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Modeling Drivers' Visual Attention Allocation While Interacting With In-Vehicle Technologies

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In 2 experiments, the authors examined how characteristics of a simulated traffic environment and in-vehicle tasks impact driver performance and visual scanning and the extent to which a computational model of visual attention (SEEV model) could predict scanning behavior. In Experiment 1, the authors manipulated task-relevant information bandwidth and task priority. In Experiment 2, the authors examined task bandwidth and complexity, while introducing infrequent traffic hazards. Overall, task priority had a significant impact on scanning; however, the impact of increasing bandwidth was varied, depending on whether the relevant task was supported by focal (e.g., in-vehicle tasks; increased scanning) or ambient vision (e.g., lane keeping; no increase in scanning). The computational model accounted for approximately 95% of the variance in scanning across both experiments.

Keywords: visual attention, driving, models of scanning, in-vehicle technologies, driver distraction

In recent years, driver distraction and cell phone use have received considerable attention in the research literature and in the popular media, as well as in several legislative efforts across the U.S. (e.g., Strayer, Drews, & Johnston, 2003). However, there also are growing concerns over new in-vehicle technologies (IVTs), telematics, and "infotainment" devices that offer drivers a wide variety of *visual* information (McGehee, 2001). These IVTs may provide drivers with navigation, traffic and road information, and vehicle status information, as well as many other wireless web or cellular applications. As more IVTs are inserted into the automobile, drivers may use these devices while driving—an obvious safety concern to the extent that these devices compete with driving tasks over limited visual resources (Wickens, 2002). These concerns are well founded, as it is estimated that 25–37% of crashes involve some form of driver distraction or inattention, although these estimates include non-IVT distractions as well (Sussman, Bishop, Madnick, & Walter, 1985; Wang, Knipling, & Goodman, 1996).

In determining the potential dangers of visual distraction from IVTs, the design community and legislative decision-makers may seek input from accident statistics and controlled experiments, though each has its own shortcomings. Accident statistics are often subject to unreliable or incomplete data and can, therefore, lead to unreliable or incomplete interpretations. Furthermore, accidents are frequently the result of several factors and it is therefore difficult to parse out the relative contribution of driver distraction or inattention. Whereas controlled experimentation may address some of these issues (from low- to high-fidelity driving simulators to field studies), this research is often difficult, time-consuming, and expensive. Ideally, designers and lawmakers could examine the extent of visual distraction from IVTs through validated computational models of visual attention, which can be both flexible and cost-effective. Visual scanning models can provide estimates of driver visual behavior while interacting with IVTs as well as estimate the vulnerability of drivers for missing important, safety-critical highway information. Such models, along with data from empirical work, provide the framework for the current research.

Models of Visual Attention

Because vision is the premier resource for highway safety (Hills, 1980), computational models should focus on visual scanning (particularly in-vehicle, head-down scanning) to predict hazard exposure (Horrey & Wickens, 2004b). Visual scan models for supervisory control and visual sampling provide the foundation for our efforts here, although we acknowledge other approaches to modeling driver behavior (e.g., cognitive architectures, Salvucci, Boer, & Liu, 2001). In general, supervisory control models characterize the eye as a *single-server queue* and visual scanning as a means of serving this queue (e.g., Carbonell, 1966; Moray, 1986; Senders, 1964, 1983).

Previous research has examined the role of expectancy and information bandwidth on visual scanning (e.g., Senders, 1964, 1983; Sheridan, 1970). When relevant information from a given information channel or area of interest occurs more frequently (i.e.,

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a higher information bandwidth), observers will tend to sample this channel more often. That is, they will look at particular areas when they expect to find relevant information there. For example, with respect to lane keeping in driving, drivers will compare their current lane position with their desired lane position to determine whether they need to make a corrective input with the steering wheel. The error in position is the information sought by the driver. On a smooth road with no curves or wind turbulence, uncertainty about lane position will grow less rapidly (a condition we would refer to as low bandwidth). In contrast, as the amount of wind turbulence or curvature increases (high bandwidth), so too will the uncertainty about lane position, thus requiring more frequent sampling of information regarding lane position. This coupling of visual scanning has been observed both with information bandwidth in generic visual scanning tasks (Moray, 1986; Senders, 1964), as well as with lane curvature (Tsimhoni & Green, 2001), a variable directly related to bandwidth. For example, Senders (1964) showed that, to effectively monitor a display, it was necessary to sample the display at a rate twice its bandwidth. Moray (1986) later argued that the optimal sampling rate could be equal to the bandwidth. Calibration of drivers' expectations to actual information bandwidth develops with experience. Underwood, Chapman, Bowden, and Crundall (2002) showed that, on more demanding sections of roadway, experienced drivers had more extensive visual scanning than novice drivers (e.g., had more fixations on vehicles in an adjacent lane), suggesting that experienced drivers had a greater understanding of where to expect and seek out relevant driving information (see also Mourant & Rockwell, 1972).

Subsequent scan models have extended Senders' (1964) original model to include the relative *value* of perceiving different information from different sources. For example, Carbonell and colleagues (Carbonell, 1966; Carbonell, Ward, & Senders, 1968) suggested that optimal scanning strategies should attempt to maximize the benefits of perceiving certain information or minimize the costs of missing it. In the context of driving, the potential costs associated with a lane departure impose a high value on attending to information regarding position error. In contrast, missed billboard information has few costs for driving, and hence has a low value for that particular task.

Wickens and colleagues (Wickens, Goh, Helleburg, Horrey, & Talleur, 2003; Wickens, McCarley, Alexander, Thomas, & Zheng, in press) further elaborated on these early models of visual scanning in describing a conceptual model in which the allocation of visual attention to different parts of the visual field is driven by four factors: Salience, Effort, Expectancy, and Value (the SEEV model). Whereas the two latter parameters, Expectancy and Value, are consistent with the Senders (1964) and Carbonell (1966) models, the first two parameters are derived from other models of visual search and visual scanning. The Salience parameter characterizes the conspicuity of information or events that occur within a given information channel and has been a fundamental aspect of models of visual search (e.g., Itti & Koch, 2000). Thus, it can capture differences between a brightly clad and a dark-clad pedestrian against a dark background. And finally, Effort, as manifested by differences in visual angle between information (display) sources, may inhibit visual scanning (Kvalseth, 1977; Sheridan, 1970).

Wickens et al. (2003) validated a computational model based on some of the parameters of the SEEV model in the aviation context. For this model, the expected probability of attending a given area of interest (AOI) is a function of the value of all tasks supported by that AOI, the relevance of the AOI for those tasks, and the bandwidth of task-relevant information in that AOI. Thus, Expectancy is expressed as bandwidth and Value is expressed as the product of relevance and rank priority of the particular task. Wickens et al. (in press) expanded this model to accommodate an Effort component, which reduces the probability of scanning when the necessary effort increases.

Although Salience is an important determinant of the momentary allocation of visual attention, it was not included in the computational model used by Wickens et al. (2003, in press). In contrast to the other parameters, Salience more adequately describes an object or event occurring within a given information channel as opposed to properties of the channel itself. As such, it does not lend itself to the current computational model, which predicts overall probabilities and proportions of scans to different areas of interest. An important feature of the model is that it allows parameter values to be specified a priori, given display constraints and assumed task priorities.

