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The role of driver's situational awareness on right-hook bicycle-motor vehicle crashes

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ABSTRACT

Objective: The objective was to explore the effect of driver Situational Awareness (SA) on "right-hook" bicycle-motor vehicle crashes involving right turns into adjacent bicyclists.

Background: Previous literature suggests that improper allocation of motorists' visual attention, inadequate surveillance, and poor SA are contributing factors to bicycle-motor vehicle crashes in other types of encounters.

Method: Fifty-one participants completed this driving simulator study. Right-turning motorists' SA was measured using the SAGAT technique in the presence of a through-moving bicyclist in an adjacent bicycle lane during the latter portion of the green phase at a signalized intersection using a three (bicyclist's relative position) by two (presence of oncoming left-turning vehicle) within-subject factorial design. Each participant made 21 right turns, nine of which were immediately followed by SA queries, and crash avoidance behavior was measured at the last intersection, which involved a crash-likely scenario.

Results: The bicyclist's position significantly influenced motorists' overall SA ($p < 0.05$) and Level 2 SA (comprehension) ($p < 0.05$). Level 1 SA (perception) degraded when oncoming vehicles were present and the bicyclist was approaching from behind ($p < 0.05$). Level 3 SA (projection) degraded when the bicyclist was ahead of the motorist and oncoming vehicles were present ($p < 0.05$). Level 1 SA and crash occurrence were negatively correlated ($r_{pbi} = -0.3$, $p < 0.05$).

Conclusion: Motorists focused more attention on cars in front of them and less attention on bicycles in the peripheral vision. A common cause of observed crashes in the simulator was detection error. The bicyclist approaching from behind the motorist is the most vulnerable to a right-turning motorist.

1. Introduction

As U.S. cities have made investments in non-motorized transportation infrastructure, bicycling has become a meaningful alternative mode of transportation for activities such as commuting to school or work, shopping, and recreation (Pucher et al., 1999, 2011; SAFETEA-LU Section 1807, 2012). However, research has shown that safety is a primary concern for many people in the decision to use a bicycle for transportation. The National Highway Traffic Safety Administration (NHTSA) reports that there were 840 fatal bicycle-related crashes in 2016, which accounted for 2.2% of transportation-related fatalities in the U.S. (NHTSA, 2018). The majority of these fatal bicycle crashes (60%) occur in urban areas with 40% of them at intersections. At intersections without space for both a separate right-turn and bicycle lane, bicyclists are often to the right of motorists as they approach an intersection. This configuration sets up the "right-hook" bicycle-motor vehicle type crash where right-turning vehicles and through-moving bicycles conflict. These crashes occur frequently and can sometimes be severe. They can happen either (1) at the start-up period (the onset of the green or departing from a stop sign) or (2) during the "moving" phase after the signal turns green and the standing queue has cleared (i.e. the latter part of the green phase). In the second case, the approach speeds of the right-turning motorist and the through-moving bicyclist are higher, and their relative positions are more variable. It is important to note that the motor vehicle operating laws in U.S. states vary and in the study location (Oregon), drivers may not encroach in the bicycle lane unless in the process of making a turn.

Although the subject of right-turning vehicle crashes with bicycles appears in the literature with some frequency (Summala, 1988; Weigand, 2008), little substantive research on the crash causation mechanism has been conducted. In addition to the fact that crashes are rare events, police-reported crash records sometimes lack robust information on the behavior of road users and presence or status of other traffic hazards during the crash. It can be difficult to infer the awareness and behavior of each party (perceptions, decision making, and trajectories) from these data.

A safe right-turning maneuver requires that the motorist complete at least two tasks: (i) look and detect the bicyclist, (ii) make the appropriate decision based on that information and corresponding conditions at the intersection. In this regard, the Situational Awareness (SA) of motorists can help explain their behavior with reference to several key factors: anticipation, attention, perception, expectations,

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and risk (Endsley, 1998). SA is the term given to the awareness that a person has of a situation and an operator's dynamic understanding of 'what is going on' (Endsley, 1995a). It has been shown to influence both decision-making and task performance of the operator during the tasks of driving and flying. While the issue with SA is obviously important in the aviation domain, other complex real-time tasks such as driving also suffer the consequence of poor SA.

Motorists' behaviors in crash events are difficult to systematically analyze in large numbers due to the low frequency of crashes and the variety of external factors that must be considered and controlled. In this regard, driving simulation and eye-tracker technology have emerged as useful research tools for exploring the contribution of human driving behavior to traffic crashes (Durkee, 2010). Driving simulators can place motorists into crash-likely scenarios from the relative safety of the laboratory.

This research used a high-fidelity driving simulator to investigate the causal factors of right-hook crashes related to motorist behavior. This paper presents the results of an experiment designed to determine motorist's SA during right-turn maneuvers at signalized intersection in the presence of a through-moving bicyclist in an adjacent bicycle lane. Although SA is key to decision making in a dynamic environment, it does not necessarily guarantee successful task performance (Salmon, 2009). Therefore, in addition to the explicit recall measures of SA, it is also important to assess operator's SA with indirect performance-based measures (Gugerty, 1997), so in this case motorist's performance was measured through the global performance measure of crash avoidance. Finally, this experiment analyzed if there is any correlation between motorist's SA and crash avoidance behavior. The overarching research objective of this experiment was to assess if right-turning motorists have the necessary knowledge for safely executing a right-turning maneuver during the latter portion of the green phase, which is important to avoid a potential RH crash with an adjacent bicyclist.

