiple behavioral demands of driving. Moreover, as even a small amount of performance impairment may increase the potential of critical safety issues, we would argue that the current results indicate the importance of minimizing the visual complexity of HUDs. The current study demonstrates that the visual complexity of HUDs should be minimized to a level that incorporates only the information essential to driving (e.g., current speed, speed limit, and navigation) while removing driving-irrelevant information and unnecessary visual details.

## LIMITATION

The present study, while effective in offering caution against the use of complex HUDs, still has limitations that should be considered in future research. One major concern is the small effect sizes observed in the results. Although the two-way interaction between HUD complexity and probe location was found significant, the pairwise comparisons of the accuracy differences between HUD Level 1 and other complexity conditions, as illustrated in Figure 7, were relatively small (Cohen's *d*s < .359). Since the current evaluation of attentional capacity was based on highly controlled visual settings and novel, limited task requirements, it is plausible that the effect of attentional tunneling may exhibit variance when tested under more realistic experimental settings (Nilsson et al., 2018).

An additional concern is the lack of a consistent or linear pattern in the increments of visual complexity among the four different HUD complexity levels. Visual complexity is defined by various features including the number, distribution, color variability, and symmetry of items (i.e., Schnur et al., 2018; Miniukovich & De Angeli, 2014). In the current study, although the additional items increased visual complexity within the HUD area, the level of complexity was not numerically quantifiable due to the mixture of different visual features of the items. A systematic implementation of the visual features that affect complexity levels may open the discussion for a more fine-grained diagnosis of the use of complex HUDs.

## CONCLUSION

A biased distribution of visual attention is a major threat to safe driving that can lead to fatal consequences. The present study demonstrated that the visual complexity of HUDs in automobiles is a key factor resulting in attentional tunneling towards the visual field near HUDs. The results showed that the use of complex HUD increases attentional tunneling, sacrificing the detection of external objects that reside in the peripheral field of the driver's far-domain visions, compared to the central field of the far-domain visions and the near-domain visions. Therefore, the study implies that the visual complexity of HUDs should be minimized by incorporating only the essential information relevant to driving. Moreover, careful deliberation based on the dynamics of human cognition should be reflected in designing future HUDs.

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## KEY POINTS

- The present study examined the effect of HUD visual complexity on the attention allocation within the far domain.
- The asymmetry between the detection accuracies of central and peripheral probes increased as a function of HUD visual complexity.
- The results suggest that visual complexity of HUD is a key modulatory factor for attentional tunneling in driving.

## AUTHOR'S NOTE

The corresponding datasets are available at the Open Science Framework: https://osf.io/m8bzd/

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## SUPPLEMENTAL MATERIAL

Supplemental material for this article is available online.

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