Glass half-full: On-road glance metrics differentiate crashes from near-crashes in the 100-Car data

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A T R I C L E  I N F O

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A B S T R A C T

Background: Much of the driver distraction and inattention work to date has focused on concerns over drivers removing their eyes from the forward roadway to perform non-driving-related tasks, and its demonstrable link to safety consequences when these glances are timed at inopportune moments. This extensive literature has established, through the analyses of glance from naturalistic datasets, a clear relationship between eyes-off-road, lead vehicle closing kinematics, and near-crash/crash involvement.

Objective: This paper looks at the role of driver expectation in influencing drivers’ decisions about when and for how long to remove their eyes from the forward roadway in an analysis that consider the combined role of on- and off-road glances.

Method: Using glance data collected in the 100-Car Naturalistic Driving Study (NDS), near-crashes were examined separately from crashes to examine how momentary differences in glance allocation over the 25-s prior to a precipitating event can differentiate between these two distinct outcomes. Individual glance metrics of mean single glance duration (MSGD), total glance time (TGT), and glance count for on- and off-road locations were analyzed. Output from the AttenD algorithm (Kircher and Ahlström, 2009) was also analyzed as a hybrid measure; in threading together on- and off-road glances over time, its output produces a pattern of glance behavior meaningful for examining attentional effects.

Results: Individual glance metrics calculated at the epoch-level and binned by 10-s units of time across the available epoch lengths revealed that drivers in near-crashes have significantly longer on-road glances, and look less frequently between on- and off-road locations in the moments preceding a precipitating event as compared to crashes. During on-road glances, drivers in near-crashes were found to more frequently sample peripheral regions of the roadway than drivers in crashes. Output from the AttenD algorithm affirmed the cumulative net benefit of longer on-road glances and of improved attention management between on- and off-road locations.

Conclusion: The finding of longer on-road glances differentiating between safety-critical outcomes in the 100-Car NDS data underscores the importance of attention management in how drivers look both on and off the road. It is in the pattern of glances to and from the forward roadway that drivers obtained critical information necessary to inform their expectation of hazard potential to avoid a crash.

Application: This work may have important implications for attention management in the context of the increasing prevalence of in-vehicle demands as well as of vehicle automation.

1. Introduction

Drivers today are faced with increased competition for their attention due to the increased presence of in-vehicle information systems (IVIS) and cellular connectivity applications, from satellite navigation, in-car infotainment systems and embedded vehicle systems, to smartphone applications. In interacting with these devices, drivers must manage their attention to and from the roadway, deciding when and for how long to remove their eyes from the forward roadway – as such, often fracturing attention to the driving task. Driving even in its most basic form requires management of visual resources to multiple locations, including the immediate road surroundings, general

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surroundings, in-cab instrumentation, passengers, and other objects. Naturally occurring ancillary activities — mind-wandering, roadside advertising, etc. — can compete to draw attention away from the roadway. In the past several years, increased vehicle automation (e.g., power steering, automatic transmissions, adaptive cruise control, lane keeping aids, etc.), in its affordances for reduced physical and attentional demands of the driving task, frees-up attentional resources, which drivers may allocate to non-operational activities. Over the coming years, further increases in vehicle automation are expected to occur, potentially amplifying observed changes in the allocation of attention. Methods are needed that provide a deeper understanding of the foundations of attentional strategies to assist in the development of interfaces, assistive technologies, and management systems that promote more effective attention allocation under both traditional manual control as well as in drivers’ use of vehicle automation. Given the expected competition for drivers’ attentional resources, it is important to understand behaviors that lead to adverse events (those well-documented within the annals of driver distraction work) — the glass half-empty perspective — as well as to study those that are preventive of such outcomes — the glass half-full perspective.

Much of the driver distraction and inattention work has focused on concerns over drivers removing their eyes from the forward roadway to perform non-driving-related tasks, and its demonstrable link to safety consequences when these glances are timed at inopportune moments. This broad and exceptional line of work has established, through the analyses of glance from naturalistic datasets, a clear relationship between eyes-off-road, lead vehicle closing kinematics, and near-crash/crash involvement (Klauder et al., 2006; Victor et al., 2015). Large-scale naturalistic datasets such as those collected as part of the 100-Car Naturalistic Driving Study (Dingus et al., 2006) and the SHRP 2 Naturalistic Driving Study (Hallmark et al., 2013) contain safety-critical events (SCeS) and periods of baseline “normal” driving that have allowed study of human behaviors that are assumed to have a contributing role to crashes. In previous analyses of these datasets, the role of driver expectation influencing drivers’ decisions about when and for how long to remove their eyes from the forward roadway — i.e., an indicator of how drivers allocate their attention — have been discussed but not directly analyzed. Instead, analyses are primarily constrained to characterizing the interacting set of driver, task, and environmental factors, i.e., the event dynamics, in the seconds leading up to near-crashes and crashes. In this paper, we focus on how glance behaviors further upstream from the typically considered 0–15 s of time surrounding SCeS can provide insight into downstream consequences. Using data collected in the 100-Car Naturalistic Driving Study (NDS), this study separates near-crashes from crashes to examine how momentary differences in glance allocation over the 25 s prior to the events can differentiate between these two distinct outcomes (i.e., crashes result in significantly different outcomes in terms of loss of life or injury, and property damage as compared to near-crashes, in which these consequences are avoided).

1.1. Driver distraction and inattention problem — the glass-half-empty perspective

Driver distraction is commonly referred to as “the diversion of attention away from activities critical for safe driving toward a competing activity, which may result in insufficient or no attention to activities critical for safe driving” (Regan et al., 2009, p. 7). From this definition, attention refers to visual, auditory, cognitive, and manual resources, and all may play a role in affecting driver performance (e.g., Regan et al., 2009). Expanded considerations of vocal and haptic resources in many modern interfaces may also need to be considered in this context (Reimer et al., 2016). Diverted attention from the road can lead to deteriorated control of the vehicle (Grisler et al., 2008; Drews et al., 2009; Hosking et al., 2009), missed events (Fitch et al., 2009; Hosking et al., 2009), and delayed reaction times (Drews et al., 2009; Horrey and Wickens, 2004; Lee et al., 2004). Concurrently timed with other contributing factors (Angell et al., 2006), such as the presence of a junction, urban driving or unexpected events, these lapses in performance can lead to crashes. Considerable research, from in-depth accident analysis to findings from naturalistic driving studies, have documented this link between failures of attention and road crashes (e.g., Dingus et al., 2006; Hickman et al., 2010; Olson et al., 2009; Treat et al., 1977; Wang et al., 1996).