2. Theoretical background

2.1. Crash factors attributable to the motorist

Vehicle collisions often result from the lack of attention or a failure to detect the other party or, sometimes, the loss of control by one or more of the parties involved (Korve and Niemeier, 2002; Summala, 1988; Summala et al., 1996; Räsänen et al., 1998; Rumar, 1990). The first thorough investigation of the contributing factors for crashes was conducted in the 1970s by a research team from Indiana University for NHTSA, and is known as the Tri-Level Study of Accident Causes (Treat et al., 1979). This study investigated 2,258 different types of police-reported crashes. Results from this study reported that improper lookout and inattention, which are two important aspects of SA, were the two leading direct human causes of those crashes. Improper lookout or inadequate surveillance consisted both of "failed to look" and "looked but failed to see" behaviors (Treat, 1980). Gugerty found that improper lookout and inattention were cited as causes of more crashes than factors related to decision making (e.g., excessive speed) and psychomotor ability (e.g., improper driving technique) (Gugerty, 2011). More recently, NHTSA conducted a study to examine the general characteristics of motor-vehicle traffic crashes at intersections using the National Motor Vehicle Crash Causation Survey (NMVCCS) from 2005 to 2007 (NHTSA, 2010). Among those records, there were 756,570 intersection-related crashes; the most frequently assigned critical reason (44.1%) was found to be inadequate surveillance. This failure can occur at an intersection when the motorist looks at the required direction before making a turn, but fails to see the approaching traffic (Dingus et al., 2006).

Specifically for bicycle motor vehicle crashes, Summala et al. found that improper allocation of a motorist's visual attention while making turns at an intersection and failure to detect the bicyclist was a contributing factor to many crashes (Summala et al., 1996).

2.2. Situational awareness

Perception and attention are very important factors for safe driving (Castro, 2008; Gugerty, 2011). Therefore it is essential to measure motorists' attention correctly to gain insight into the driving task (Gugerty, 2011). Suggesting that motorists' SA is similar to motorists' attention, Gugerty has defined SA as, "the updated, meaningful knowledge of an unpredictably-changing, multifaceted situation that operators use to guide choice and action when engaged in real-time multitasking" (Gugerty, 2011). In the context of the driving task, this meaningful knowledge can include the motorists' route location, roadway alignment, location of nearby traffic and pedestrians, fuel level, and other information. Gugerty also categorized the perceptual and cognitive processes required to maintain SA into three levels:

- Level 1: automatic, a preattentive process that occurs unconsciously and places almost no demands on cognitive resources;
- Level 2: recognition-primed, a decision process that may be conscious for brief periods (< 1 s) and place few demands on cognitive resources; and
- Level 3: conscious, a controlled process that place heavy demands on cognitive resources (Gugerty, 2011).

In the context of driving, Gugerty described vehicle control, such as maintaining speed and lane position as mostly an automated process, but other tasks requiring some regular conscious decisions during driving, such as lane changing or stopping at a red light, are recognition-primed processes. At the final level, he described hazard anticipation and making navigational decisions in an unfamiliar environment during heavy traffic as requiring a controlled, conscious process (Gugerty, 2011).

To safely accomplish the driving task, motorists need to perceive, identify, and correctly interpret the elements of the current traffic situation, including immediately adjacent traffic, road signs, route direction, and other inputs, while being vigilant for obstacles and making predictions of near-future traffic conditions to maintain control, guidance, and navigation of the vehicle (Baumann et al., 2007). Endsley's definition of SA incorporates the great variability of information that needs to be processed in dynamic real time tasks such as driving, air traffic control, or flying. Endsley states that, "Situation awareness is 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, 1988). Endsley's definition of SA was expanded into three hierarchical phases:

- Level 1 SA involves the *perception* of the elements in the environment;
- Level 2 SA is the *comprehension* of the current situation by integrating various pieces of data and information collected in Level 1 SA in conjunction with operator goals; and
- Level 3 SA involves the *projection* of future status from the knowledge of the elements and comprehension of the situation achieved in Level 1 and Level 2 SA. Level 3 SA allows the motorist to perform timely and effective decision making (Endsley, 1995b).

Although the two models are conceptually different, Gugerty has compared his three levels of perceptual and cognitive processes with Endsley's three levels of SA in the way that perceiving the elements of a situation (Endsley's Level 1 SA) is mostly highly automated, while comprehension and projection (Level 2 and 3) mostly use recognition-primed and controlled processes (Gugerty, 2011; Endsley, 1995a,b).

The above discussion underlines the importance of SA, which is required for hazard anticipation and safe driving. A high degree of SA generally helps motorists to accomplish these goals as well as provide a basis for subsequent decision making and good performance in the driving task. In the context of right-hook crash scenarios, a high degree

Fig. 1. Simulated environment in OSU driving simulator.

of SA could help motorists to detect bicyclists in the adjacent lane, anticipate their maneuvers, and make decisions based on this information to safely accomplish right-turn maneuvers at signalized intersections.

2.3. Measuring situational awareness

SA plays an important role in human interaction with a dynamic and changing environment in a real time task such as driving, flying, or air traffic control (Gugerty, 2011). Although the concept of SA was initially applied and is better developed in the aviation domain, SA has been applied to the driving condition as well, since both domains share similar dynamic environment characteristics, where system input variables and states change over time. Over the past decade, several techniques have been developed to measure SA. Gugerty classified SA measurement techniques into two groups – (i) Online, where motorist behavior is measured in a simulated driving environment with little or no interruption, and (ii) Offline, where the driving scenario is not visible during behavior measurement (Gugerty, 2011). Examples of online SA measurement include eye tracking measures, Situation Present Awareness Method (SPAM), and Useful Field of View (UFOV) test. Offline measures include the Situation Awareness Global Assessment Technique (SAGAT) proposed and validated by Endsley (1995a). Other classifications to measure SA include direct and indirect measures or subjective and objective measures. In direct measures participants are asked to recall events from their experience (Gugerty, 2011), whereas indirect measures assess SA from subject's performance. For example, Sarter & Woods described an indirect measure of SA where the time to detect irregularities in an environment was the measure of SA (Gonzalez et al., 2007; Sarter et al., 1992). Subjective measures involve assigning a numerical value to the quality of SA during a particular period and rely on a subject's self-assessment of SA (Jones, 2000*)*. Conversely, objective measures rely on querying participants to recognize a situation and then comparing their views of the situation with reality (Gonzalez et al., 2007; Endsley, 2000). SAGAT by Endsley is an example of a direct and objective measure of SA.