Despite the promise of the SEEV model in predicting visual scanning in driving—in particular, head-down (in-vehicle) viewing time—there are reasons to expect some limitations. In particular, the model characterizes the momentary allocation of focal (foveal) vision and, indeed, most of the tasks used by Wickens et al. (2003, in press) required foveal vision to be completed. However, there are tasks that are well-supported by ambient vision (Leibowitz & Post, 1982; Previc, 1998), so the relevant information does not necessarily need to be fixated in order to be processed. Models (such as the SEEV model) that predict focal visual scanning may not be adequate for those tasks that utilize ambient vision.

Focal and Ambient Vision

Leibowitz and Post (1982) and, later, Previc (1998) distinguished between the focal and ambient visual channels. These systems vary in function, extent, and underlying neurophysiology. The primary functions of the focal visual system are visual search, object recognition, and other tasks requiring high visual acuity, including reading text. Although focal vision can extend beyond the fovea, its strengths are greatest in the fovea. Thus, use of focal vision is tightly linked to eye movements.

In contrast, the ambient visual system is involved in orienting in earth-fixed space, spatial orientation, and postural control in locomotion. While the capabilities of ambient vision are strong in the fovea, they degrade far less with peripheral eccentricity than do those capabilities of focal vision (McKee & Nakayama, 1984). Ambient and peripheral vision are correlated, but not identical, particularly because peripheral vision *can* engage in object recognition (although often degraded; Sekuler & Blake, 1994), while the fovea is actually quite adept at the sort of ego-motion processing characteristic of ambient vision; only this ability does not rapidly degrade with peripheral eccentricity.

Studies have shown that ambient vision can support certain driving tasks, but not others. For example, Summala, Nieminen, and Punto (1996) used a technique known as the *forced-peripheral* *driving* technique, whereby drivers performed the lane-keeping task relying exclusively on ambient vision. Drivers were instructed to remain fixated on different in-vehicle locations and to avoid scanning upward to the outside world. The results showed that experienced drivers could use ambient visual resources to maintain vehicle control (lane keeping), even without fixating directly on the outside world. However, in subsequent work, Summala, Lamble, and Laakso (1998) showed that ambient vision did not effectively support the important driving task of hazard detection. Drivers engaged in the same forced-peripheral technique were asked to detect and brake in response to the slowing of a lead vehicle. Response times rose significantly with increased viewing eccentricity (by up to 2.9 seconds), suggesting that timely hazard detection requires some degree of focal visual resources. Collectively, these studies highlight the dissociation between the driving tasks of hazard response and lane keeping.

Figure 1 presents a conceptual model of the linkages between focal and ambient vision, the SEEV model, and the various driving and IVT tasks to be performed. As shown, focal vision is driven through eye movements by the SEEV parameters to different areas of interest (AOIs), which in turn support different tasks: hazard response, IVT, and navigation/reading road signs. In contrast, ambient vision can directly support the lane-keeping task without necessarily requiring an eye movement. Note also that focal vision can support the lane-keeping task as well.

Summary and Present Research

In the current experiments, we explore various parameters from a model of visual attention, the SEEV model (Wickens et al., 2003), and the extent to which ambient vision use may mitigate the utility of scan measures to predict driver safety. In Experiment 1, we examined the influence of task bandwidth and priority (value) on visual scanning for a given display location. Thus, we were able to assess trade-offs between the expected frequencies of relevant events with their relative importance. In Experiment 2, we explored IVT bandwidth in conjunction with critical road hazard events.

Bandwidth was chosen as a driving variable for several reasons. First, it lies at the core of engineering models of optimal visual sampling theory (e.g., Carbonell, 1966; Moray, 1986; Senders, 1964; Sheridan, 1970), and has some generic task-invariant properties (e.g., expressed in Hz). Second, it underlies two salient influences on the performance of both tracking (Isreal, Chesney, Wickens, & Donchin, 1980; Vidulich & Wickens, 1986) and highway driving (Tsimhoni & Green, 2001): wind gust disturbance inputs and roadway curvature command inputs. Third, previous research has shown that bandwidth influences subjective ratings of task difficulty (Vidulich & Wickens, 1986). Finally, its manipulation will prove to be important in distinguishing processing of ambient from focal vision.

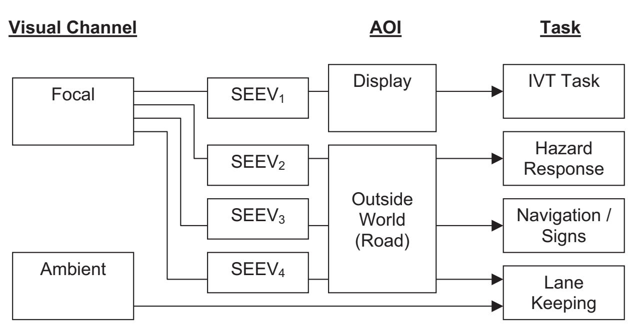

Figure 1. Conceptual model of the links between focal and ambient vision, the parameters of the SEEV model (Salience, Effort, Expectancy, Value), the different areas of interest (AOIs), and the various tasks (1 – 4). IVT = in-vehicle technology.

The objective of the current studies was to examine and try to model focal vision in a high-fidelity driving simulation when both visual systems (focal and ambient) are challenged by changing traffic and IVT information. In doing so, we highlight several key elements: (a) observing driver scanning behavior while interacting with IVTs; (b) observing task interference from a concurrent IVT task; (c) using a high-fidelity driving simulator; (d) probing *both* lane-keeping performance and hazard response; (e) considering the role and limitations of ambient vision for some tasks; and (f) assessing the computational modeling and validation of focal visual scanning behavior. While others have examined several of the underlying elements in isolation or in partial combinations (e.g., Antin, Dingus, Hulse, & Wierwille, 1990; Jamson, Westerman, Hockey, & Carsten, 2004; Salvucci et al., 2001; Summala et al., 1996, 1998; Tsimhoni & Green, 2001; Wickens et al., 2003, in press), no one has combined them in a single experimental paradigm as we do here. Both experiments adopted variations of the fundamental paradigm used by Horrey and Wickens (2004a) in which drivers performed an in-vehicle task on a visual display while driving in a simulator through different traffic environments.

Experiment 1

In this experiment, we examined the impact of the relative value of tasks, supported by a given information source, on visual sampling behavior. We also explored the impact of driver expectations as governed by the bandwidth of IVT and driving information. Drivers in this study performed a task on a visual in-vehicle display while driving in a simulator down a rural highway. To manipulate value in a way that might capture differences in engagement in an in-vehicle task, drivers were offered incentives for prioritizing the driving task, the IVT task, or both tasks. Given the role of task value in previous scanning models (e.g., Carbonell, 1966), we expected that prioritizing a given task would increase the percentage of scans (percent dwell time, PDT) directed toward the area that supports the task (Hypothesis 1).

We also varied the bandwidths of both tasks: the rate of IVT presentation and the frequency of wind turbulence in the driving environment, extrapolating the work of Senders (1964, 1983) to this more realistic environment. Following Senders (1964), we expected that increasing the bandwidth of the IVT task—a focal task—would increase the amount of scanning (PDT) to the IVT display (Hypothesis 2). As noted previously, the frequency of wind maps onto the growth of uncertainty in lane position (Senders, 1983); however, ambient vision can support lane-keeping performance (as shown by Summala et al., 1996). Thus we expected that increasing wind turbulence would have a less powerful effect on scanning than increasing focal-based IVT bandwidth (Hypothesis 3). The single-server model of visual attention would predict a fairly large effect size for our manipulation of bandwidth (e.g., Senders, 1964). Therefore, we consider moderate to large effect sizes ($d > 0.5$) to be of practical significance here. For Hypothesis 3, we expected that wind bandwidth will have a smaller effect size ($d < 0.3$) than IVT bandwidth ($d > 0.5$), with respect to scanning behavior.