Glance location can be used as a proxy for determining what information a driver is processing; for example, glances (or gaze direction) can be used to infer if the driver’s attention is directed to the forward roadway, or to objects near the road or within the vehicle (Bellenkes et al., 1997; Taylor et al., 2013; Wickens et al., 2003). Though gaze direction and focus of attention are closely linked (Theeuwes et al., 1998; Yantis and Jonides, 1990), they do not have a perfect coupling (Hafed and Clark, 2002; Hunt and Kingstone, 2003; Posner, 1980). Direction of gaze may sometimes be separately located from cognitive attention, as is represented by glance behaviors such as “vacant staring” (Fletcher and Zelinsky, 2007; Pohl et al., 2007), “look but not see” (e.g., Fletcher and Zelinsky, 2009), and gaze concentration (Recarte and Nunes, 2000; Reimer et al., 2012; Victor et al., 2005; Wang et al., 2014; Zhang et al., 2006). Recognizing this limitation of glance-based analyses, there is, nonetheless, a large body of research that has established the close relationship between the location of a glance and the information to which an individual is attending under many conditions in normal visual perception (e.g., Birrell and Fowkes, 2014; Liang et al., 2012; Regan et al., 2013).

Individually, analyses of glance duration and of glance frequency have shown a quantifiable link to safety. Single long off-road glances — those greater than 2 s — in controlled experiments are associated with more frequent lane deviation and slower response to lead vehicle braking (Dingus et al., 1989). In the study of visual time sharing between the driving task and secondary activities, drivers do not tend to hold glances away from the road for durations beyond 1.6–2.0 s for more difficult or longer tasks (Liang et al., 2014; Sodhi et al., 2002), likely due to the relatively robust performance consequence of departures from the lane with glances longer than 2 s (e.g., Senders et al., 1967; Wierwille, 1993b); instead, drivers more typically increase their number of glances away from the road (e.g., Victor et al., 2005; Young et al., 2005). In a recent analysis of the 100-Car NDS, such an increased frequency of off-road glances in the approach to near-crash/crash events is evident (Liang et al., 2014). However, in interpretation of off-road glance frequency, it is necessary to consider its relationship with task duration, i.e., longer tasks led to more frequent off-road glances but individual glance durations tended to be under 2s. Accumulated off-road glances to in-car devices and secondary activities have also been shown to be detrimental to safety at long durations (e.g., Donmez et al., 2007; Klauder et al., 2010; Senders et al., 1967). A higher percentage of eyes-off-road time has also been associated with an increased likelihood of the occurrence of SCeS (Klauder et al., 2006; Olson et al., 2009; Hickman and Hanowski, 2012). Duration of off-road glance, then, both in the form of a single long duration and in aggregated form across a unit of time provides a robust measure of visual distraction when predicated on safety-relevant outcomes (e.g., Liang et al., 2012; Liang et al., 2014).

In addition to single metrics of off-road glance behavior, a number of glance-based algorithms have considered the combined effects of duration and frequency over time in predicting safety outcomes (e.g., Ahlström et al., 2009, 2013; Donmez et al., 2007, 2008; Klauder et al., 2006; Liang, 2009; Pohl et al., 2007; Rydström, 2007; Senders, 1967; Tian et al., 2013; Victor et al., 2005; Zhang and Smith, 2004). More comprehensive overviews of driver distraction detection algorithms exist within the volumes of driver distraction research (e.g., Dong et al., 2011; Lee et al., 2017; Moekli et al., 2013; Liang et al., 2012).

Behind this focus on off-road glances is the distraction-based grounding: when drivers divert their gaze from the forward roadway (often the result of a visual-manual activity) and allow themselves to...
become less aware of the driving environment, they increase their risk of a safety-critical event (Klauer et al., 2006; Olson et al., 2009; Hickman et al., 2010; Victor et al., 2015). While off-road glance metrics have definitive links to safety outcomes, these measures do not consider the attentional precursors to a driver’s decision to initiate long glances away from the forward roadway. A proposed alternative perspective to the more traditional distraction-related study of off-road glance behavior is to take an attention management perspective and also consider how drivers allocate their glances on-road over time — analyzing both single on-road glance behaviors and patterns of glance on- and off-road well upstream of a precipitating event. Such an analysis is expected to help develop deeper insight into the previously-attended information motivating perceived relative risk probabilities that underlie a driver’s decision to redirect gaze.

1.2. Importance of on-road sampling behavior — the glass-half-full perspective

On-road glance behavior provides a complementary and important mirrored perspective to off-road glance behavior in understanding the effects of visual demand on attention management.

Drivers must sample the road environment long enough in-between off-road glances to build and maintain an accurate representation of the driving scene to maintain basic vehicle control, and to detect cues in the environment that may signal potential hazards (e.g., Angell, 2007; Taylor et al., 2011). A useful concept to characterize the effect of an on-road glance on a driver’s awareness of the meaning of dynamic changes in their environment is situation awareness (SA), defined as “the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future” (Endsley, 1995, p. 36). A higher level of SA — that in which projection of environmental state occurs — depends upon perception and comprehension of relevant cues. How long, when, and where drivers look on-road dictates the visual information used to form expectations for how variables used to perform the driving task will evolve in the next moments of time. Cues such as the vehicle’s position in the lane, relative to surrounding traffic, and on the location of relevant features of the environment relative to the path of travel are used to generate a moment-to-moment situation model, which affects decision-making and action behaviors used to perform the driving task.

From vision science work on scene perception we know that the “gist” of individual scenes can be acquired very rapidly — well within the duration of a single fixation, and typically less than a second (Biederman et al., 1982; Chun and Jiang, 1998; Friedman, 1979; Greene and Oliva, 2009; Potter, 1999; Schyns and Oliva, 1994; Thorpe et al., 1996). However, when knitting together dynamic scenes and in projecting the locations and trajectories of events and objects required as part of the hazard identification and response task of driving, scene awareness is more complex.

The type of cuing influences the amount and type of processing resources deployed for event detection and response. Salient visual properties induce automatic, reflexive, bottom-up attention selection. However, this reflexive selection effect is attenuated with increased eccentricity of the stimuli from the direction of gaze (Anstis, 1974), or, if masked by a visual disruption such as a blink, saccade (fast eye movement), occlusion, or an initial onset outside of the visual field of view (an effect well-cited within a large body of research on change blindness; e.g., Rensink, 2002; Stelmach et al., 1984). In addition to effects from such data limits due to missing or occluded information, event detection and response can also be affected by resource limits on bottom-up perceptual processes (e.g., Angell, 2007).

Event detection and response also depends on top-down facilitation (and/or inhibition), i.e., supervisory control processes (e.g., Angell, 2007). These processes function to “prime” or “cue” a driver to a relevant event’s possible occurrence at a spatial location, and enable a driver to ignore irrelevant stimuli competing for his/her attention (Lavie, 1995, 2005). With experience, drivers learn to anticipate hazards (Crandall and Underwood, 1998; Falkmer and Gregersen, 2005). The role of knowledge or expectation is evident in comparisons between novice and experienced drivers, in which poor hazard anticipation performance for novices is attributed to their lack of knowledge for how to navigate them (e.g., McKnight and McKnight, 2003) and of the information that should be sampled in the driving scene. In one example, novice and experienced drivers were placed in situations in which latent threats (those difficult to detect either because they are not visible until the last moment, e.g., a pedestrian emerging from behind a stopped truck in the right parking lane of an un-signalized midblock crosswalk, or because they are visible but not yet fully materialized, e.g., a car that is stopped in a long line of cars in a left turn lane, but which might pull out in front of a driver who is in the adjacent, right lane of travel; Taylor et al., 2011) were presented at multiple locations. In this study, experienced drivers were more likely to gaze at locations indicative of their anticipation of the latent threats as compared to novice drivers, and consequently detected more of the resultant hazards (82% detected for experienced drivers versus 47% for novice drivers).