The most widely used offline SA technique is SAGAT, which provides an evaluation of SA based on the operator's objective opinion. In SAGAT, all of the operator's displays are made temporarily blank during periodic, randomly timed freezes in a simulation scenario and memory-based queries are directed at the operator to assess his knowledge of what was happening at that time. Queries are determined based on an in-depth cognitive task analysis across all three levels of SA defined by Endsley (1998). The main advantage of SAGAT is that it measures operator SA across a wide range of elements that are important for SA in a particular system giving an unbiased index of SA. It does not require user self-assessment or any inferences of user behavior. It is also relatively unobtrusive to the participant's performance because of the short (< 1 min) and random interruptions it employs (Bolstad and Endsley, 1990). Further, no significant effect on participant's performance were found with number of stops (as many as 3 for up to 2 min) or duration of stops of up to 5 min (Endsley, 1995a) in the simulation. However, the main disadvantage of SAGAT is the issue of intrusiveness: it may change the phenomenon of interest, and therefore fail to provide data about the natural character and occurrence of SA. Also, this method relies on operator's memory and therefore may not reflect a true representation of the operator's SA. Using SAGAT, Gugerty (2011) assessed SA of motorists in a low fidelity driving simulator. The present study expanded on Gugerty's to exame driver SA in right-hook crashes.

3. Methodology

3.1. Experimental environment

The study was conducted in the Oregon State University (OSU) driving simulator, which consists of a fully functional full-size 2009 Ford Fusion cab mounted on an electric pitch motion system that allows for onset cues for acceleration and braking events (Oregon State University, 2011). The cab is surrounded by screens where the simulated environment is projected. As shown in Fig. 1, three projectors project a 180 degree front view. A fourth projector displays the rear image in the driver's center mirror. Two side mirrors have embedded LCD displays that permit the driver to see both rear sides. The cab instrument includes a steering control loading system that accurately represents steering torques based on speed and steering angle. The computer system consists of a quad core host that runs the "SimCreator" Software (Realtime Technologies, Inc.). The data update rate for the graphics is 60 Hz. It is a high-fidelity simulator that can capture and output highly accurate performance data such as speed, position, braking, and acceleration. Fig. 1 shows views of the simulated environment created for this experiment from inside (left) and outside (right) the vehicle.

3.2. Participants

This research complied with the American Psychological Association Code of Ethics and was approved by the Oregon State University IRB, Number 5983. Informed consent was obtained from each participant. A total of 67 individuals, primarily from the community surrounding Corvallis, OR, participated in the study. The population of interest was licensed Oregon drivers; therefore, only licensed Oregon drivers with at least one year driving experience were recruited for the experiment. Recruitment of participants was accomplished through the use of flyers posted around campus and emailed to different campus organizations and a wide range of email mailing lists.

Fig. 2. Screen capture of an intersection approach in a simulated environment.

Older participants were specifically recruited by email using the Center for Healthy Aging Research (CHAR) registry (LIFE Registry). This registry includes people aged 50 or over who reside in the State of Oregon and wish to volunteer for research studies. We did not screen interested participants based on gender until the quota for either males or females had been reached, at which point only the gender with the unmet quota was recruited further. Although it was expected that many participants would be OSU students, an effort was made to incorporate participants of all ages within the specified range of 18–75 years. Each participant was randomly assigned a number to remove any uniquely identifiable information from the recorded data. Among 67 participants (35 male and 32 female), approximately 24% (11 female and five male) of participants reported simulator sickness at various stages of the experiment. All responses recorded from the participants who exhibited simulator sickness were excluded from the original data set. Thus, the final data set was comprised of 51 participants with age ranging from 19 to 69 years ($\mu = 30.24$, standard deviation [*SD*] = 13.99).

3.3. Hypotheses

The Situation Awareness Global Assessment Technique (SAGAT) (Endsley, 1995a,b) was used to measure a right-turning motorist's SA. We hypothesized that the right-turning motorist's SA would be affected by the relative position of the bicyclist. We also hypothesized that the motorist's SA would be affected when oncoming cars turn left in front of the motorist as they would compete for limited mental resources and would increase motorists' perceptual workload. Finally, we hypothesized that the interaction effect of the presence of oncoming vehicles and relative positions of bicyclists would impact right-turning motorists' SA due to greater demand on working memory load.

We also inferred that a right-turning motorist unable to avoid a crash with a through-moving bicyclist has poor knowledge of the bicyclist's location in the adjacent bike lane. Since the SA questionnaire in this experiment involved queries on bicyclist position, we hypothesized that there would be a correlation between motorists' crash avoidance behavior and their SA score, in particular the Level 1 SA score that explicitly assesses the detection of a bicyclist's location. Our research hypotheses were as follows:

- H_0 (SA1): The relative positions of adjacent bicyclists' have no effect on right-turning motorists' SA in a driving simulator environment.
- H_0 (SA2): The presence of oncoming left-turning traffic has no effect on right-turning motorists' SA in a driving simulator environment.
- H_0 (SA3): The interaction of left-turning oncoming traffic and relative position of bicyclists have no effect on right-turning motorists' SA in a driving simulator environment.
- H_0 (SA4): There is no correlation between the number of correct responses and the crash avoidance behavior of right-turning motorists in a driving simulator environment.

3.4. Experimental design

The experiment consisted of a three (bicyclist's relative position) by two (presence of oncoming left-turning vehicle) within-subject factorial design. The within-subject design provides the advantage of greater statistical power and reduction in error variance associated with individual differences (Cobb, 1998). To control for practice effects, the order of the presentation of the scenarios to the participants was counterbalanced.

3.5. Scenario Layout

The cross section of the roadway included three 12-foot traffic lanes with 5.5-foot bicycle lanes in each direction. The intersection approaches included a single shared lane and a single receiving lane, whereas the opposing direction had two lanes. No exclusive left-turn or right-turn bay was provided at the intersection. The intersection approaches had a posted speed limit of 35 mph (Fig. 2). This particular scenario includes the opportunity for oncoming left-turning vehicles waiting in the queue, and a bicyclist riding ahead of the right-turning motorist during the latter portion of green phase.