Method

Drivers. Eight young drivers from the University of Illinois volunteered for this study (aged 19 to 26 years, $M = 22.1$). This group was composed of 4 men and 4 women. Each participant had a valid driver's license. Mean number of years driving experience was 5.9, and mean annual driving distance was 9860 km (range = 4800 to 14,400 km). All drivers had normal or corrected-to-normal visual acuity. Drivers were paid $8 for each hour of participation and were given a $16 bonus as incentive for good performance for prioritized tasks.

Materials. This study was conducted in the Beckman Institute Driving Simulator at the University of Illinois. The fixed-based simulator consisted of a 1998 Saturn SL sedan positioned in a wraparound environment. Six Epson Powerlite 703C projectors (1024 × 768 pixels of resolution) projected the driving scenes onto separate screens. Both the forward and rear horizontal fields subtended 135° of visual angle. The head-down IVT display was an AEI 6.4" LCD monitor with 640 × 480 pixels of resolution. Eye and head movements were measured using a Smart Eye Pro eye tracker system (Version 3.0.1), which consisted of three Sony XC HR50 monochrome cameras, equipped with two IR-illuminators.

The simulator control dynamics were modeled after a typical four-door sedan and were coordinated through Drive Safety's Vection Simulation Software™ Version 1.6.1. The various driving environments and traffic scenarios were generated using HyperDrive Authoring Suite™ Version 1.6.1. The wind turbulence, IVT task, and other environmental features were coordinated through TCL programming scripts. In-house software was developed to reduce and analyze eye data for the various areas of interest.

Driving environment overview. As shown in Figure 2a, the road was a single-lane rural road with a single opposing lane. We elected to use only straight, level roads, so the bandwidth of the driving task would be determined only by the wind turbulence and not by other factors, such as curvature. Wind turbulence involved a simulated lateral force of 700 to 1200 N (randomly determined) exerted on the vehicle—well within a range of peak forces that has been observed in field studies (Klasson, 2002). The wind turbulence was reflected by changes in visual, but not vestibular, information.

Procedure. At the start of the 2-hr session, drivers completed an informed consent form, simulator sickness questionnaire, and a brief demographic questionnaire. Visual acuity was assessed using a Snellen chart. After being seated in the simulator, adjustments to the seat and mirrors were made to suit the size and preference of the driver. They were introduced to the various components of the simulator. Drivers were then given a short training scenario in order to familiarize themselves with the control dynamics (e.g., steering) of the simulator vehicle.

Following the practice block, investigators built a profile (head model) of the driver for the eye tracker. This process involved taking 40–50 digital photos with the three tracker cameras of the driver looking in different directions. While the driver completed some questionnaires, the investigator manually inserted digital markers in each photo for several visible facial features (e.g., eye and mouth corners, nostrils, ear lobes). The eye tracker software used the cumulative positional information from these markers to build a 3-D head model, allowing the eye tracker to accommodate driver head movements. Following this procedure, drivers were then provided with a brief description of the experimental tasks.

Drivers were asked to perform two concurrent tasks: driving and an IVT phone number task. For the driving task, drivers were asked to keep their vehicle as close to the center of their lane as possible and to maintain a velocity at or near the speed limit (50 mph). Wind turbulence was presented at two different bandwidths: low wind occurred every 5.5 s, on average, while high wind occurred an average of every 2.5 s (with approximately ± 1 s variability around each of these means in order to generate some unpredictability).

The IVT task involved reading and voice-dialing 7-digit phone numbers presented on the head-down LCD screen. The LCD was located near the vehicle's midcenter console (approximately 38° offset from the center of the horizon line; 22° below and 31° to the right) (Figure 2b). The bandwidth of the IVT task was also manipulated. In the low IVT condition, the IVT task was presented approximately every 8.5 s. In the high IVT condition, IVT task information was presented approximately every 4.5 s. As with the wind turbulence, there was some random variability around these two values (approx. ± 1 s). When the digits appeared, drivers were instructed to press a steering wheel-mounted button at the start of their verbal response. New IVT information could replace old, even if they had not yet finished the task. Rapid responses were required in order to perform this task. Finally, we purposely reduced the discriminability (salience) of the digits such that they would be less easily detected with peripheral vision yet would be easily read with focal (foveal) vision. Drivers, therefore, were required to scan often to the display to determine whether new IVT information was available.

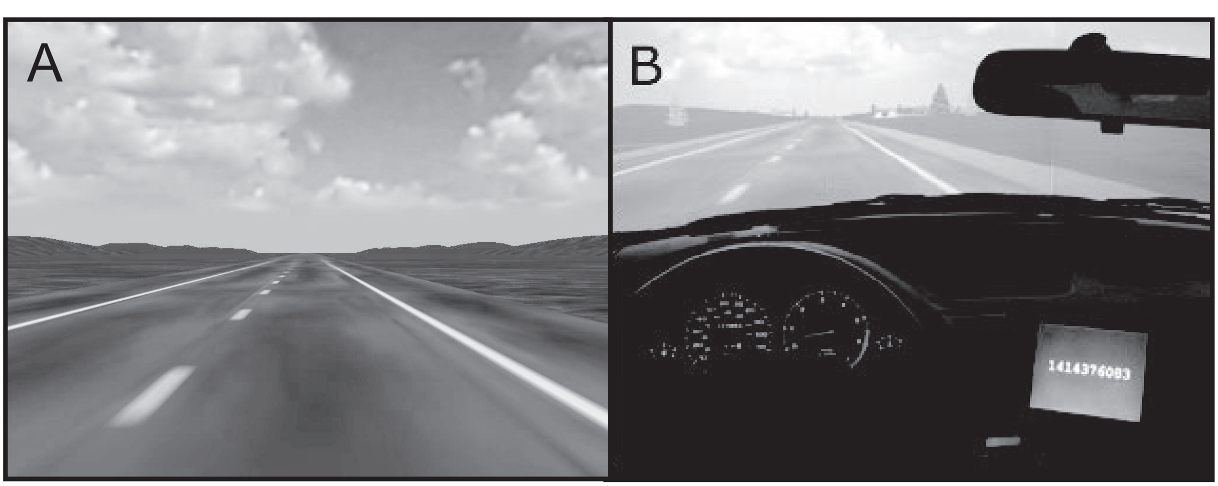

Figure 2. (a) Rural environment used in Experiment 2. (b) in-vehicle technology (IVT) display location.

When the driving task was priority, drivers were told to do their best to keep their vehicle in the center of the lane and to complete the phone number task whenever they felt they could divert attention away from the roadway. When the IVT task was priority, drivers were instructed to respond to the digits as quickly as possible and to return to the driving task only when they had completed the voice dialing task. In equal priority conditions, drivers were told to perform both tasks as best they could. Drivers were instructed that if they were able to prioritize the appropriate task and perform well on that task, they would be eligible to receive a monetary bonus ($16) at the end of the session, in addition to their hourly wage. (All drivers received the bonus following the experiment, regardless of performance.)