The duration of a glance to the road importantly reflects the processing required to resolve information needed to reduce uncertainty about evolving road/traffic dynamics and environmental state (e.g., Henderson, 2003). If cued to return gaze to the forward roadway, it takes drivers 2–4 s to verify hazard presence and to then initiate a response (Glaser et al., 2016; note: this range reflects a dependency on the properties and dynamics of individual hazards, and the time required to both detect and respond to a hazard following from an off-road glance). In his meta-analysis of simulator studies, controller road studies, and naturalistic observation, Green (2000) cited a response range as low as 0.7 s for expected signals, 1.25 s for unexpected signals, and 1.5 s for surprise events. All of the included studies in his meta-review, however, used overt cuing to signal the event, and measured responses constrained to ideal detection conditions — i.e., daylight, good weather, clear visibility, etc. The combined range of reported hazard response (0.7 s–4 s) points out that not all hazards are created equal: some are more difficult to correctly recognize as hazards because they are further afield, have low salience in contrast to the surrounding environment, or due to the absence of bottom-up cuing to signal their presence.

To detect the presence of potential hazards that require top-down (or schema-driven) processing of the driving environment, Samuel and Fisher (2015) recently reported that drivers need 4 s of on-road glance time at a minimum, but potentially on the order of 7 s or more for reliable detection; notably, this time estimate does not factor in the additional time required for response selection and action. In this study, drivers were asked to perform simulated vehicle tasks, alternating between views of the forward roadway and an in-vehicle location in which the length of provided on-screen information varied from 1 to 4 s in between 2 s off-road glance intervals (thus providing drivers a maximum, fixed 2 s of viewing time to the in-vehicle task location). During this alternating glance sequence, multiple potential (or latent) threats were presented. A glance towards the region of a potential threat at a specified location in advance of its unfolding was used to define detection. Drivers detected significantly more events when provided with the longest view of the forward road (4s). Further, there was evidence that drivers’ top-down processing of events — or lack of hazard anticipation as defined from the lack of a glance to the specified region — was inhibited at the shorter on-road glance durations, supporting the hypothesis that longer on-road viewing time provides an opportunity for drivers to sample relevant cues, enabling them to form adequate SA, and to in turn guide their expectancy of events. In sum, when events are expected, detection is speeded by top-down attentional facilitation, and when events are unexpected, detection occurs in a bottom-up, stimulus-driven way — which is a different attentional process — one slower on the order of hundreds of milliseconds to seconds. To build and maintain an accurate representation of the driving scene to support expectancy of events, drivers must sample the
road environment long enough to both detect predictive cues and to have an understanding of the locations in the driving environment relevant for detecting potential hazards.

In addition to the importance of the length of an individual on-road glance towards providing a driver with adequate time to perceive relevant cues to then develop appropriate expectations about upcoming events, the pattern of glances off-road may produce a cumulative effect on a driver’s awareness of roadway context (Liang et al., 2012). In studying the distribution of off-road glances leading up to near-crash/crash events in the 100-Car dataset as compared to baseline conditions, Liang et al. (2014) noted that “not only are crashes and near-crashes more likely to occur when drivers look away from the forward road, but there is a distinct pattern of glance behavior (compared to baseline) occurring as early as 30 seconds before a critical event” (p. 2105); the authors extrapolated these results to infer a likely cumulative role of neglect of the forward roadway in contributing to crash risk.

Of the algorithms proposed to estimate the effects of off-road glances (e.g., Liang et al., 2012; Lee et al., 2013), the AttenD algorithm is the only one that considers the effect of on-road and off-road glances over time in either building or deleting, respectively, a reserve of information about the roadway (akin to scene awareness or SA; Kircher and Ablström, 2009, 2012). This algorithm takes existing glance data – multiple, discrete variables of glance duration, frequency, and location – and combines them into a single continuous hybrid metric. Using simple rules for how these variables affect this scalar value; the output value is a real-time estimate of information decay and recovery – also referred to as a “buffer”. The initial buffer value is set at 2 and for each second of off-road glance decreases at a rate of one unit until a minimum value of 0 is reached, at which point it does not decrease further but stays at 0 until the driver glances back to the roadway. The value increases at the same rate for each second of on-road glance after a latency period of 0.1s, which reflect a psychological refractory period from the cost of switching attention back to the roadway, until it returns to 2, at which point it does not increase further. If a driver glances at the mirrors or the speedometer (regions that inform a driver’s ability to perform the primary vehicle control tasks relative to surrounding traffic dynamics), there is a latency of 1 s before the scalar value decreases. By design, the AttenD algorithm was intended by its authors to predict distraction potential in which a 0 value demarks a distracted state (Kircher and Ablström, 2009, 2012). However, in its ability to represent glance history in the form of a profile that dynamically changes to reflect the amount of stored information about the roadway, it produces a pattern of glance behavior meaningful for examining attentional effects. The output value offers the potential to delineate situations in which drivers have appropriately sampled on-road information to avoid a crash versus those situations in which they have insufficiently maintained an awareness of the roadway. It is from this perspective – of its output value providing an indication of how effectively attention is allocated to the roadway across time – from which the AttenD algorithm is analyzed within this paper.

1.3. Implications for analyzing glance behavior in SCEs

Previous analyses of naturalistic data have focused on tasks which elevate crash risk (using odds-ratios), and on eyes-off-road glance measures in predicting distraction potential, focusing on the few seconds, typically 0–15 s, prior to near-crash/crash or SCEs. This common focus around the seconds leading up to SCEs may not provide a large enough analysis window to evaluate the role of expectancy in inferring downstream glance behavior. Previous reports of the 100-Car NDS have shown that drivers are typically looking away from the roadway at the time of near-crash/crash events (e.g., Liang et al., 2014; Victor et al., 2015) – but, the unanswered question is why? Were drivers simply inopportunely in their glance away from the roadway at the moment an event happened (Victor et al., 2015)? Or, were these off-road glances in the moments before a crash an outcome of poorly-formed expectations of the driving environment due to insufficient on-road sampling? An analysis of glance behavior in the seconds prior to safety-critical outcomes is expected to reveal breakdowns in upstream information processes, i.e., a breakdown in a proactive barrier — those mismatches between proactive schema selection and the actual situation (Engström et al., 2013), or from a depleted situation model (e.g., Horswill and McKenna, 2004) to the extent there are significant differences in the pattern and length of on-road sampling between near-crash and crash events.