To minimize the occurrence of simulator sickness and to provide opportunities to freeze the simulation six times to measure motorists' SA, the experimental driving was divided into seven individual grids of intersections, and the crash-likely scenario was presented at the last intersection of the seventh grid. The number of right-turning scenarios included in each grid was varied so that the simulation could be stopped at various intervals, a recommended best practice for measuring SA (Endsley, 1995b). Each scenario was randomly assigned a position on a grid, except for the crash-likely scenario which had to appear last. The order of presentation of Grids 1–6 was counterbalanced to minimize the practice effect on driver performance. This arrangement also introduced random nature to the experiment, which helped to reduce the practice-effect limitation of the within-subject design, and made it more difficult for participants to predict when the simulation would stop, which was necessary for the SA measurement.

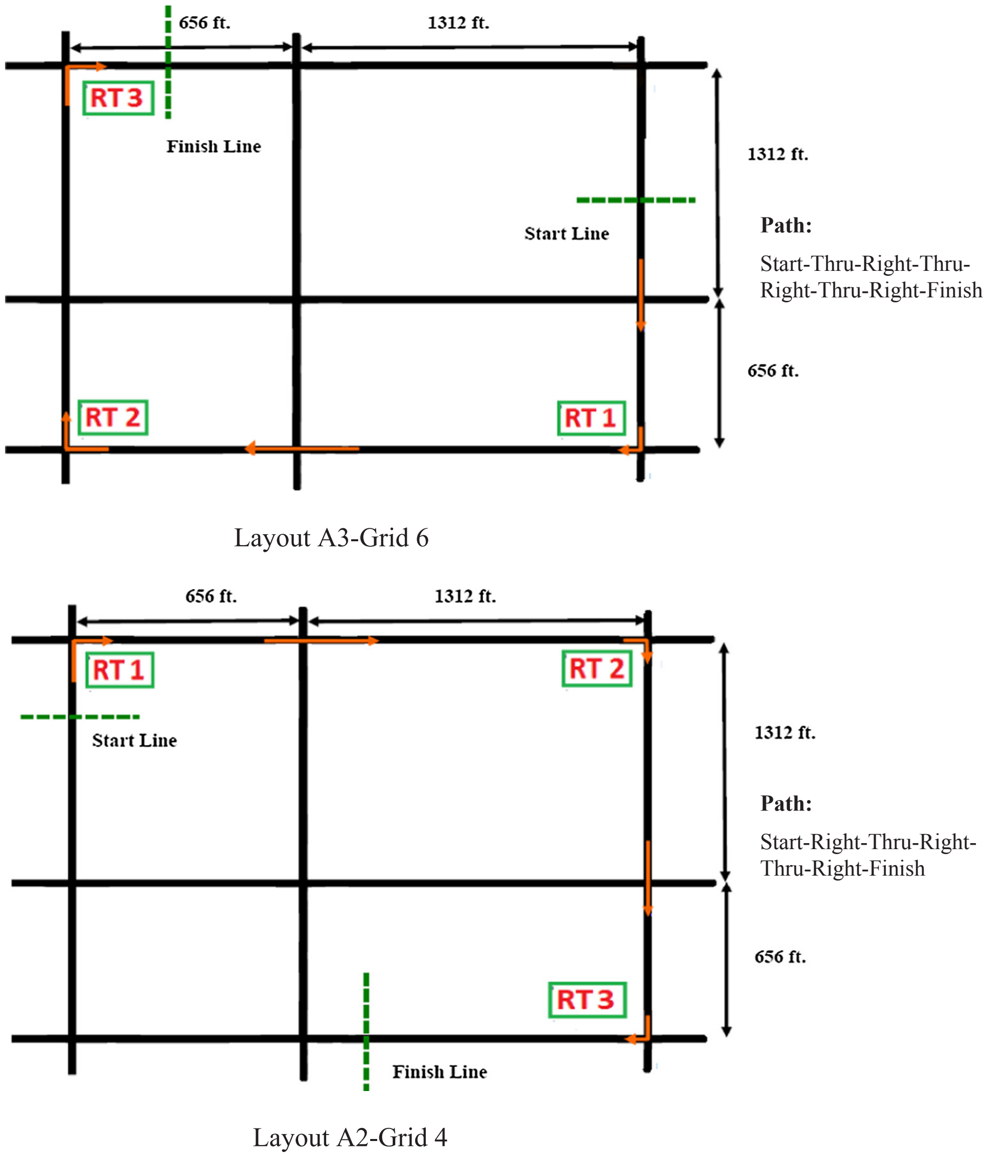

Fig. 3. Different Grid Layout of Three Right-turning Intersections – different Start and Finish Point.

Five grids consisted of three right-turning maneuvers, and the other two grids consisted of two or four right-turning maneuvers each, resulting in a total 21 right-turning maneuvers during the course of experiment. This distribution of these 21 right-turning scenarios across seven grids provided participants with the opportunity to take small breaks between clusters of scenarios. Grids 1, 2, 4, 6 and 7 were comprised of three right-turning intersections. To provide more variability in the grid presentation, the start and finish locations of these grids were not consistent. Also, the right-turning scenarios were interrupted by through movements at intersections that were not experimental scenarios to prevent participants from anticipating the motivation for the study and to reduce the likelihood of simulator sickness. Fig. 3 shows an example of grid layout of three right-turning scenarios and the path that the participant drove through. The layout represents how the right-turning intersections are distributed in different grids with different Start and Finish points. For example, Layout A2 and A3 both represent grids with three right-turning intersections but different Start and Finish locations to introduce variability. Similarly, Layout A1 shows the distribution of four right-turning intersections.

Participants (n = 51) were exposed to different combinations of relative positions of bicyclist and presence of oncoming left-turning traffic at the last intersection of first six grids to assess SA (Table 1). The

Table 1
Layout of the last intersection of first six grids.