Drivers completed a 2-min block for each task combination (12 total) as well as a 3-min baseline block that included single-task driving (low and high wind) and single-task IVT performance (low and high IVT). To facilitate the recall of task priority instructions, drivers performed all the blocks for a given priority together (i.e., in 4-block sets). The order of priority blocks and the individual blocks within each level of priority were counterbalanced across driver. Drivers were offered a 1-min break in between each block (or longer, if needed).

Experimental design. This experiment employed a 3 × 2 × 2 within-subjects design with the variables of priority (driving; IVT; equal), wind bandwidth (low; high), and IVT bandwidth (low; high). Additionally, there were single-task baseline blocks for both driving and IVT tasks that were administered before or after the experimental blocks (counterbalanced across participant). An alpha level of .05 was used for all statistical tests. We note that, across individuals, our dependent measures were not highly correlated with one another (mean absolute r = .11, range = .02 to .25).

Table 1
Performance and Scanning Measures From Experiment 1

Variable and priority condition	Wind bandwidth: Low	Wind bandwidth: High
Variability in Lane Keeping, in m		
Driving	0.34 (0.03)	0.38 (0.04)
Equal	0.40 (0.05)	0.46 (0.05)
IVT	0.43 (0.04)	0.52 (0.04)
Driving alone (baseline)	0.32 (0.04)	0.42 (0.04)
	IVT bandwidth: Low	IVT bandwidth: High
IVT Response Time, in sec		
Driving	1.85 (0.37)	1.54 (0.18)
Equal	1.09 (0.17)	0.97 (0.10)
IVT	0.83 (0.09)	0.69 (0.06)
IVT alone (baseline)	0.76 (0.11)	0.59 (0.05)
Percent Dwell Time to Outside World		
Driving	76.2 (4.4)	70.3 (5.8)
Equal	70.3 (4.0)	60.4 (5.1)
IVT	55.7 (4.3)	42.2 (5.6)

Note. To ease comprehension, these variability in lane keeping values reflect the raw variability data (versus the log-transformed data). Standard errors appear in parentheses. m = meters; IVT = in-vehicle technology; sec = seconds.

Results

Driving performance. Measures of lane position were sampled at a rate of 2 Hz, and the cumulative samples for each trial were used to calculate the variability (standard deviation) in lane keeping. These data are shown in Table 1. Prior to analysis, the variability data was transformed using a log-transformation (Kirk, 1982). The results from a repeated-measures ANOVA, shown in Table 2, revealed significant main effects for priority and wind bandwidth for variability in lane keeping. Tracking performance was greater (i.e., variability was lowest) when drivers were prioritizing the driving task (M = 0.36 m) compared to the equal priority (M = 0.43 m; d = 0.5) and IVT priority conditions (M = 0.48 m; d = 1.1). Also, lane-keeping performance was better in the low wind condition (M = 0.37 m) relative to the high wind condition (M = 0.45 m; d = 0.6). There was no significant effect of IVT bandwidth on lane-keeping performance, or any significant interactions.

IVT performance. IVT response time (IVT RT) was the time from the onset of a digit string until the driver pressed the input button (at the start of their verbal response). These data and ANOVA results are shown in Tables 1 and 2. There was a significant main effect for priority; however, there was no significant effect for wind bandwidth or IVT bandwidth. Responses were fastest in the IVT priority condition (M = 0.76 s) compared to the equal (M = 1.03 s; d = 1.0) and driving priority conditions (M = 1.70 s; d = 1.8).

Eye movement data. For each area of interest, we calculated the percent dwell time (PDT), which represents the proportion of time that the driver spent looking there. In general, scanning to the in-vehicle display was fully complementary to outside world scanning (given that these areas of interest were the only ones that offered task-relevant information; scans to the instrument panel occurred infrequently). Thus, we primarily discuss the proportion of scans to the outside world, shown in Table 1.

The results from a repeated measures ANOVA for scans to the outside world, shown in Table 2, revealed significant main effects for priority and IVT bandwidth. There was a greater proportion of scans to the outside world when driving was prioritized (M = 73%) compared to the equal (M = 65%; d = 0.6) and the IVT priority conditions (M = 49%; d = 1.8). Also, the proportion of scans to the outside world decreased as IVT bandwidth increased (by 10%, on average; d = 0.7). There was also a significant Priority × IVT Bandwidth interaction such that the magnitude of the decrease in outside world scanning from low to high IVT bandwidth was smaller in the driving priority condition (6% reduction; d = 0.3) compared to the other two priority conditions (10–14% reduction; d = 0.7 – 0.8). However, the main effect of wind bandwidth on the proportion of scans to the outside world was not significant (Low, M = 62%; High, M = 63%; d = 0.1). Although we have limited statistical power to observe a meaningfully sized effect for our sample size (~65%), we highlight that this lack of a significant effect is replicated in Experiment 2 (with ~80% power) and in previous work (Experiment 1 from Horrey, Wickens, & Consalus, 2005).

Scan data and performance. In Figure 3a, we plot the mean variability in lane keeping by the mean percent dwell time (PDT) to the outside world for each priority and bandwidth condition. This plot represents a performance–resource function, described by Norman and Bobrow (1975), in showing how lane-keeping performance depends upon the availability of focal visual resources. PDT accounted for approximately 41% of the variance in lane keeping, with increased scanning to the outside world result-

Table 2
ANOVA Results for Variables From Experiment 1

Source	Variability in lane keeping			IVT response time			Percent dwell time (OW)		
	MSE	*F*	*d*	*MSE*	*F*	*d*	*MSE*	*F*	*d*
Priority (P)	0.010	12.5[a],**	0.7	7.41	14.3[a],**	1.3	4918.4	30.1[a],**	1.2
Wind Bandwidth (W)	0.008	101.7**	0.6	0.05	1.6	0.1	67.7	4.7	0.1
IVT Bandwidth (IVT)	0.001	0.5	0.1	0.84	3.2	0.4	2283.0	33.6**	0.7
P × W	0.001	2.2[a]	0.6	0.05	0.8[a]	0.9	35.5	0.8[a]	0.8
P × IVT	0.001	0.8[a]	0.5	0.08	0.3[a]	1.0	113.5	5.1[a],*	1.0
W × IVT	0.001	3.9	0.3	0.24	3.0	0.3	26.2	1.5	0.4
P × W × IVT	0.001	0.01[a]	0.6	0.07	0.8[a]	0.9	39.9	2.0[a]	1.0

Note. Variability in lane keeping data was transformed using a log transformation, $Y' = \log_{10}(Y + 1)$, based on Kirk (1982). Tests of the skewness and kurtosis of the resulting distributions did not reveal any significant departures from normality (see Tabachnick & Fidell, 1996). *df*s are all (1, 7). ANOVA = analysis of variance; IVT = in-vehicle technology; OW = outside world.
[a] $df = 2, 14$.
* $p < .05$. ** $p < .01$.

ing in improved lane-keeping performance. We do note that the covariance in PDT and lane keeping is largely due to task priority (and bandwidth). That is, approximately 68% of the variance in lane keeping (up from 41%) is accounted for when plotting only the means of the different priority conditions. This influence of task value or priority is also evident in our modeling efforts, described later.

Figure 3b plots the performance on the IVT task as a function of PDT on the in-vehicle display. As shown, a logarithmic function accounted for 69% of the variance in IVT RT. We used a logarithmic model fit because the RT data asymptotes at a given point (i.e., performance will not improve beyond a certain level, simply because of human performance limitations).