Commonly, near-crash and crash events in naturalistic driving analyses are combined in assessments of risk associated with glance behaviors, placed under a presumed equivalence label of “safety-critical”. While challenges to this approach have appeared (Knippling, 2015), this combining of near-crashes and crashes is typically due to low sample sizes of crash events (for the purpose of computing odds ratios) — along with what has been argued to be a similarity in the kinematics of the two categories in the final moments prior to a precipitating factor. However, in this study, we hypothesize that the way in which near-crashes differ from crashes is, in fact, an important difference. Namely, in a near-crash, the driver successfully avoids a crash — presumably by shifting attention at the “right time” and to the right place in a way that enables him/her to take an avoidance action and prevent a crash. A key question is this: what pattern of glancing or attending enables a near-crash to be different from a crash, and can a reliable and distinct pattern be identified that differentiates these two outcomes? In this paper, consequently, crashes were analyzed separately from near-crashes due to their inherent inequality in causality and harm (Knippling, 2015) to study temporal differences in on-road visual sampling.

It is in recognizing the important role that hazard awareness and anticipation plays in crash risk (e.g., Horswill and McKenna, 2004) that this paper proposes to analyze on-road glance behavior (both single glance duration and the pattern of glances over time) using the existing publicly-available 100-Car NDS dataset. The central thesis of this paper is that the ability to form appropriate expectations of events (informing a driver when to time off-road glances in the moments prior to a precipitating events) depends on the amount of information sampled from the forward roadway — its frequency and duration. In differentiating between near-crash and crash events in the 100-car dataset, it is hypothesized that allocation of on-road glances over time induces a cumulative a priori for ill-timed off-road glances near to SCEs.

2. Method

2.1. The 100-Car naturalistic driving study data

The 100-Car Naturalistic Driving Study continuously recorded on-road data from 100 vehicles between January 2003 and June 2004, collecting approximately 2 million vehicle miles or nearly 43,000 h of data from 241 primary and secondary drivers in unobtrusively instrumented vehicles (Dingus et al., 2006). The data contains periods of normal, daily driving; epochs of fatigue, impairment, judgment error, risk taking, engagement in non-driving related tasks, aggressive driving, and traffic violations – behaviors and performance outcomes representative of real-world driving.

Two databases with video and electronic driver and vehicle performance data were constructed from the data by the Virginia Tech Transportation Institute (VTI): a baseline database and an event database. The baseline database was created by stratifying the entire dataset based upon the number of crashes and near-crashes each vehicle was involved in and then randomly selecting 20,000 6.1-s segments from the driving data. This stratification of the baseline epochs was performed to create a case-controlled dataset in which there were multiple baseline epochs per each crash or near-crash event to allow for calculation of odds ratios. The baseline database for the 20,000 epochs includes vehicle, environmental, and driver state variables. Eye glance
analyses were performed for 5000 of these baseline epochs.

The event database includes vehicle and glance data for a set of near-crashes and crashes for a period of time surrounding each event: up to 30 s prior to and until 10 s after the precipitating factor: in total, 68 crashes and 760 near-crashes. Glance sequences for each event in these two databases were scored by a single trained reductionist at VTTI from the video in a frame-by-frame manner, i.e., human reductionists viewed video of each driver’s face and coded for each frame (at 10 Hz) the location of gaze among a set of 13 locations: “cell phone,” “center stack,” “instrument cluster,” “interior object,” “passenger,” “left forward,” “left mirror,” “left window,” “rearview mirror,” “right forward,” “right mirror,” “right window,” and “forward.” Two additional glance codes were possible for recording instances of missing data: “eyes closed” and “no video.”

The glance sequences and location codes from the 100-car database were downloaded from the online repository (http://forums.vtti.vt.edu/index.php?/files/category/3-100-car-data/) for the full period of available data for baseline epochs and for events. Key operational definitions are listed in Table 1.

As detailed above, for each near-crash (NC) and crash (C) event, additional glance data were coded after the precipitating factor (Klauer et al., 2006). For the analyses reported in this paper, all of the epochs were truncated at the precipitating factor (i.e., the seconds after the precipitating event were not included in the analysis window). Setting the precipitating event as the cutoff point for the epochs allowed us to isolate our analysis to driver glance behavior leading up to a critical event. We assumed that after the precipitating factor, glance behavior would fundamentally change—moving from a “proactive” state to a “reactive” state (Engström et al., 2013), in that the precipitating event is expected to induce different attentional processes (those triggered from a precipitating event’s exogenous stimuli versus from endogenous cues, i.e., changes in the driver’s internally-active goals or processes). The salient properties of this event in the form of transient onset or looming are expected to dictate attention to NC/C conditions at or in the time following the precipitating factor (Markkula et al., 2016). In particular, driver response following this point would depend on kinematic urgency and reaction speed to initiate an avoidance maneuver. More practically, the precipitating factor is a normalized point at which to cut the epochs to create a cleaner dataset for comparison of near-crashes and crashes. Epochs with missing eye-glance data were filtered from the downloaded data, reducing the number of events for analysis within this paper to 55 crashes and 724 near-crashes (from the original set of 68 crashes and 760 near-crashes).

2.2. Epoch filtering

Epochs in the event dataset reflected a mixture of pre-crash behaviors. However, the objective of this research was to examine the relationship between attention and glance behavior prior to crash. It was important to filter out any epochs of crash and near-crash that may have arisen from factors that would confound this relationship, or alter its interpretation in a fundamental (and perhaps unknowable) way. Therefore, filters were applied in a controlled manner to distill the set of epochs to a set which would provide a clean and clear test of hypotheses — and to allow effects of filtering to be examined and reported.

Epochs were filtered by applying four criteria:

2.2.1. Aggressive driving

Epochs containing aggressive driving, as coded in the 100-car dataset, were not included in the filtered dataset. It was hypothesized that the relationship between glance behavior and attention would be different in an aggressive driving epoch than a non-aggressive driving epoch.

2.2.2. Parking lots

Epochs that were recorded in driving contexts that were classified as being in a parking lot were not included in the filtered dataset. It was hypothesized that glance behavior in a parking lot would be different than glance behavior outside of a parking lot, with more driving-relevant glances away from the windshield.

2.2.3. Drowsiness

Epochs that were coded as containing drowsy driving were not included in the filtered dataset. It was hypothesized that the relationship between glance behavior and attention could be categorically different in drowsy driving epochs, with either more frames coded as “eyes closed,” or more coded as “eye forward,” but “inattention,” glances forward”.

2.2.4. Missing video

Epochs that contained frames coded as “missing video” were not included in the filtered dataset. Because we were ultimately interested in the effect of glance behavior over time on the outcome of SCEs, we did not want to remove “missing” frames while retaining the larger epoch, since doing so would either have resulted in treating the frames as missing data or would have forced non-contingent glances into temporally-contingent locations. Therefore, we excluded epochs containing missing video.