Grid #	Relative position of bicyclists	Oncoming traffic	Number of total right-turns in the grid
1	1 bicyclist behind	No vehicles	Three
2	1 bicyclist ahead	3 vehicles	Three
3	1 bicyclist behind	3 vehicles	Four
4	No bicyclists	No vehicles	Three
5	No bicyclists	3 vehicles	Two
6	1 bicyclist ahead	No vehicles	Three
7[a]	1 bicyclist behind	3 vehicles	Three

[a] Crash-likely scenario – 1 Pedestrian crossing the intersection at the conflicting crosswalk.

highest complexity combination of the two experimental factors (i.e., bicyclist approaching from the behind at 16 mph, and three oncoming conflicting vehicles) were presented in this crash-likely scenario. The bicyclist approach speed is an above average speed but was chosen to explore the additional complexity of higher speed bicyclists (i.e. an approach on a downgrade). In addition, a pedestrian was introduced crossing the conflicting crosswalk at the intersection during the crash-likely scenario. Participants were instructed to follow typical driving rules, including compliance with the 35 mph speed limit in the experiment. The average speed of the bicyclist for this experiment was 16 mph at all intersections.

Participants were given the instruction to turn right at an intersection through an automated voice command saying "*Turn Right at the Next Intersection*" at a consistent location upstream of the intersection for all participants.

3.6. Experimental procedure

Each of three SA levels was measured using an adaptation of the SA global assessment technique, SAGAT (Endsley, 1988, 1995a,b, 2000). In this experiment, the simulation was frozen as soon as the motorist completed the last right-turn maneuver in each grid at various points in time. The total number of right-turns for different grids was not equal so that the simulation could be frozen at various intervals and participants could not predict in advance when the simulation would freeze. During a freeze, the simulation was stopped and the display was blanked and participants were presented with a questionnaire for assessing their SA using an online survey tool administered on a small laptop computer. Participants were given as much time as needed to complete the SA questionnaire. After participants completed the questionnaire, the simulation was activated with a new grid of driving scenarios. Participants were not provided with feedback on their responses. This deterministic SA measurement has been validated for assessing how aware individuals are about elements in the environment (Salmon, 2009), an important objective of this experiment.

In addition to the explicit recall measures of SA, it is also important to assess operators' SA with indirect performance-based measures since many real-time tasks require well-practiced automatic processes (Gugerty, 1997). In this experiment, participants' task performance was measured by investigating if they could avoid a crash with a through-moving adjacent bicyclist to their right while turning right at a signalized intersection during the latter portion of the green phase. This performance measure was termed motorist crash avoidance behavior. To detect crashes, motorist's driving in the simulated environment was observed continuously from the simulator's operator station and records were taken at the moment a crash occurred. Motorists were also verbally asked at the end of the experiment if they caused any crashes during the experiment. The recorded crash data was further validated by checking the locations of the subject vehicle and bicycle centroid, recorded as dynamic variable data in the driving simulator.

3.6.1. Presentation of situational awareness questions

Participants were presented with a total of nine SA queries each asking three questions for each level of motorist SA (perception, comprehension and projection). Each participant received the same nine queries every time, but in a randomized order. The queries were presented randomly so that the participant could not associate any particular question with a particular portion of the driving task while turning at each intersection.

3.6.2. Level 1 SA – perception of the elements in the environment.

The first step in achieving SA is to perceive the status, attributes and dynamics of relevant elements in the environment (Endsley, 2000). To assess Level 1 SA, participants were asked to recall relevant elements in their driving environments, such as the last road sign they saw, the number of bicyclists present in the adjacent bicycle lane, and the number of oncoming vehicles that turned left just before the simulation freeze.

3.6.3. Level 2 SA – comprehension of the current situation.

This level of SA requires the comprehension of the significance of objects and events through the synthesis and integration of disjointed Level 1 elements in conjunction with operator goals (Endsley, 2000). Assessment of Level 2 SA investigated whether they could integrate various elements in the built environment, such as the turning signal indicator of the oncoming left-turning vehicles that were waiting in the queue or the current location of a motorist's vehicle with respect to the location where they started driving.

3.6.4. Level 3 SA – projection of future status.

The third and highest level of SA requires the ability to project the future actions of elements in the environment, achieved through the knowledge and comprehension of Level 1 and Level 2 SA. To assess Level 3 SA, participants were asked if they could project times to certain events, such as the time required to reach the approaching intersection, or project the location of their vehicle relative to the crossing pedestrian in order to avoid a collision.

Participant's SA was measured by assessing the average percent of correct responses to Level 1, Level 2 and Level 3 queries and an overall SA score (sum of all three SA level scores) across all questionnaires. Participants were not aware of the scoring system.

4. Results

4.1. Descriptive data analysis

The independent variables were the relative position of bicyclists while approaching the intersection with three levels (no bicyclists, bicyclist approaching from behind the motorist in the blind spot, and a bicyclist ahead of the motorist being overtaken), and the presence of oncoming vehicular traffic with two levels (no oncoming vehicles and three oncoming vehicles).

The dependent variables for the experiment were motorists' SA measured through their responses to SAGAT queries in perception (Level 1 SA), comprehension (Level 2 SA) and projection (Level 3 SA) queries and overall SA score across all questionnaires. SAGAT scoring of SA responses are based on binomial data (e.g., correct or incorrect responses) when compared to what was actually happening in the simulation at the time of the freeze. Participant responses to the SA queries were scored either as 1 (correct) or 0 (incorrect). Participants' overall SAGAT scores for a specific query were calculated by summing all correct responses in Level 1, Level 2, and Level 3 SA queries. Data reduction and visualization was performed in both Microsoft Excel (Microsoft, 2013) and SPSS (IBM SPSS Statistics, V22.0), and the statistical analysis was performed in SPSS.

Fig. 4 presents the mean SA scores to the Level 1, Level 2, Level 3 queries and the mean of overall SA scores as a function of relative position of bicyclists and volume of oncoming vehicular traffic. Inspection of the plot reveals that, on average, right-turning motorists exhibited better overall SA in the base condition (i.e., when there was no bicyclist or oncoming vehicle present) ($\mu = 4.88$, $SD = 1.56$) at the intersection and exhibited the worst overall SA when the bicyclist was approaching from behind the motorist, but when no oncoming vehicles were present ($\mu = 3.63$, $SD = 1.76$).

The mean scores in both Level 1 SA ($\mu = 1.41$, $SD = 0.75$) and Level 2 ($\mu = 0.90$, $SD = 0.76$) SA were the lowest when an oncoming vehicle was turning in front of the motorist and a bicyclist was approaching from behind. The plot also reveals that right-turning motorists' Level 1 and Level 2 SA scores degraded for the base condition (i.e., when no bicyclist and oncoming vehicles were present).