Discussion

The results from Experiment 1 suggest that drivers are able to effectively prioritize the appropriate task, with enhanced performance on either the driving or IVT task. Improvements in performance were associated with increases in focal visual resource allocation (Hypothesis 1), as indicated by percent dwell time (PDT)—a result that follows from our performance–resource function (Norman & Bobrow, 1975; Figure 3). As the value of the task increases and more resources are invested (as indicated by PDT), performance will benefit. Furthermore, evidence from the scanning data would suggest that the priority schemes for each task are not equal. That is, the outside world (here a proxy for the driving

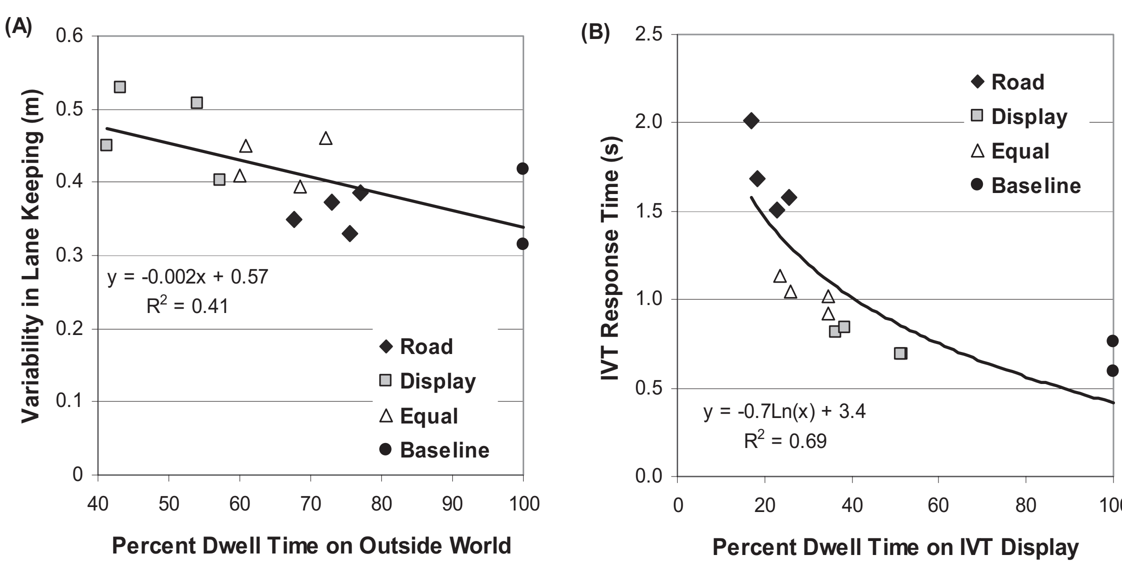

Figure 3. (a) Variability in lane keeping by percent dwell time (PDT) to the outside world. (b) in-vehicle technology (IVT) response time by PDT to the in-vehicle display. Each point represents a different priority, wind bandwidth, and IVT bandwidth condition.

task) almost always receives proportionally more PDT than does the in-vehicle display (IVT task; see Table 1). This fact is reassuring, as a failure to give priority to the driving task can have important safety repercussions, whereas a failure to attend to an in-vehicle task does not likely have such serious repercussions, and speaks to the role of task value in controlling resource allocation.

There was degraded lane tracking as wind turbulence increased; however, there was little evidence to suggest that increasing wind bandwidth increased the amount of scanning to the outside world, contrary to what would be predicted by most optimal scan models (Senders, 1983; Moray, 1986), given the twofold increase in input bandwidths between the low and high wind conditions (Hypothesis 3). We infer that this muting of the effect was due to the role of ambient vision in lane-keeping performance. As shown by others, drivers can still perform a lane-tracking task, even when scanning is prohibited (Horrey et al., 2005 [Exp. 1]; Summala et al., 1996). Thus an increase in wind turbulence may not necessarily require a one-to-one increase in scanning. However, the data indicated that the amount of visual scanning to the IVT display increased with IVT bandwidth, suggesting that this focal task was more consistent with single-server queue models of visual attention (Hypothesis 2).

Thus, in Experiment 1, we showed that task value (as indicated by priority) does impact visual scanning behavior as well as task performance. However, expectancy (as indicated by information bandwidth) may influence visual scanning differentially, depending on the type of task and the extent to which ambient vision may be used to support the task.

Experiment 2

The purpose of Experiment 2 was threefold. First, we introduced critical hazard events, similar to those used by Horrey and Wickens (2004a), as these events are an important consideration when assessing driving performance and safety and predicted to be dependent upon focal vision. We hypothesized that drivers' response times to hazards would be degraded while completing an IVT task and that this loss in performance would be amplified for the more complex IVT tasks (Hypothesis 1). Second, we wished to increase the difficulty of the IVT task by changing the nature of the IVT number task but preserving the visual appearance of the task from Experiment 1. We continued to use digit strings; however, the new task involved processing information from the sets of digits, rather than simply reading them back. We varied the complexity of this task by manipulating the amount of information to be processed (an alternate manipulation of information bandwidth). We anticipated that increasing the complexity of the IVT task would yield a greater proportion of scanning to the in-vehicle display ($d > 0.5$; Hypothesis 2). We also manipulated wind bandwidth, as in Experiment 1. Using the same criterion described earlier, we expected a diluted effect ($d < 0.3$) on scanning (Hypothesis 3). Finally, we used a more realistic traffic setting, with traffic in the opposing lane, vehicles parked by the roadway, as well as buildings and other objects. Thus the cost of a lane departure was increased, relative to Experiment 1.

Method

Drivers. Eleven drivers from the University of Illinois volunteered for this study (aged 19 to 37 years, $M = 25.6$). This group was composed of 6 men and 5 women. Each participant had a valid driver's license. Mean number of years driving experience was 8.9, and mean annual driving distance was 9200 km (range = 2400 to 20,800 km). All drivers had normal or corrected-to-normal visual acuity. Drivers were paid $8 for each hour of participation.

Materials. This study was conducted in the Beckman Institute Driving Simulator at the University of Illinois. The hardware and software were the same as in Experiment 1.

Driving environment overview. The road used in this experiment was a single-lane, light industrial city road with a single opposing lane. The road environment included some buildings and a limited number of parked vehicles on the side of the roadway (approximately 9–10 per km of roadway). Additionally, there was some traffic in the oncoming lane of travel at an approximate rate of 5 per km of roadway. There was no traffic in the drivers' lane. As in Experiment 1, we elected to use only straight roads with the same levels of wind (low; high).

Critical hazard events. We included several hazard events that replicated some of those employed by Horrey and Wickens (2004a). At various points along the roadway, a pedestrian, animal (dog), bicyclist, or vehicle encroached upon the simulator vehicle's path from behind a parked car, at a constant speed of 2.7 m/s. In each instance, drivers had approximately 2.5 seconds to respond and avoid a collision. This time afforded drivers sufficient time to maneuver safely, yet was still urgent enough to require a timely detection and response. The synchrony of these events was controlled by time-based triggers, which factored in the speed of the vehicle to keep the timing constant across individuals and occurrences. The frequency of these incursions was limited in order to reduce the driver's expectancies (i.e., 6 discrete hazards across 8 blocks).