These filtering choices represented a compromise between reasonably eliminating confounds in the relationship between attention and glance behavior, and preserving an adequate number of epochs for a statistical analysis. The numbers of epochs removed at each stage of filtering are presented in Table 2, further broken down by the amount of data available from the online 100-car event database in each temporal bin (see next section). The bolded final row of Table 2 represents the filtered set of epochs used for the remaining analyses. For any row of the table, the number of epochs with glances in a bin increases across the row, moving from those with at least 25 s of data to those with ≤5 s of data, reflecting the varying length of epochs in the event dataset.

To reduce the effects of missing data on the crash/near-crash contrast, we restricted our analysis to the 20 crash epochs and 368 near-crash epochs with at least 25 s of data, and cropped the onset of each epoch to 25s, leaving us with a substantially smaller dataset of identical duration epochs.

Notably, this filtered set of epochs does not represent a set of independent observations, as multiple near-crash epochs may originate from one driver, and some drivers were associated with epochs in both near-crash and crash conditions. To adjust for this lack of independence
of samples, we evaluated three methods to account for the uneven crossing of drivers by SCE condition: by looking at those fully-crossed (drivers with both crash and near-crash epochs), looking at those fully-uncrossed (drivers with only epochs in either SCE condition) or a mix (in which all crash epochs [crossed or otherwise], and only near-crash epochs from drivers who did not crash, were included). The later approach was selected in a final filtering of the epochs because it yielded the highest number of crashes, which were particularly sparse as compared to the filtered set of near-crashes (Table 2). The final dataset for analysis therefore included glance data points for 77 drivers, including 16 drivers involved in crashes and 61 drivers involved in near-crashes. Reported findings therefore represent independent observations, calculated from exclusive crash or near-crash epochs of identical lengths.

3. Results

Analysis of the pre-precipitating event glance data was first computed using the following metrics for both off- and on-road glance locations: Mean single glance duration (MSGD); a count of glances; and total glance time (TGT).

3.1. Mean single glance duration (MSGD)

The duration of individual glances was computed as the number of frames subtended by an individual glance. Individual glances were categorized using the coding format of the publicly available 100-car data (Table 3): an individual glance was defined from when the glance location code of an individually-coded frame of glance data changed in the glance log, indicating the onset of a new glance, to when the glance location code changed again, indicating the offset of that same glance. Glances within “off-road” locations were coded separately for the purposes of these glance metrics; two consecutive glances to locations categorized as “off-road” but coded as having been made to different specific locations (such as “center stack” and “right window”) were computed as two individual glances when computing MSGD and number of glances. This same convention was used to designate individual “on-road” glances. In the publicly-available 100-car data dictionary, definitions for glance location to the forward roadway were split into three regions, defined as being “out the ‘left’, ‘straight’, or ‘right’ windshield”, respectively. As defined in Table 3, left and right forward locations were included in the “on-road” category, and all other locations were included in the “off-road” category in order to assess high-level on-/off-road attention distribution over the studied epochs. Left and right forward locations were included in the on-road category as these locations contain information used for detecting hazards peripheral to forward view (Lamble et al., 1999; Recarte and Nunes, 2000).

MSGD was computed for crash and near-crash epochs, and was further subdivided by off-road and on-road locations (see Table 4 and Fig. 1).

The effects of glance location (on-road vs. off-road) and epoch-type (crash vs. near-crash) on MSGD were evaluated using a 2-way ANOVA, with epoch-type as a between-subjects factor, and glance location and the interaction between epoch-type and glance location using a repeated measures error term. The main effect of epoch-type was significant, $F(1,75) = 4.65, p < 0.05$, partial $\eta^2 = 0.02$; crash epochs had significantly shorter MSGD than near-crash epochs overall. The main repeated-measures effect of glance location was also significant, $F(1,76) = 111.82, p < 0.0001$, partial $\eta^2 = 0.43$; on-road glances had significantly longer MSGD than off-road glances. The interaction between epoch-type and glance location was significant, $F(1,76) = 4.47, p < 0.05$, partial $\eta^2 = 0.02$; notably, the difference between near-crash and crash MSGD was especially pronounced for on-road locations, with on-road glances being, on average, 3.91 s longer for near-crash drivers than crash drivers. In other words, near-crash epochs were associated with longer glances out the windshield — to the roadway — than crash epochs, although both made similarly short glances away from the roadway.

It is important to note that the maximum length of any glance is limited by the window over which the glance data were coded by VTTI (and, hence, available for analysis in this study). Because drivers in near-crash and crash epochs appear to be making long glances on-road, which are interrupted by shorter glances off-road, we chose to evaluate the effect of this as a function of when in the pre-precipitating event epoch the glance was initiated. This was accomplished by “binning” glances as a function of how far from the onset of the precipitating
event the glance was initiated.

3.2. The temporal effects of glance behavior: binned glance statistics

To evaluate the effect of time on MSGD for on-road glances, we divided glances into three bins, using the temporal distance between the onset of a glance and the onset of the precipitating event of each epoch. For example, a glance initiated within a window between 20 s prior to the precipitating event and 25 s prior to the precipitating event was placed into a “20-25 s” window, and its associated glance duration was compiled into that window’s MSGD statistics. These were computed for each bin, for on-road glances (i.e., glances falling within windshield glance locations, namely forward, left forward, and right forward), for the filtered set of epochs (see Table 2 for the number of epochs with data in each bin for the filtered dataset).

As hypothesized, the greatest nominal difference in MSGD for on-road glances is at the earliest bin (20–25 s upstream from the precipitating event), with near-crashes being associated with 12.39 s
crashing. Critically, this trend appears, however subtly, in the earliest—be greater for crashes in the 0

\[ \eta = 62.86, p < 0.0001, \eta^2 = 0.15, \text{ of glance location, } F(1,76) = 291.80, p < 0.0001, \eta^2 = 0.28, \text{ and a significant interaction effect, } F(2,152) = 53.54, p < 0.0001, \eta^2 = 0.13. \]

In decomposing the interaction effect, there was a significant main effect of bin for on-road

\[ F(2,152) = 60.07, p < 0.0001, \eta^2 = 0.37, \text{ but a non-significant effect of bin for off-road }\]

\[ F(2,152) = 2.20, p = 0.12, \eta^2 = 0.01, \text{ indicating that it is the longer upstream length of on-road }\]

\[ \text{glances (as opposed to an increase length of off-road glance nearer to} \]

\[ \text{the precipitating event) that drive differences in SCE outcomes seen at} \]

\[ \text{the summed epoch level (Fig. 1).} \]

While Fig. 2 depicts a clear trend, in which the greatest differences between near-crash and crash epochs occur as a result of earlier long on-road glances being ended earlier in crash epochs than in near-crash epochs, the use of MSGD to statistically evaluate this trend was unsuccessful — due principally to the great deal of variability in the MSGD values, and the small number of crashes available. Other metrics were analyzed to reveal the attentional mechanisms behind this trend. If long glances made earlier in pre-precipitating event epochs ended earlier in crash epochs, as the MSGD analysis indicated, then other glance metrics, such as number of glances or total glance time, are expected to reveal significant differences in subsequent bins.

