Author-accepted manuscripts. Modeling Brake Perception Response Time in On-Road and Roadside Hazards Using an Integrated Cognitive Architecture
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IEEE Transactions on Human-Machine Systems 54 (4), 441-454, 2024

Modelling Brake Perception-Response Time in On-Road and Roadside Hazards Using an Integrated Cognitive Architecture

Umair Rehman, Shi Cao, and Carolyn Macgregor

***Abstract*— In this study, we used a computational cognitive architecture called QN-ACTR-SA (Queuing Network – Adaptive Control of Thought Rational – Situation Awareness) to model and simulate the Brake Perception Response Time (BPRT) to visual roadway hazards. The model incorporates an integrated driver model to simulate human driving behavior and uses a dynamic visual sampling model to simulate how drivers allocate their attention. We validated the model by comparing its results to empirical data from human participants who encountered on-road and roadside hazards in a simulated driving environment. The results showed that BPRT was shorter for on-road hazards compared to roadside hazards and that the overall model fitness had a Mean Absolute Percentage Error of 9.4% and a Root Mean Squared Error of 0.13 seconds. The modelling results demonstrated that QN-ACTR-SA could effectively simulate BPRT to both on-road and roadside hazards and capture the difference between the two contrasting conditions.**

***Index Terms*—Brake Perception Response Time, Situation Awareness, Cognitive Architectures, Road Hazards, Human Performance Modelling**

I. Introduction

Driver error due to poor hazard perception is one of the leading reasons for motor-vehicle collisions [1]–[3]. Delayed or missed hazard perception can lead to decision errors, thereby increasing the risk of traffic collisions [1], [4]–[6]. Therefore, drivers' ability to perceive possible hazards and respond appropriately to critical events is vital for traffic safety. According to a recent 100-car naturalistic driving study [7], a major factor contributing to traffic accidents (including both vehicle-to-vehicle collisions and instances of a vehicle veering off the road) is inattention due to improper perception of roadway hazards. The findings from this study strongly underscore the critical role of driver awareness in preventing vehicle crashes and collisions. A staggering 80% of these crashes were tied to drivers not paying attention to the road, spotlighting the enormous risk posed by inattention.

Hazard perception can be defined as the driver's ability to identify and respond to roadway hazards [8], [9]. In this context, roadway hazards are potential sources of danger or threat to the safety of road users, such as obstacles, poor road conditions, or the behavior of other road users. Hazard perception is sometimes also used to refer to the perceptual processes necessary for hazard avoidance [4], [10]. Hazard perception tests have been used in the last five decades to investigate human factors within driving safety research (refer to Moran et al. [6] for review). Reaction time to critical events can be used as a measure to assess the driver's hazard perception ability because it influences the success rate of evading emergency scenarios [11]. In formal terms, the time duration for a driver to perceive and respond to a hazard is referred to as hazard-perception response time (HPRT) [12], [13]. HPRT can be further categorized into brake-perception response time (BPRT) and steering-perception response time (SPRT), capturing individual brake or steering response latencies. Most studies have focused on BPRT (refer to [14] for review), whereas a few studies have also used SPRT [15]–[17].

Numerous studies have been conducted to examine how various factors impact drivers' HPRT [14], [18], [19]. These factors typically encompass age and driving experience [9], [12], the unique nature of hazards [11], [20], [21], distraction [20], [22]–[24], and the transition of control from automated driving [25], [26]. Moreover, HPRT has been employed to evaluate the safety of road designs [27] and serves as valuable evidence in court proceedings related to motor vehicle accidents [28].

HPRT has been investigated in various scenarios with different types of hazards, including static objects on the road [27], signalized intersections [29], lead vehicle braking scenarios [30], auditory stimuli [31], pedestrian incursions [32], [33], and intruding vehicles at intersections and merges. [34], [35]. Most of these studies have been conducted in simulated settings using driving simulators, whereas some have also been conducted on actual roadways and test tracks.