Unlike the Level 1 and Level 2 SA, the right-turning motorists' Level 3 SA score was the lowest when a bicyclist was riding ahead of the motorist while no oncoming traffic was present ($\mu = 1.14$, $SD = 0.92$).

4.2. Statistical analysis

A repeated-measure general linear model (GLM) was used for this data analysis. Since the measurements were taken on each participant under each of several conditions, there was a violation of the

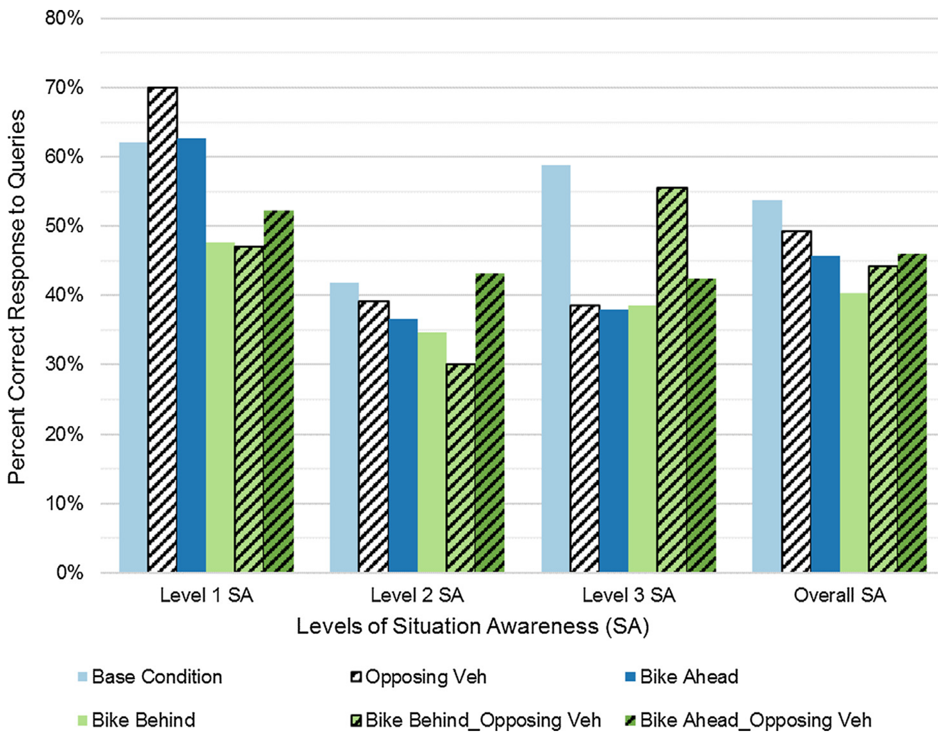

Fig. 4. Mean percent correct responses to SA queries for bicyclists' position and oncoming vehicular volume.

"independence of observation" condition (Weinfurt, 2000). Therefore, a "repeated-measures" approach was considered for this data analysis. To control for the experiment-wide error rate associated with conducting multiple analyses of variance (ANOVA) on different dependent variables a multivariate analysis of variance (MANOVA) was performed (Kass et al., 2007). MANOVA accounts for the correlation between the dependent variables (Mayers, 2013). In addition a repeated-measures ANOVA is sensitive to the violation of the compound symmetry assumption and the assumption of sphericity (Weinfurt, 2000). When these two assumptions are violated, MANOVA is a more valid and statistically powerful procedure. To perform a MANOVA, the assumptions required for MANOVA were verified for the data set. The independent variables were categorical, and the dependent variables (SA scores) were interval data. The dependent variables were reasonably normally distributed (skewness and kurtosis z-values between -1.96 and 1.96) and were reasonably correlated (for negative correlation, $r < -0.40$ and for positive correlation, $r < 0.90$). Therefore, the data set met the assumption criteria to perform a repeated-measures MANOVA.

The full model in the repeated-measures MANOVA included all of the variables as additive variables. Table 2 shows the output of the MANOVA analysis that includes different outcomes for measuring the multivariate significance. According to Bray and Maxwell (1985), Pillai's Trace (V) is the most powerful option when the samples are of equal size. Therefore, results from the Pillai's Trace (V) was considered to report the significance of the test in this experiment.

Repeated-measures MANOVA results (Table 2) revealed a significant main effect of the "bicyclist's position" on SA measures ($V = 0.227$, $F(2, 49) = 7.183$, $p < 0.01$, partial $\eta^2 = 0.227$). Therefore, we rejected the first null hypothesis (H_0 (SA1)), which stated that the relative positions of adjacent bicyclists' have no effect on right-turning motorists' SA. There was no significant main effect of the "presence of oncoming vehicles". Also, there was no interaction effect of the "bicyclist's position" and "presence of oncoming vehicles". Therefore, we failed to reject the second (H_0 (SA2)) and third null hypothesis (H_0 (SA3)) of this experiment, which stated the effect of the presence of the oncoming vehicle and the interaction effect on right-turning motorists' SA respectively.

Table 2
Multivariate statistics.

Multivariate tests[a]							
Effect		Value	F	Hypothesis df	Error df	Sig.	Partial eta squared
BikePos	Pillai's Trace	0.227	7.183[b]	2.000	49.000	0.002	0.227
VehVol	Pillai's Trace	0.001	.073[b]	1.000	50.000	0.789	0.001
BikePos * Veh-Vol	Pillai's Trace	0.076	2.024[b]	2.000	49.000	0.143	0.076

Within Subjects Design: BikePos + VehVol + BikePos * VehVol.
[a] Design: Intercept.
[b] Exact statistic.

Since the MANOVA main effects of bicyclist's position were found, a univariate analysis revealed that right-turning motorists' overall SA score was significantly degraded when a bicyclist was approaching from behind the motorist when compared to no bicyclist presence at the intersection ($p < 0.05$).