### 3.3. Glance count

A count of glances within any given bin was computed following the procedure used by Krause et al. (2015): glances that were initiated within a bin incremented that bin’s glance count by 1; glances that subtended later bins incremented those bin’s glance counts by a fraction representing the proportion of the bin subtended. For example, a glance that was initiated in the 20–25 s bin incremented that bin by 1; if it then subtended eight of the 10 s of the 10–20 s bin (i.e., it ended at 12 s) it would increment the 10–20 s bin by 8/10, or 0.80. This method ensured that long glances initiated in earlier bins were reflected in subsequent bins, and that every bin for every epoch for which there was available data would get a glance count of at least 1. To account for the difference in the number of epochs available for each crash and near-crash driver, glance counts were averaged within bins across all epochs for a driver rather than summed.

Fig. 3, right panel, depicts the count of off-road glances for each bin for near-crash and crash epochs using the filtered set of epochs. While none of the observed differences are statistically significant, the source of shorter on-road MSGD for crash drivers can be reasonably identified: more off-road glances, especially pronounced in 10–20 s and 0–10 s bins. The number of glances on-road (Fig. 3, left panel) appears to also be greater for crashes in the 0–10 s bin, suggesting that it is more glancing, not long off-road glancing, that is associated with drivers crashing. Critically, this trend appears, however subtly, in the earliest bin (20–25 s before the onset of the precipitating event linked to crashing).

Additionally, the data suggests that crashes were associated with a greater standard deviation of glance counts (1.55 for off-road and 1.31 for on-road) than near-crashes (0.99 for off-road and 1.04 for on-road). These values were computed across drivers, and while not statistically tested, supports the trend evident in the confidence intervals in Fig. 3: of greater variability in glancing behavior for epochs ending in crashes than in near-crashes.

### 3.4. Total glance time

Total glance time (on- and off-road) was computed as the total amount of time within a bin that glances were coded as either on-road (i.e., within the set of forward, left forward, and right forward glance locations) or off-road (all other locations). Because not all bins were the same size (namely, the 20–25 s bin was half the size of the others) we converted raw times into percentages. Also, because every frame is coded as either on-road or off-road, total off-road glance times are directly dependent upon on-road glance times; consequently, only statistics for on-road glance times are reported.

Across all three bins, crash and near-crash epochs were associated with similar total glance time on-road (86.45% and 88.60%, respectively), \( F(1,75) = 0.46, p = 0.50. \) However, there was a main effect of bin, \( F(2,150) = 3.61, p < 0.05, \eta^2 = 0.02, \) with bins closer to the precipitating event having less total on-road glance time, and an interaction between bin and type of epoch, \( F(2,150) = 3.99, p < 0.05, \eta^2 = 0.02. \) As is shown in Fig. 4, the downward slope of the relationship between time until precipitating event and total on-road glance time for crash epochs drives this interaction effect. This continues to support the hypothesis that increased glancing in approach to the onset of a precipitating event is linked to both the large decrease in mean on-road glance duration and to the failure to anticipate a precipitating event in crashes as opposed to near-crashes.

### 3.5. Distribution of glance across on-road regions

The cumulative findings of MSGD, glance count, and total glance time point to the importance of on-road glance length and the threading of these glances in between off-road glances. To examine in more depth the role of on-road glance behavior and its effects on downstream safety-critical outcome, sampling to peripheral road regions were separately considered from the central road region in a secondary analysis of mean single glance duration. In particular, this analysis aimed to uncover if drivers were differentially accessing information from peripheral regions (those areas of the driving scene cited as relevant for hazard and event detection) in near-crash compared to crash situations.

Glance durations were examined for left forward, center forward, and right forward locations. As is evident in Fig. 5, there was a tendency in the peripheral locations (i.e., left forward and right forward) for MSGD to be longer in near-crash epochs than crash epochs, regardless of bin. Right forward glances were significantly longer for near-crash epochs than crash epochs within the 10–20 s bin, \( F(1,75) = 4.26, p < 0.05, \eta^2 = 0.05. \) Differences between near-crash and crash MSGD were in the same direction for other bins for both peripheral locations, differences were not significant.

A subsequent analysis of the probability of glance within each bin indicates the differences in MSGD are likely due to an increased probability for drivers to initiate glances to peripheral road locations in near-crash situations; these drivers were significantly more likely to initiate left forward glances than those in crash situations 10–20 s before a precipitating event, \( F(1,27) = 6.52, p < 0.05, \eta^2 = 0.08 \) and marginally more likely 0–10 s before a crash, \( F(1,75) = 3.43, p = 0.07, \eta^2 = 0.04. \) Near-crash drivers were also marginally more likely to initiate right forward glances 20–25 s before a precipitating event, \( F(75,1) = 3.82, p = 0.054, \eta^2 = 0.05, 10–20 s \) before a precipitating event, \( F(75,1) = 3.77, p = 0.06, \eta^2 = 0.05, \) and significantly more likely 0–10 s before a precipitating event, \( F(75,1) = 4.67, p < 0.05, \eta^2 = 0.06. \) Those involved in crashes. Differences between center forward MSGD and between near-crash and crash epochs were not significant, although glances initiated to the center forward region 20–25 s before the precipitating event were 3 s longer for near-crash than crash epochs (MSGD = 12.68 s vs. 9.67 s, respectively).

To evaluate reported differences in glance behavior between near-crashes and crashes at a higher temporal resolution than in 10 s periods, we evaluated glance behavior using the AttenD algorithm, which
produces a continuous measure indicative of how attention is allocated over time; notably, considering the effect of on-road and off-road glances in either building or depleting, respectively, a reserve of information about the roadway.

3.6. The AttenD or “Buffer” algorithm

The AttenD algorithm was used to annotate each frame of glance data with an associated “buffer” value, based on the glance history of each epoch. Fig. 5 depicts aggregated buffer values for near-crash and crash epochs, for each frame across the possible 25 s of pre-precipitating event glance data for the filtered set of epochs. Because of the buffer design, where the buffer is initialized as “full” (i.e., having a score of 2.0) and declines as off-road glances are made, both the near-crash and crash buffer lines begin at 2.0 at the 25 s marker. For the crash epochs, it drops significantly lower, and, in aggregate, fluctuates markedly until terminating at a value roughly one tenth of a buffer value lower than near-crash buffers. For the near-crash epochs, it fluctuates, in aggregate, more moderately above a value of 1.9 until the time of the precipitating event (Fig. 6). These patterns suggest the buffer is sensitive to the effects of glancing that were identified in the other, more typical reported glance metrics. Further, they highlight the buffer’s ability to reveal cumulative effects of making more/longer on-road glances to the road over time. On-road glances act to refill the buffer, i.e., to restore a driver’s awareness of scene information critical to hazard anticipation and response.