A multitude of studies have investigated the effectiveness of video-based hazard perception tests in evaluating driver skill and safety [36], [37]. Scialfa et al. [38] highlight the successful employment of these tests in discriminating between experienced and novice drivers, thus demonstrating their efficacy as predictive measures of accident involvement. Hazard perception research by Isler et al. [39] underscores the importance of training and experience in the quick recognition of potential road hazards, suggesting that video tests may also be useful for educational purposes. A study by Horswill et al. [40] indicates that reaction times on video-based tests correlate with crash risk for older adults, further corroborating their validity, the consensus suggests that video-based hazard perception tests provide a valuable tool in assessing driving safety and ability.

Despite the rigorous work in the domain, most hazard

perception theories are conceptual and lack rigorous mathematical formulations or computational implementations. Hazard perception results have mostly been construed from controlled experiments requiring human participants. Existing methods for assessing hazard perception are either experimental or through the analysis of driver data from naturalistic settings. There is a paucity of research that attempts to model and simulate drivers' hazard perception skills.

Computational modelling can facilitate simulation of HPRT and can allow researchers to predict HPRT in different driving conditions. Such modelling endeavors can reduce dependency on empirical experimentation and decrease the overall research expenditure [41]. Model-based simulation of HPRT can also offer cost-benefit evaluations of various extreme case traffic scenarios that are impractical to enact in simulated settings or observe through real-world driving. The current study is motivated by the lack of computational models that can be employed for the simulation and prediction of HPRT.

In the research literature, a limited number of studies have introduced computational models for capturing HPRT in different conditions. The examples include microsimulation models that follow a stimulus-response paradigm. Such models are usually built using a standard two-stage process. First, a causal relationship between perception-response times and some other variables, such as deceleration rate, and time headway, is established. In the second phase, a statistical method is utilized to create a predictive model by analyzing human driving data. Commonly employed techniques for this purpose include log-normal modeling [42]–[44] and regression [45]–[49]. Although these models effectively address traffic-related patterns, they fail to consider the cognitive processes that elucidate drivers' ability to perceive hazards. These models lack human information processing mechanisms and cannot offer detailed insights into human-machine interaction from the lens of human cognitive abilities and limitations. Consequentially, the potential of these models to prescribe human factor countermeasures is severely constrained.

In contrast to most microsimulation models, cognitive-architectures-based simulation takes into account human cognitive processes by unifying psychologically plausible models of human perception and attentional mechanisms, memory resources, and motor functionality [50]. A cognitive architecture represents a cohort of computational cognitive models integrated within a unified framework. Cognitive architectures can be represented in a computer simulation program that is capable of directly interacting with the task environment using synthetic visual and motor subsystems [51]. Cognitive-architecture-based models are inherently stochastic and flexible enough to cater to different test cases and driving scenarios. We propose a cognitive-architecture-based approach for modelling HPRT to visual roadway hazards that require emergency avoidance responses.

We use QN-ACTR-SA (Queuing Network – Adaptive Control of Thought Rational – Situation Awareness), a computational cognitive architecture, to model and simulate HPRT [52]. QN-ACTR-SA is an improvement to the QN-ACTR architecture, adding the capability to model Situation Awareness (SA). SA in the current context is the driver's ability to perceive (Level 1 SA), understand (Level 2 SA), and predict (Level 3 SA) roadway hazards in real-time to make informed decisions and perform safe driving maneuvers. Previously, QN-ACTR-SA has been effective in modelling driver responses to SA probes in both easy and complex driving conditions using the SAGAT technique [52]. However, the scope of QN-ACTR-SA's functionality is somewhat constricted, as it does not integrate higher SA levels into its architectural framework. In particular, it neglects Level 2 SA, which deals with comprehension, and Level 3 SA, which encapsulates projection. Hence, it is essential to note the limitations inherent in the current cognitive architecture of the QN-ACTR-SA model. This research primarily focuses on modelling drivers' hazard perception skills and not SA. Previous research has highlighted a potential link between the concept of hazard perception and the three-stage model of SA [5], [53]. Hazard perception, often assessed via response time to stimuli, serves as a frequent measure for SA in driving research, it does not equate to Level 1 SA or Perception [5], [53]. The former strictly identifies potential threats, whereas the latter delves deeper, examining the status, attributes, and dynamics of environmental elements. Hence, Level 1 SA encapsulates a more comprehensive concept, including hazard perception. Employing hazard perception tests in SA studies offers an empirical, though simplified, reflection of the more expansive Level 1 SA framework [4], [5].