A repeated-measures ANOVA was used to analyze the Level 1 SA score. Results indicated that there was a significant interaction effect of the bicyclist's position and oncoming vehicular volume on the Level 1 SA score ($F(2, 49) = 4.52$, $p < 0.05$). Motorists' perceptual knowledge of the driving environment was the lowest when a bicyclist approached from behind the motorist and oncoming vehicles were present.

Repeated-measures ANOVA analysis on the Level 2 SA scores revealed a significant effect of the bicyclist's position ($F(2, 49) = 3.85$, $p < 0.05$). No significant effect of the oncoming vehicular volume or interaction effect was found on the Level 2 SA score. A Bonferroni post-hoc analysis indicated that motorists' comprehension of the traffic elements degraded when a bicyclist was approaching from behind the motorist when compared with no bicyclist present ($p < 0.05$) or when the bicyclist was riding ahead of the motorist on the approach to the intersection ($p < 0.05$).

Similar to the Level 1 SA score, a repeated-measures ANOVA analysis on the Level 3 SA score revealed that there was a significant interaction effect of the bicyclist's position and oncoming vehicular volume on a right-turning motorist's Level 3 SA score ($F (2, 49) = 8.26$, $p < 0.05$). However, unlike the Level 1 SA, motorists demonstrated reduced ability to project status of the driving environment when both the bicyclist was riding ahead of and oncoming vehicles were turning in front of the motorist as compared to when a bicyclist was approaching from behind and oncoming vehicles turned in front of the motorist.

4.3. Correlation analysis

Motorist's crash avoidance behavior was also used as an indicator of their SA while performing a right-turn maneuver at the intersection. To determine if there was any significant association between the right-turning motorist's overall SA score and crash avoidance behavior, a Point biserial correlation analysis was performed. Participant's crash avoidance behavior was measured in terms of crash occurrence, a dichotomous nominal variable, and scored either as 1 (crash) or 0 (no crash). Since the Point biserial correlation coefficient (rpbi) indicates the degree of relationship between a naturally occurring dichotomous nominal scale and an interval scale (Brown, 1988), it was chosen to calculate the association between crash occurrence (dichotomous variable) and motorist's overall SA score (interval scale).

The rpbi indicated a reasonably negative linear association between overall SA scores and crash occurrence, although not statistically significant (rpbi = −0.14, ns). The negative association between overall SA score and crash occurrence (Fig. 5a) indicated that motorist having lower scores in overall correct responses to SA queries tended to show lower performance in avoiding a crash.

Since perception and detection of the hazard is an important criterion of crash avoidance, the Point biserial correlation analysis was also conducted between participant's Level 1 SA score and crash occurrence. In this case, The Point biserial correlation coefficient (rpbi) indicated a significant negative linear association (Fig. 5b) between Level 1 SA score and crash occurrence (rpbi = −0.3, $p < 0.05$). This finding suggests that a common cause of the observed crashes was a failure to detect the presence of a conflicting bicycle.

In summary, the analyses indicated that the relative position of a bicyclist significantly influenced right-turning motorist's overall SA. The volume of oncoming vehicles was found not to have a statistically significant effect on right-turning motorist's overall SA. The interaction effect between bicyclist's relative position and oncoming vehicular volume was also found not to have a statistically significant influence on right-turning motorist's overall SA. However, the interaction effect was found to be statistically significant for Level 1 and Level 3 SA. The Point biserial correlation coefficient indicated a reasonably negative linear association between right-turning motorist's crash avoidance behavior and overall SA, although not statistically significant. However, a significant negative linear relationship was found between right-turning motorist's crash avoidance behavior and Level 1 SA.

5. Discussion

This study investigated motorists' SA in the real-time complex task of simulated driving as a possible factor in right-hook crashes. Specifically, the objective was to determine if right-turning motorists had the knowledge needed for the driving subtask of monitoring and hazard avoidance, (i.e., the knowledge of the traffic around them) to successfully complete a safe right-turn maneuver at a signalized intersection during the latter portion of the green phase.

As expected, participant's overall SA scores indicated that before turning right, motorists were significantly less aware of the presence of bicyclists in the adjacent bike lane when the bicyclist was approaching from behind the motorists as compared to when the bicyclist was riding ahead of the motorist ($p < 0.05$). This suggests that right-turning motorists used cues of the surrounding traffic to focus their attention during driving. For example, an adjacent bicyclist riding ahead of the motorist posed an immediate driving hazard to motorists and they focused more attention on the bicyclist. However, when the bicyclist was approaching from behind in the motorist's blind spot, motorists did not