As with the other measures, buffer values were broken down by bin (Fig. 7). Overall, the near-crash epochs are associated with higher buffer values (1.93 vs. 1.86, respectively), \(F(1,75) = 4.25, p < 0.05\), partial \(\eta^2 = 0.02\). Additionally, there was a marginally significant main effect of bin, \(F(2,150) = 3.02, p = 0.052\), partial \(\eta^2 = 0.02\), and a significant interaction between bin and epoch type, \(F(2,150 = 4.69,\)
As with total on-road glance time, the buffer value associated with crash epochs drops as the bins get temporally closer to the precipitating event, with a maximal difference at the 10–0 s bin, immediately before the precipitating event. Additionally, the confidence intervals around the buffer mean values grow substantially for the crash epochs, in support of the reasoning from the glance count analysis of an increased rate of glancing as the precipitating event draws nearer. An analysis of the average standard deviation of buffer value (Fig. 6, right panel) supports this reasoning. Overall, the main effect of epoch type was significant for buffer standard deviation, $F(1, 75) = 4.37$, $p < 0.05$, partial $\eta^2 = 0.03$, as was the main effect of bin, $F(2, 150) = 4.30$, $p < 0.05$, partial $\eta^2 = 0.03$, and the interaction between the two was marginally significant, $F(2, 150) = 2.92$, $p = 0.06$, partial $\eta^2 = 0.02$. Crash epochs have a
higher standard deviation of buffer value, with the two bins closest to the precipitating event producing the highest deviations.

3.7. Baseline vs. near-crash vs. crash

Because AttenD buffer values appeared to maximally differ between crash and near-crash epochs in the moment before the precipitating event, we also looked at the short baseline epochs available from the 100-car study to evaluate whether the AttenD algorithm could also differentiate SCE epochs from baseline epochs during this short time window.

There were 4935 baseline glance-coded epochs of 6.1 s available. As in previous analyses, we applied a filter to the epochs, removing 246 epochs that contained missing video or parking lot driving (because the baseline epochs were not scored for aggressive driving or drowsiness within the available online dataset, filters for these behaviors were not applied). Buffer values were averaged across the 6.1 s of available data for each epoch in the three conditions (baseline, near-crash, and crash epochs), and summary values are plotted in Fig. 8. Overall, buffer value significantly varied by epoch type, $F(2,5693) = 17.24$, $p < 0.0001$, $\eta^2 < 0.01$, with baseline having a significantly higher buffer value than near-crashes ($p < 0.0001$, Holm-Bonferroni-corrected) and crashes ($p < 0.05$, Holm-Bonferroni-corrected). Crashes and near-crash mean buffer values were statistically equivalent ($p = 0.19$). Standard deviation of buffer value also significantly varied by epoch type, $F(2,5693) = 8.95$, $p < 0.001$, $\eta^2 < 0.01$, with baseline having significantly lower buffer standard deviations than near-crashes ($p < 0.001$, Holm-Bonferroni-corrected) and crashes ($p < 0.05$, Holm-Bonferroni-corrected). Crash and near-crash buffer standard deviations were also statistically equivalent ($p = 0.18$).

4. Discussion

This analysis revealed that naturalistic driving epochs ending in
crash vs. near-crash differ in critically important ways that suggest new insights into driver behavior and crash avoidance. In a near-crash, the driver may successfully avoid a crash by more effectively balancing attention on and off the road at earlier points in the driving sequence prior to the occurrence of a precipitating event, in particular by spending more time during individual glances looking at the road. When shifting their gaze off-road, drivers in near-crash situations do so at a more consistent duration and rate. This pattern — in which forward attention to the road is interleaved with off-road glances, and for longer amounts of time to encode critical information from the forward roadway, may equip drivers with the information they need to avoid a crash. This distinct pattern of glancing at the road and of attending, as revealed from the AttenD buffer plot (Fig. 6), appears as a significant differentiation between near-crash and crash epochs. These findings, if replicated through other work, have the potential to change the paradigm used for thinking about crash risk and crash avoidance.

4.1. Effects of common individual glance metrics

Common glance metrics of mean single glance duration, glance count, and total glance time across the available epoch lengths point to the significance of longer on-road glances and more frequent glances between on-road and off-road locations in differentiating near-crash from crash outcomes. Looking at glance patterns across the 25 s of pre-precipitating data examined in the 10 s bin analysis, there are clear trends indicating that the period of time 10–25 s in advance of the precipitating event plays a critical role — a time period, which has, until now, been largely overlooked in the analysis of SCEs. Drivers spend less time looking at the road as they move closer to the precipitating event — an effect that was more pronounced for crashes than near crashes, as evident from mean glance duration and total glance time results. Concomitant with reduced on-road glance times, drivers engage in increased glancing between on- and off-road locations, with increased variability in this switching for crash epochs — an effect that alludes to a destabilized allocation of attentional resources (Hancock and Warm, 1989). Finally, as evident from the breakout of central and peripheral road regions, drivers neglect information in the periphery in the moments prior to crashes (as far back as 25 s) to a larger extent than in near-crash situations.

4.2. Glance patterns over time

The findings of this work are in line with the proposition that safety-related behavior lies in the pattern of glances on and off the road. Simple single metrics (such as mean single glance durations to one location or another, or total glance time off-road) only partially capture this pattern. The important finding from this work is that it is how glances on- and off-road are interleaved that supports drivers in developing adequate information about the situation that is vital. This type of pattern may be best captured by a hybrid measure.

Viewed from the output of the AttenD algorithm in Fig. 6, drivers engaged in shorter mean on-road glances for crashes compared to near-crashes in the 25 s prior to the precipitating event, but, in aggregate, starting in the 20–10 s period prior to this event initiated comparatively more frequent glances on-road and off-road, together producing the temporary spike centered around 10 s. The precipitous drop in buffer value following this period for crashes is reflected in the longer total glance time spent off-road (in contrast to near-crashes) in the 10–0 s prior to the precipitating event (see Fig. 4, right panel).

When considering the temporal effects of glance behavior across the full 25 s of data for both near-crashes and crashes, it is evident that drivers generally demonstrated more attenuated attention across time. The lower AttenD buffer values in the 6.1 s epoch analysis for SCEs compared to the baseline epochs confirm this reduced attention to the forward roadway from that seen during normal (non-safety-critical) periods of driving.

4.3. A glass half-full perspective indicates a need to consider on-road glance behavior in analyses of SCEs

Overall, drivers in the safety-critical situations showed reduced glance duration to on-road locations and an increase in glances between on- and off-road locations in the approach to the precipitating event. This glance pattern is evident to a larger extent in the lower, more variable buffer profile in the seconds leading up to crashes compared to near-crashes. A downward sloping profile signals degrading awareness of the roadway environment.