II. Methodology

In this study, we investigate the QN-ACTR-SA model's performance in predicting HPRT. For validation, we compared HPRT results generated by QN-ACTR-SA against empirical data from human participants. To collect empirical data, we conducted an experiment in a driving simulator where participants encountered different types of hazards. The QN-ACTR-SA model was connected to the same driving simulator and exposed to the same experimental conditions as human participants. In this experiment, only simple reaction time for brake responses was taken into account; therefore, we measured BPRT only. The empirical study was purposely designed to reflect this restraint, and it was ensured that drivers' reactions were limited to brake responses only. Human drivers' responses to emergencies can include both steering and brake responses, which need to be studied and modelled separately. In the current study, we chose to limit the scope to brake responses only to simplify model building and leave steering responses for future studies.

While many elements on the road could broadly be considered hazards, our study specifically defines a 'hazard' as an event that suddenly demands the driver's attention and impacts BPRT. We examine four main types: two on the road, like abrupt braking, and two roadside, such as vehicles unexpectedly entering from an intersection. This focus helps maintain clarity and scope, considering only those elements that require an immediate driver response.

QN-ACTR is the integration of two isolated but complementary architectures – Queueing Network (QN) [54] and Adaptive Control of Thought-Rational (ACT-R) [55]. QN-

ACTR has previously been employed to simulate driver behavior in different contexts, such as investigating drivers' lateral control performance [56], simulating the effect of driving experience on collision avoidance braking [57], understanding the effect of limited sight distance on car-following performance [58], modelling concurrent processing of vehicle lane-keeping and speech comprehension tasks [59], simulating reaction time in reading directional signs on roadways [60], and predicting takeover reaction time in automated driving scenarios [61]. However, QN-ACTR lacked the visual attention mechanisms that are necessary for simulating driver attention allocation patterns. To address this limitation, a computational theory of visual attention allocation, called Salience-Effort-Expectancy-Value (SEEV) [62], was integrated within QN-ACTR to form QN-ACTR-SA. The modeling mechanisms of QN-ACTR-SA are described in greater detail in section II.B.

The SEEV model is a predictive model of visual attention and resource allocation. The SEEV model provides a theoretical framework for understanding why certain cues in the environment are more likely to be perceived than others. By applying the SEEV model, we can gain insights into the factors that influence the driver's hazard perception skills. Numerous studies across various contexts, including driving [52], [63]; aviation [64], [65]; and healthcare [66], have utilized the SEEV model to understand and assess operator attention allocation. The findings from these studies consistently demonstrate a significant positive correlation between the SEEV model fit and attention allocation scores. While the SEEV model has been extensively applied across various contexts, its use in performance-based assessments of hazard perception skill in driving, such as BPRT, is limited. This area of study remains underexplored and could benefit from additional research to further evaluate the model's utility in this specific application.

In our study, the allocation of attention, as modeled by SEEV, can indicate whether a driver is capable of perceiving and responding to a potential hazard in a timely manner. Our research's primary aim is not to validate the SEEV model against driver scanning behavior. Instead, we employ the SEEV model, previously validated for its ability to predict human attention allocation patterns [52], [63], as a tool to predict BPRT when coupled with a cognitive architecture. This approach also delves into facets of human cognitive behavior that the SEEV model doesn't fully encompass but is covered by the QN-ACTR architecture. This incorporates elements such as driving behavior, which influences and shares time with attention allocation, as well as response latency to impending hazards, among other factors.