Procedure. The preexperimental questionnaires, test of acuity, practice blocks, IVT display location and appearance, and levels of wind turbulence for this 70-min experiment were the same as for Experiment 1. We wished to preserve the visual appearance of the IVT task, so we continued to use numerical stimuli. However, we changed the task by asking drivers to determine whether there were more odd numbers or more even numbers presented in a string of digits presented on the IVT display. Thus, drivers had to extract their responses from the presented digits, rather than simply read them out. The digit strings were either 5-digits (simple condition) or 11-digits long (complex condition). The IVT task was presented on the head-down display approximately every 8.5 ($\pm$ 1) s. Drivers were instructed to press a steering wheel-mounted button to indicate their response (one button for "Odd" and one for "Even"). For example, '58632′ has more even digits and '39482937652′ has more odd digits. Strings were generated randomly, with the constraint that the difference in total odd and even digits needed to be $\pm$ 1, thereby forcing perceptual processing of nearly all the digits in the string on every trial. New IVT information could replace old, even if they had not yet finished the task. Rapid responses were required in order to perform this task.

The experiment comprised eight experimental blocks, each lasting approximately 3 min. Drivers were offered a 1-min break in between each block (or longer, if needed). Drivers completed each task combination twice (at both levels of wind bandwidth and IVT task complexity). These blocks were counterbalanced across participant. For each of the first two blocks, there was no critical hazard event. However, in each of the final 6 blocks there was a critical hazard event at a random location in the drive and often in conjunction with an IVT task (simple or complex). For all blocks, drivers were instructed to do both tasks as best as they could (the same as the equal priority condition in Experiment 1).

Experimental design. This experiment employed a 2 $\times$ 2 within-participants design with the variables of wind bandwidth (low; high), and IVT complexity (simple; complex). An alpha level of .05 was used for all statistical tests.

Results

Driving performance. As in Experiment 1, the variability data for lane keeping was log-transformed prior to analysis (Kirk,

Table 3
Performance and Scanning Measures From Experiment 2

Variable and IVT complexity	Wind bandwidth Low	High
Variability in Lane Keeping, in m		
Simple	0.35 (0.01)	0.40 (0.02)
Complex	0.43 (0.02)	0.47 (0.03)
Hazard Response Time, in sec		
Simple	1.61 (0.17)	1.51 (0.56)
Complex	1.73 (0.70)	1.87 (0.46)
IVT Response Time, in sec		
Simple	3.26 (0.28)	3.29 (0.25)
Complex	5.62 (0.29)	5.53 (0.31)
Percent Dwell Time to Outside World		
Simple	67.0 (3.5)	66.7 (3.4)
Complex	49.0 (3.2)	49.6 (3.5)

Note. To ease comprehension, these variability-in-lane-keeping values reflect the raw variability data (versus the log-transformed data). Standard errors appear in parentheses. IVT = in-vehicle technology; m = meters; sec = seconds.

1982). However, the pretransformed data are shown in Table 3. A repeated-measures ANOVA for variability in lane keeping, shown in Table 4, revealed that: (1) tracking performance was better when drivers were completing the simple IVT task ($M = 0.38$ m) compared to the complex task ($M = 0.45$ m; $d = 1.2$); and (2) high wind bandwidth ($M = 0.44$ m) disrupted lane keeping more than low wind bandwidth ($M = 0.39$ m), with an effect magnitude ($d = 0.7$) that was similar to the analogous condition in Exp. One ($d = 0.6$). There was no significant interaction between IVT complexity and wind bandwidth.

For the critical hazard events, we measured response time (hazard RT) from the onset of the hazard event until the initial maneuver response, whether braking or steering. Response times are shown in Table 3. Hazard responses did not differ across the different types of hazards. Contrary to our expectations, a repeated-measures ANOVA for log-transformed hazard RT values, shown in Table 4, did not reveal any significant effects. This may have been due to the relative few hazard events and low N involved in these comparisons. We estimate that, for our sample size, we had only 32% statistical power to observe an RT difference of 150 ms.

Although we attempted to have some hazard events coincide with IVT tasks and some to occur in between tasks, we cannot automatically assume that the driver was or was not engaged in the IVT for any given hazard (e.g., some drivers were looking upward during IVT intervals while others were looking down when no IVT information was available). Therefore, we decided to examine the eye data to determine (a) where the eyes were fixated at the onset of the hazard events and (b) if the eyes were initially directed toward the in-vehicle display, how long before they returned to the outside world. In Figure 4, we plot hazard RT performance as a function of the time until the eyes returned to the road. A time of zero indicates that the eyes were on the road when the event occurred. Each data point represents a unique hazard event for one subject.

First, we note that the time until the outside world is fixated accounted for 66% of the variance in hazard RT. This offers more evidence that ambient vision is not sufficient for the effective detection of hazard events (e.g., Horrey & Wickens, 2004a; Summala et al., 1998). Otherwise, we might expect no relationship between the two variables. However, the slope of the overall function (0.48) is significantly less than 1 (95% CI: 0.39, 0.58), suggesting that some processing of the hazard must occur with ambient vision. Otherwise, we might expect that every x-second delay in upward scan would produce a corresponding x-second delay in hazard response (echoing single channel theory, Pashler, Johnston, & Ruthruff, 2001). (Applying a correction for attenuation due to measurement error yields an adjusted slope of 0.64 (95% CI: 0.51, 0.76) (e.g., Trochim, 2000).)

IVT performance. IVT response time (RT) was the time from the onset of a digit string until the driver pressed the input button. These data are shown in Table 3. A repeated measures ANOVA for IVT complexity and wind bandwidth, shown in Table 4, revealed a significant main effect for complexity ($d = 2.5$), however not for wind bandwidth.

Eye movement data. The percent dwell times (PDT) to the outside world are shown in Table 3. A repeated measures ANOVA revealed that increasing IVT complexity reduced outside world scanning (by 18%, on average; $d = 1.6$; see Table 4), with more scans being directed toward the display and away from the roadway. As in Experiment 1, there was *no* significant effect of wind bandwidth (low and high, $M = 58\%$; $d = 0.01$), nor a significant interaction between the two variables. As noted previously, we estimated an approximate 80% statistical power to observe a meaningful effect size for these comparisons, given our sample size.

Table 4
ANOVA Results for Variables From Experiment 2

Source	Variability in lane keeping *MSE*	*F*	*d*	Hazard response time *MSE*	*F*	*d*	IVT response time *MSE*	*F*	*d*	Percent dwell time (OW) *MSE*	*F*	*d*
IVT Complexity (IVT)	0.005	26.0**	1.2	0.25	3.1	0.5	58.00	143.40**	2.50	3368.0	188.90**	1.60
Wind Bandwidth (W)	0.002	19.0**	0.7	0.02	0.2	0.1	0.01	0.04	0.03	0.3	0.03	0.01
IVT × W	0.001	0.2	0.9	0.29	3.7	0.3	0.04	0.45	1.20	2.3	0.49	0.80

Note. Variability-in-lane-keeping data was transformed using a log transformation, $Y' = \log_{10}(Y+1)$, based on Kirk (1982). Tests of the skewness and kurtosis of the resulting distributions did not reveal any significant departures from normality (see Tabachnick & Fidell, 1996). *df*s are all (1, 10); ANOVA = analysis of variance; IVT = in-vehicle technology; OW = outside world.
** $p < .01$.