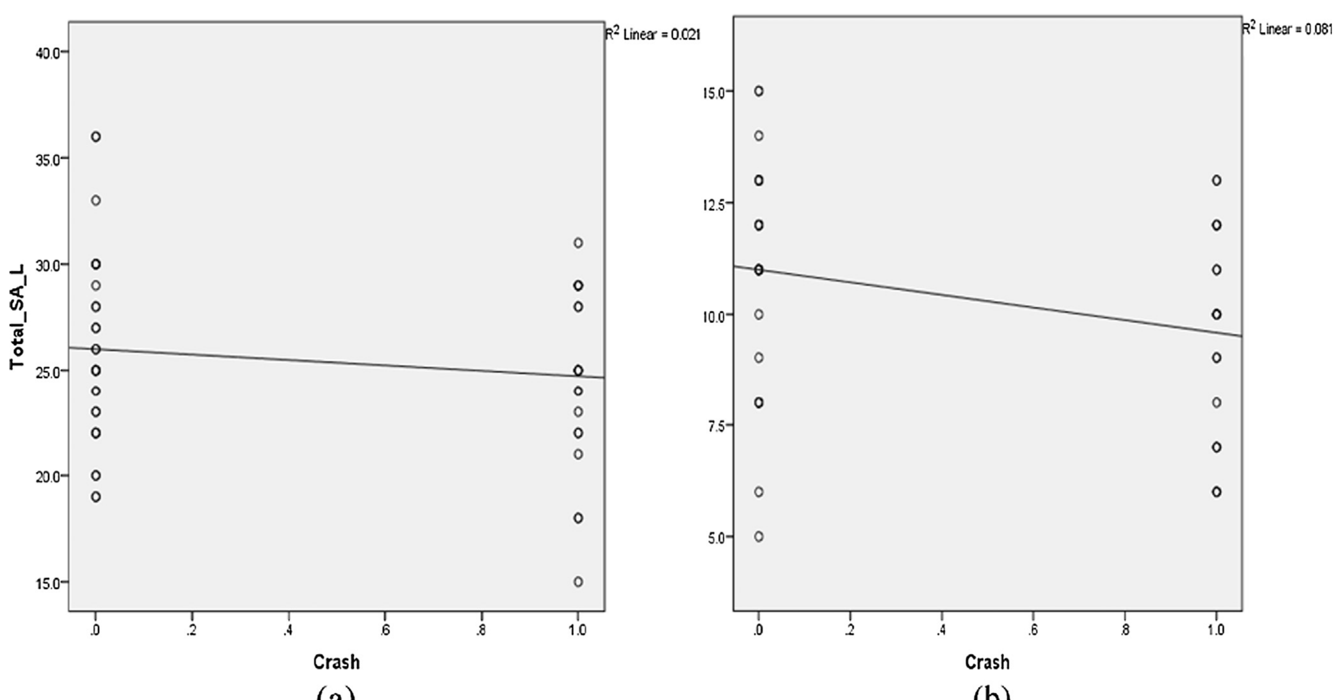

Fig. 5. Correlation between Crash Occurrence and (a) Overall SA Score, (b) Level 1 SA Score.

focus attention on the bicyclist in their peripheral vision, in the rear-view or side view mirrors. This may be due to the fact that tracking an object in the blind spot of a car demands greater working memory (Gugerty, 2011). This finding is also consistent with previous research by Gugerty (2011), Falzetta (2004) and Crundall et al. (1999). Gugerty measured motorist's SA through hazard detection, blocking car detection, and crash avoidance during a simulated driving task and found that participants focused more of their attention on nearby cars and cars in front of them that were perceived more likely to pose a hazard and focused less attention on cars in the blind spot. While assessing motorists' attention allocation by location and type of event, Falzetta (2004) found that participants detected forward events better than rear events, and generally allocated more attention to the road ahead. Crundall et al. (1999) also found that the frequency of detecting peripheral visual onsets decreased as the cognitive demand of the focal hazard-perception task increased.

Motorists' perception (SA Level 1) of traffic was found to be the lowest when oncoming vehicles were turning left in front of the motorist and the bicyclist was approaching from behind ($p < 0.05$). This observation could be explained by the Cue Utilization Study, which evaluated the extent to which participants' behavior is constrained by environmental cues (Brunswik, 1956; Hursch et al., 1964). In this experiment, motorists allocated attention to the oncoming vehicle that posed a potential driving hazard to them, not to the bicyclist in their peripheral vision. Since focal hazard-perception tasks compete for limited cognitive resources, it eventually decreased the frequency of detecting peripheral visual events (Crundall et al., 1999), and this was evidenced by decreased Level 1 SA.

Motorists' perception (Level 1 SA) and comprehension (Level 2 SA) of the driving environment was better when the bicyclist was riding ahead as compared to when the bicyclist was approaching from behind. However, an opposing trend was found for Level 3 SA (projection queries), where motorists' projection of the driving environment significantly degraded when the bicyclist was riding ahead of the motorist and oncoming vehicles were turning left in front of the motorist ($p < 0.001$). This can be explained by the limitation of motorist's attentional capacity. With excessive demands on attention due to multiple environmental stimuli (e.g., presence of a bicycle and oncoming cars) to attend to in their focal vision, motorist's task performance declined corresponding to reduced SA. Real world behavior of bicyclists is variable and drivers may not be bicyclists themselves, leaving them without a reference point to accurately project bicycle behaviors or positions.

In the simulated driving task, motorists' perception and comprehension of the driving environments (i.e. lower level SA) also degraded in the scenario where there was no oncoming vehicle and no bicyclist present, although the difference was not statistically significant. This was likely because in the absence of any type of environmental stimuli (i.e. car, bicyclist), the motorist was not allocating much visual attention to the observation of the driving environment and their knowledge of surrounding traffic degraded.

A significant relationship between motorist's crash avoidance behavior and lower level SA (perception) suggested that a motorist who is good at detecting adjacent traffic might exhibit better crash avoidance behavior with a bicyclist situated in the vehicle's blind spot. This finding suggests that observed crashes were primarily due to the detection error. Gugerty (2011) similarly found that better explicit recall of car locations was associated with better performance in hazard detection and blocking car detection.

Results from this experiment should be interpreted with caution. High SA scores do not always correlate to safe performance (e.g. motorists with relatively high SA may not always complete the right-turn maneuver successfully). Endsley (2000), for example, indicated that many other factors are involved in turning good SA into successful performance and it is possible to have poor performance with perfect SA and good performance with poor SA.

6. Conclusion

This research contributes to the gap in the body of knowledge by presenting a better understanding of causal factors of right-hook crashes involving human error. Scores from motorists' three levels of SA, i.e. Level 1 SA (perception), Level 2 SA (comprehension), Level 3 SA (projection) and the overall SA revealed the following findings:

- Motorists focus the majority of their attention on nearby cars and cars in front of them that were perceived to most likely pose a hazard. They focused less attention on cars in the blind spot or in peripheral vision.
- Motorists' Level 1 SA of the surrounding traffic significantly degraded when oncoming vehicles were present and the bicyclist was approaching from behind. However, motorists' projection (Level 3 SA) of the driving environment significantly degraded when the bicyclist was riding ahead of the motorist and oncoming vehicles were present.
- Correlation between participant's Level 1 SA score and crash occurrence suggests that a common cause of observed crashes was a failure to detect the presence of an adjacent bicyclist before turning right during the latter portion of the green phase at intersections.
- The bicyclist approaching from behind the motorist is the most vulnerable to a right-turning motorist and failure to detect this bicyclist may lead to a RH crash.
- The findings agree well with anecdotal evidence and common experience, but they lend objectivity to the issue and the methods employed offer tools and an approach to better understanding and ultimately reducing the incidence of right-hook crashes.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.ssci.2018.07.025.

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