The development of the cognitive architecture of the QN-ACTR-SA model requires experimental work at Level 1 SA, before we can move on to incorporating Level 2 and Level 3 SA. Thus, the current functional model is unable to adequately represent these more advanced levels of SA. It falls short when it comes to understanding the environment, interpreting states within the context of goals, and predicting potential changes - essential elements of Level 2 and Level 3 SA. In the case of driving, a more comprehensive understanding of SA would facilitate a driver's decision-making process in the face of hazards, allowing them to proactively adjust their actions or strategies. This could involve choosing to execute a braking or steering command based on the situation at hand. However, since the QN-ACTR-SA model is currently restricted to perception, the study was constrained to simple reaction time. To accommodate this, the experiment design permitted only one response type - the braking command, thereby intentionally omitting the steering option. The focus was thus shifted geared toward examining brake perception reception time.

Any assessment of perception, whether performance-based or recall-based, implicitly involves aspects of Level 2 and Level 3 SA, such as recognition and projection. However, our methodology intentionally simplified these higher-level SA processes within the scenario design to concentrate on immediate reaction times to stimuli. This decision was made to specifically explore the perception aspect within our study's constrained scope, thus avoiding the complexities associated with full-scale modeling of recognition and projection. While our approach may touch upon Level 2 and Level 3 SA, we treated these as baseline assumptions, not detailed components, to maintain our focus on reaction times in straightforward stimulus-response scenarios. This allowed us to isolate and measure the hazard perception aspect of SA we aimed to examine, acknowledging that a more extensive model would encompass a broader range of SA dimensions.

The investigation in this paper focuses primarily on measuring simple reaction time [67], which is defined as the period necessary for an individual to react to a single stimulus. This reaction time encapsulates the cognitive shift from perceiving the stimulus to formulating a corresponding response, bypassing the intricacies of identifying the hazard's nature or the type of response required. In contrast to simple reaction time, choice reaction time accounts for the duration required to discern both the nature of the hazard and the necessary response. This involves a more profound exploration into higher tiers of SA, encompassing comprehension and projection stages. These stages are associated with Level 2 and Level 3 SA, respectively, and represent an integral part of choice reaction time.

A. EMPIRICAL STUDY

In this empirical study, we investigate drivers' BPRT to four distinct surprise roadway hazards, focusing on both on-road and roadside conditions. The two on-road conditions include lead vehicle braking scenarios on either side of the dual carriageway, whereas the two roadside conditions include unexpected intrusion from an intersection and a car suddenly coming in front of the driver’s vehicle from the merge lane. These hazards necessitated emergency avoidance maneuvers. We hypothesized that BPRT to on-road hazards would be faster due to drivers' primary visual attention being focused ahead rather than on the periphery. An experiment was designed on the above-stated hypothesis. The study involved 11 participants with varying driving experiences, using a fixed-base driving simulator equipped with a realistic driving setup. The experiment was conducted on a simulated dual carriageway,

featuring a mix of hazardous and non-hazardous tracks. The design of the study and the experimental controls were specifically tailored to ensure that the drivers' reactions were confined to braking responses only, eliminating steering as a possible response. This setup allowed for a precise measurement of BPRT, providing valuable insights into drivers' response behaviors in different hazardous scenarios. Ethics approval for conducting the study was obtained from the University of Waterloo Office of Research Ethics.

PARTICIPANTS

A total of 11 participants (seven males and four females) aged 21 to 26 years (M = 24.0, SD = 1.1) took part in this research study. All participants had a valid driver's license and had a driving experience of at least one year. All participants had normal or corrected-to-normal visual and auditory acuities.