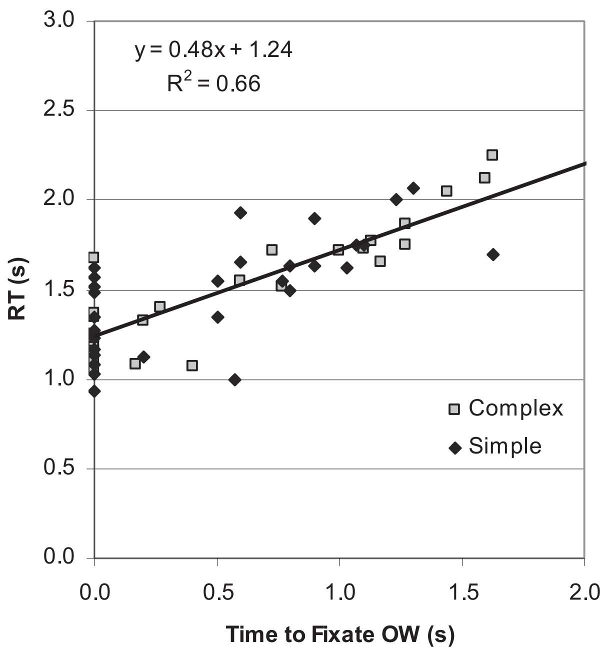

Figure 4. Scatter plot of hazard response times (RTs) by the time, from the event onset, until the eyes fixated the outside world (OW) for both the simple (diamonds) and complex (squares) in-vehicle technology conditions. Zero-time indicates that the eyes were already on the outside world when the event occurred. The regression equation includes these zero-time points.

Discussion

As in the previous experiments, increasing road turbulence degraded lane-keeping performance. Also, increasing the complexity (bandwidth) of the IVT task increased tracking error—in contrast to Experiment 1. This new effect of IVT bandwidth is associated with a *transfer* of visual attention from the road to the IVT display with increasing IVT complexity (Hypothesis 2). Performance of the IVT task worsened as its complexity increased; however, when the RTs are corrected for the number of information bits processed, we note that responses to the complex IVT are more efficient than in the simple condition (simple = 0.66 s/digit vs. complex = 0.51 s/digit).

In Figure 4, we explored the relationship between hazard response and visual scanning. When drivers were looking at the roadway, they responded to the hazard in 1.25 seconds, on average—a value that is consistent for unexpected, surprise events (Green, 2000). When the eyes are initially diverted from the roadway, hazard response time is degraded (Hypothesis 1) and there is a positive relationship between the time until the eyes move upward and the response time, suggesting the role of focal vision. However, the slope of this relationship is less than 1, the value that would be predicted by a strong single channel bottleneck theory, suggesting that there is some processing of the hazard event with ambient vision before the eyes reach the road. We speculate that this involves the processing of the lateral motion of the hazard in the periphery (Tynan & Sekuler, 1982). Thus, ambient vision is involved in some aspect of hazard detection (see Figure 4), though focal vision may be required to correctly identify and respond to the hazard object (e.g., Summala et al., 1998).

As in Experiment 1, there was little evidence of an effect of increasing wind bandwidth on the amount of driver scanning behavior (Hypothesis 3; power ~80%), suggesting that ambient vision is contributing to lane keeping, even with the addition of other traffic elements and potential obstacles. However, as IVT complexity increased (bandwidth as measured in bits/sec rather than events/sec), drivers spent more time looking at the display (Hypothesis 2).

In the following section, we discuss the application of the SEEV model to the current experiments, examine how well it predicts scanning, and discuss its limitations with respect to the current data as well as for the general application to the driving context.

Modeling Visual Attention

Our objective in this section was to determine the extent to which percent dwell time (PDT) from the various conditions across all experiments could be predicted by a variant of the SEEV model.

We used the following formula to predict the likelihood of scanning to a particular area of interest (AOI; adapted from Wickens et al., 2003, in press):

$$P(AOI_j) = \sum_{t=1}^{n} [(B_t)(R_t)(P_t) - Ef_t] \qquad (1)$$

where t = task, B = information bandwidth, R = relevance, P = priority, and Ef = effort associated with accessing the AOI. In this formula, Expectancy is expressed as information bandwidth and Value is expressed as the product of Relevance and Priority. This equation allows a given AOI to contribute to multiple tasks. However, in our application, each AOI supports only one task (i.e., outside world—driving; in-vehicle display—IVT task). As noted in the Introduction, Salience is a property of specific events that occur in a given AOI and not of the AOI itself; therefore, we do not include it in the current computational model. Because there were only two areas of interest in these experiments, and the location of the display was never manipulated across condition, it was impossible to examine the influence of the Effort parameter in the model. The coefficient value for this parameter remains null in the model. (see Horrey et al., (2005) for application of the effort parameter to driving, where only 5% of the variance in scanning was accounted for by effort.)

In general, we derived the values for the model coefficients a priori using well-specified rules. That is, we adopted a lowest ordinal algorithm to assign values, rather than attempting to estimate absolute values (Wickens et al., 2003). This procedure involves the rank ordering of the different task conditions and AOIs along the model parameters. For example, we considered vehicle control to be more valuable (in terms of safety) compared to any IVT task. Therefore, the value of these tasks may be represented by 2 and 1 along the priority parameter, respectively. Similarly, increasing bandwidth conditions may be ordered 1, 2, . . . , n. The advantage of this approach is that the relationships are relatively simple, can often be easily agreed upon, and can be established prior to any formal experimentation.

Table 5 shows the parameter values for the various conditions in Experiments 1 and 2. Using these values, each AOI within each

Table 5
Coefficient Matrix Used for Computational Model for Experiments 1 and 2

	Expectancy (bandwidth)				Value (priority)			Relevance	
AOI	Mech.	Low	High	Effort	Driving	Equal	IVT	Driving	IVT
Experiment 1									
OW	Wind	2	3	0	4	3	2	1	0
Display	IVT	1	2	0	1	2	3	0	1
Experiment 2									
OW	Wind	1	2	0	—	2	—	1	0
Display	IVT	1	2	0	—	1	—	0	1

Note. AOI = area of interest. OW = outside world. Mech. = mechanism for changing bandwidth. IVT = in-vehicle technology. Values for the effort parameter are zero because we were modeling only two AOIs and we did not manipulate in-vehicle display location in these experiments. For Experiment 1, both wind and IVT bandwidth could be expressed in Hz and these values were the same for the high IVT and the low wind. Therefore, these conditions were given the same coefficient (thus, the overall 1-2-2-3 ordering of bandwidths across both tasks). In contrast, for Experiment 2, wind and IVT bandwidth could not be directly matched by frequency (Hz; since IVT bandwidth was manipulated by complexity), so we rank ordered each task separately (1–2). For the priority coefficients in Experiment 1, we started with a 2-1 (OW-Display) rating for the equal condition (same as shown for Experiment 2). We then added or subtracted 1 with increasing or decreasing priority levels (e.g., Driving priority *and* OW = +1). This process left us with one cell with a zero-value in it (driving priority and Display AOI), so we added +1 to each of the six priority coefficients to avoid this null value, but still preserving the order of coefficients.

condition received a total score derived from Equation 1. This score was then weighted against the sum total for all tasks and conditions and expressed as a proportion of the total dwell time. This was the predicted proportion of dwell time.

Table 6 shows the model fits (in terms of r^2) for various iterations of the model. The data from Experiment 1 provided us with the greatest number of conditions and data (i.e., the greatest statistical power in a correlational model validation assessment). For this experiment, there was a high correlation between predicted and actual PDT (r = .98), accounting for 97% of the variance. Following procedures used by Wickens et al. (2003), we examined two iterations of this model to determine the extent to which a simpler model, with fewer parameters, could account for the data. A one-parameter model with only information bandwidth (Expectancy), with all other values set equal, accounted for 63% of the variance in PDT. A model, based only on Value (product of Priority and Relevance), accounted for 74% of the variance. Finally, we randomized the coefficients in the model to ensure that our ordered assignments would outperform other haphazard models. The average r^2, based on 20 random models, was only .05, suggesting that our ordered assignment of coefficient values was contributing to the observed models.