Ample on-road glance time is needed to form a robust situation awareness and to trigger relevant schemata in order to accurately forecast the probabilities, rate, and consequences concomitant to unfolding event dynamics (Horswell and McKenna, 2004). It is in the perception of scene information relevant to task goals that drivers are able to prime, through top-down mechanisms, the attentional resources needed to facilitate fast reactions to looming cues (Engström et al., 2013). Reduced on-road glance durations and decreased sampling of peripheral road regions for drivers in the crash epochs in the moments leading up to the precipitating event likely left these drivers ill-equipped in their decision for when to time an off-road glance. Analyses reported in this paper suggest that just a few more seconds of on-road glance time attending to cues in the driving environment that foretell of hazard potential can indeed make the difference as to whether a driver crashes or averts a crash. In total, glance behaviors that differentiate the 100-car SCEs can be interpreted as supporting the view that ill-timed off-road glances in the moments before a crash are in fact an outcome of poorly-formed expectations of the driving environment (i.e., depleted situation models) consequent from under-sampling of predictive cues. Or, stated another way, drivers in crash epochs, to a larger extent than those in near-crash epochs, experienced breakdowns in their proactive barrier (Engström et al., 2013).

4.4. Role of non-driving related task activities on glance behaviors in the 100-Car event data

Increasingly, the presence of driver assistance systems and other higher-level automated systems may amplify the need to consider attention management and to adopt metrics such as AttenD over more traditional glance metrics. The need to understand and support attention management when drivers are engaged in non-driving related tasks is particularly crucial to the extent they have a degraded awareness of how distraction affects their driving performance and/or do not strategically plan when to initiate non-driving related tasks (e.g., Horrey et al., 2008; Lerner et al., 2008; Perez et al., 2011). Initial designs of smart systems that encourage on-road glances have shown benefits to how drivers allocate their visual resources and counter distraction effects (e.g., Birrell and Fowkes, 2014).

There are a wide variety of activities drivers engaged in prior to the SCEs in the 100-car event database (e.g., Klauer et al., 2006, p. 24; Owens et al., 2015). For SCEs that involve non-driving related tasks, inattention, or high workload as a factor, divergence of attention from the road in pre-crash/near-crash period is expected. To fully examine the attentional mechanisms at play, the preexisting categories of inattention types, as defined within Klauer et al. (2006) — secondary tasks, driving-related inattention, non-specific eye glances, and drowsiness — could be examined between the near-crash and crash epochs to determine their effects on the observed glance patterns. While these breakdowns of epochs into inattention categories have proved meaningful in the past for calculating odds ratios associated with the risks of NC/C outcomes (Klauer et al., 2006), for this work, there is an insufficient number of crashes per inattention type to perform statistical analyses in comparison with the near-crash events. Due to the relatively low number of crashes compared to near-crashes, more in-depth analyses on the role of secondary task engagement on glance behaviors that distinguish between safety-critical outcomes is an important area of
future work; the NEST dataset, which was recently made publicly accessible, provides opportunities for such efforts (Seaman et al., 2017).

5. Conclusion

Taken together with recent findings (e.g., Samuel and Fisher, 2015), this work may have important implications for attention management in the context of the increasing prevalence of in-vehicle demands and an increasing level of vehicle automation. Current human-machine interface (HMI) evaluation guidelines largely focus on minimizing off-road glance durations. While this perspective is supported by the data in the seconds leading up to a crash, a broader “glass half full” perspective that looks further in advance of a precipitating event suggests that time on-road is potentially an equally, if not more important, metric deserving deeper consideration. Evident from this analysis of the 100-Car NDS data, drivers better protect their ability to anticipate hazards if they more effectively acquire information from their roadway surroundings. Appropriately interspersed and sufficiently sustained scanning of the road mitigates the loss of awareness of the roadway environment that occurs during glances away from the road. In situations where a driver does not allocate enough attention to the road between off-road glances, effective recovery of an understanding of the driving situation may be flawed since subsequent glances will likely be based on incomplete situation knowledge, and perhaps timed inappropriately as well as located inappropriately. Hybrid measures such as the AttenD algorithm that consider the combined effects of on- and off-road glances in a temporal relationship offer a unique perspective into a driver’s capacity to develop and maintain an understanding of the driving environment that bears on their capacity to appropriately respond to emergent events. The implication of this is that a hybrid measure like the AttenD algorithm can be interpreted as indicating the ‘amount of situation knowledge’ that a driver maintains and updates (a precursor for situation awareness) while driving.

In its use of a set of rules that determine how individual parameters produce changes in a buffer value to reflect a driver’s management of attention over time, the AttenD algorithm affords building in further parameters and rule conditions to account for complex and interacting effects from secondary task load. Recent work applied a modified form of the AttenD algorithm, which built in additional rules for the temporal threading of central and peripheral glances to the forward roadway, to differentiate between periods of driver engagement with tasks of varying cognitive load (Seppelt et al., 2017). Recent application of the AttenD algorithm to alternative sources of naturalistic data (NEST dataset; cf. Owens et al., 2015) demonstrate replicability for findings reported in this paper, and began to apportion the role of an attributable parameter and type of secondary task load and their diﬀerent patterns of on- and off-road glance behavior to safety-relevant outcomes (Seaman et al., 2017). For future work, it would be desirable to have longer epochs of glance data for a wider range of SCEs that reflect vehicles with more modern, advanced features, including multi-modal interface characteristics – such as voice input, smartphone integration, etc., than have been available in datasets to date. Work may also be needed to consider the relationships between crash, near-crash, and baseline epochs of lower-risk drivers (notably, the 100-Car dataset characterizes the behavior profile of high-risk drivers and must therefore be interpreted with caution in how observed effects extrapolate to lower-risk drivers; cf. Klauer et al., 2009). The consideration of attentional strategies in lower-risk drivers (e.g. those involved in fewer SCEs per year) may lead to an increased understanding of “successful” avoidance of threats offered by a precipitating event, thereby enhancing the “glass half-full” perspective.

Finally, work by our group is ongoing in investigating and refining more advanced methods for combining information gained from on- and off-road glances over time as well as other supporting metrics of cognition into an “attention buffer” that aims, in part, to provide a greater degree of sensitivity to predict real-time failures in attention allocation that impact situation awareness and crash risk. It is hypothesized that a more optimized model can lead to an in-vehicle interface assessment methodology that builds-upon and advances the state of practice from current methods (e.g., NHTSA, 2016, Alliance, European Statement of Principles, JAMA, etc.) to one that considers the allocation of attention over time for task interactions interleaved with driving. Such an assessment perspective may offer a predictive safety validity not found in earlier distraction-based methods, and shifts the focus to positive design goals. Implemented in the context of a real-time driver state sensing system the assessment model can be applied to the active management of driver attention in the context of environmental characteristics, vehicle automation, and other inter-related factors. The approaches, i

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References


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