Table 6
Model Fits (r^2 Values) for Experiments 1 and 2

	Full model[a]	Expectancy alone	Value alone[b]	Random[c]	Individuals[d]
Experiment 1	.97	.63	.74	.05	.71–.97[e]
Experiment 2	.92	.20	.73	.06	.52–.94

[a] Includes Expectancy and Value parameters (recall that Effort is null here). [b] Value is the product of the coefficients for Relevance and Priority. [c] The average r^2 value for 20 iterations of the model using randomized coefficients. [d] The range of model fits for individual observers. [e] We exclude one individual (of 8) from this range, for whom the model fit was r^2 = .03 (see text for more details).

For Experiment 2, there was a strong correlation between predicted and actual PDT (r = .96), accounting for 92% of the variance. As shown in Table 6, a model based on Value alone accounted for 73% of the variance in PDT, while a model based on Expectancy alone accounted for only 20% of the variance. The average r^2 for 20 randomized models was .06.

Also shown in Table 6 is the range of model fits for each individual's data, as opposed to the aggregated data described above. For Experiment 1, the r^2 values for the full model ranged from .65 to .93, with one exception. For a single driver, the model did poorly in predicting scanning (r^2 = .03). This particular driver showed the biggest disparities in scanning compared to the other drivers, coupled with the best overall performance on the IVT task and the second-to-worst performance in the lane-keeping task. This pattern of results suggests that this driver may have been overprioritizing the IVT task relative to the driving task, perhaps a function of the simulated environment—a fact that would account for the poor performance of the model, based as it is on the optimal allocation prescription of expected value theory. For Experiment 2, the range of individual's model fits (r^2) was .52 to .94.

In the following, we describe how our findings relate to the SEEV model of (focal) visual attention. In particular, we ask which aspects of the computational model function effectively in the driving context, and which ones break-down—especially in light of the contribution of ambient vision to certain tasks (see Figure 1).

Summary and Limitations of SEEV

For both experiments, task value, here a proxy for area of interest (AOI; since AOI was uniquely mapped to a single task) was the strongest predictor of scanning behavior. For tasks that had a high associated value, drivers tended to scan to the appropriate area more frequently, at the expense of other areas. This positive relationship between the value of a particular AOI and the amount of scanning to that area is consistent with previous research (Carbonell, 1966; Moray, 1986; Wickens et al., 2003). The contribution of value was seen both in the explicit priority manipulations, as well as in the implicitly greater value of the outside world scanning (for the driving task) than IVT scanning, as reflected by the higher proportion of glances to the former.

In the current experiments, increasing IVT bandwidth, through frequency (Experiment 1) or complexity (Experiment 2), had a more significant effect on scanning behavior than increasing wind bandwidth, drawing a greater proportion of scans to the IVT display—a difference attributable to the greater linkage to focal visual attention. Because of the role of ambient vision in lane-keeping performance, changes in wind turbulence (at least across the levels used here) did not necessarily require a differential allocation of focal visual resources—to the extent that would be predicted by the single-server queue model (Senders, 1964), given the twofold increase in input bandwidths between the different wind conditions. The challenge for modeling is that focal vision is tied strongly to scanning behavior, whereas ambient vision is not. Muting the roadway bandwidth parameter (in the current application) may be a means of tweaking the model to account for tasks that are supported by ambient vision.

We do note several limitations in the current modeling efforts. First, there were limited data points available for Experiment 2, which may have artificially inflated the model fit. We do note, however, that Experiment 1 produced a similar fit, while contributing three times as many data points and covering a wider range of values for percent dwell time (PDT). Second, we did not manipulate the location of the in-vehicle display (i.e., Effort) in the current experiments. Thus, we were unable to assess the influence of the Effort parameter in the model. However, we do highlight the strong model fits without this variable and point to previous work in which the contribution of Effort was found to be minimal (Horrey et al., 2005; Wickens et al., in press). It is possible that the inhibitory effects of Effort on scanning do not manifest themselves until some distance threshold is met or until concurrent task load becomes excessive (Recarte & Nunes, 2000). Finally, the current application of the computational model does not account for the Salience parameter. As noted previously, the model captures the characteristics of areas of interest (AOI), as opposed to objects or events within the AOI, which tend to be characterized by the Salience parameter.

General Discussion

The purpose of the current experiments was to examine how characteristics of a simulated traffic environment and in-vehicle tasks impact driver performance and visual scanning. Furthermore, we wished to determine the extent to which a computational model of visual attention, based on objective characteristics of the to-be-performed tasks, could predict scanning behavior, and the extent to which scanning modulates two qualitatively different aspects of driving performance: hazard monitoring and lane keeping. While several studies have explored these issues, the totality of this link between scanning, computational modeling, and the two aspects of driving have not been combined before and examined in a realistic driving simulation. In the following, we describe the implications from the current work as well as the general limitations.

Implications

The most important practical implication of the current results is that a simple expected value version of the SEEV model provides a plausible and effective predictive model of scanning in driving. When coupled with further validation, designers may be able to use this model to predict the allocation of visual attention in different highway conditions and thereby predict vulnerability to missing roadway hazards. This is especially important as IVTs become more and more prevalent in automobiles (Ashley, 2001).

A key element of the current results, of both theoretical and practical significance, is the dissociation underlying the two visual systems represented in Figure 1. Performance on tasks dependent on focal vision (e.g., IVT and hazard response) was linked to visual scanning, and this, in turn was well modeled by existing optimal scanning models. In contrast, for those tasks that are less dependent upon focal vision and that can be supported by ambient vision (e.g., lane keeping), visual scanning (focal visual resources) was less of a mediating factor in performance (Figure 3a) and the information bandwidth of that task had little effect on scanning, even as it did affect tracking performance. This strong pattern of dissociation has implications for the sole use of either scanning or lane keeping as indices of driver safety. Both should be examined in conjunction. While SEEV is an incomplete model of visual input for safe driving, it may nevertheless be argued that the aspect of driving to which it is most closely linked, hazard response, may be considered the most relevant for driving safety.

General Limitations

From the current set of studies, we highlight some factors that may limit our ability to generalize these results to real world driving. First, our IVT task was simplistic, capturing some aspects of information acquisition and voice-entry (Experiment 1) as well as some aspects of information processing (Experiment 2). However, with real world IVTs, drivers will likely interact with text (e.g., email) and graphical or pictorial material (e.g., maps; Tsimhoni & Green, 2001). We believe that this material can also be characterized quantitatively along the parameters of the SEEV model, as we have done in the current studies. Second, although our manipulation of wind frequency maps onto Senders' (1983) notion of information bandwidth, there are other factors that may impact bandwidth as well, such as road curvature or traffic density. Furthermore, we note that the real traffic environment will be subject to all of these different types of information contributing to bandwidth. It is unclear whether multiple information bandwidths within a single channel would increase, cumulatively, the amount of time that the eyes are directed outside or whether the eye behavior will be impacted by the dominant bandwidth alone. Other manipulations of bandwidth and combinations of task-relevant information should be the focus of future research endeavors.

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