1) APPARATUS

A fixed-base driving simulator was used in this research that had a 2004 Toyota Corolla seat attached to a wooden base (refer to Fig .1.). Logitech Driving Force GT steering wheel, brake, and accelerator pedals were used as the main driver controls. OpenDS driving simulator software was used [68], and the driving task was displayed on a Samsung (48 inches diagonal distance) LCD television that had a resolution of 1920x1080 with a refresh rate of 60 Hz.

There were four major Areas-of-interest (AOIs) in the simulation. Firstly, the front road area was about 41 inches wide and 23 inches high on the screen. Secondly, each of the side mirrors was about 7 inches wide and 8 inches high. The third AOI was the center mirror, 13 inches in width and 6 inches in height. The viewing distance in the driving simulator setup was approximately 2.3 feet (0.7 meters) from the driver's seat to the screen. The field of view for the driving simulator setup is approximately 74.4 degrees horizontally and 46.3 degrees vertically. Lastly, the speedometer and RPM meter were both 6 inches in diameter, although part of the RPM meter was obscured by the speedometer due to its design (Fig. 2).

2) SCENARIO

The experiment was conducted on a simulated dual carriageway, located in a lowland rural landscape, with two lanes in each direction. The maximum speed of the track was 70 km/h. A total of eight straight tracks with no curves were designed for this study, and all tracks were roughly 5000m in length. Four tracks presented participants with unexpected hazards that required a hazard-evading maneuver, and the remaining four tracks did not present any hazard. In total, each participant experiences all eight completed tracks and the order of experiencing the hazardous tracks was randomized across subjects using a Latin square design.

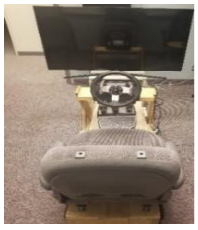


FIG.1. represents the fixed-based driving simulator used in the empirical study.

To limit the driver's response actions to brake response only, a few experimental controls were adopted. The segment where the hazardous event materializes was designed to have only a single lane open. The other lane was blocked by barriers, and a construction sign was used to indicate that it is an active work zone. We purposely implemented scenarios where one side of the road was obstructed, aiming to mimic the common real-world situation of encountering a construction zone. This was achieved by strategically placing concrete bollards to create the necessary diversion. To further enhance the authenticity of the scene, a construction sign was prominently incorporated into the scenario.

This design also ensures that participants could not consider steering as an evasive response maneuver. The drivers were instructed to engage in cruise control after reaching the speed limit of the roadway. This ensured that the first brake response received was an evasive maneuver when the drivers were attempting to disengage the cruise control to avoid the collision. The reason to instruct the driver to engage in cruise control after reaching the roadway speed limit was essential because we wanted to ensure that drivers were not braking while driving, and hence brake responses generally expected while driving were not interfering with the BPRT measurement process.

The primary method for identifying the onset of braking was based on vehicle longitudinal acceleration. We set a threshold of -1.5 m/s² for this purpose. Secondly, as a supplementary measure, we also monitored speed decrease, especially since the vehicle was maintained at cruise control at 70 km/h. This method served as a secondary verification for braking events. When the car's speed decreased, indicating a deviation from the cruise-controlled speed, it provided additional confirmation that braking had occurred.

Apart from the presence of hazards, the driving environment was adopted from one of the conditions (easy condition) experimented on in a previous research study [52]. Other elements present in this driving environment included traffic signs and surrounding traffic. The surrounding traffic was programmed to maintain a slower speed of 50 km/h to facilitate participants to perform lane changing and overtaking during the trials.

The surrounding traffic was restricted to three cars for every 3 km stretch, and these vehicles were spawned randomly. One car was positioned behind the participant's vehicle, visible through the rear-view mirror, while another car was situated in front of the participant's vehicle, visible through the front windscreen. The lane-changing task was designed in such a way that it did not require active brake responses because traffic vehicles were far apart. Furthermore, the participants were specifically instructed to disengage cruise control only when encountering an imminent hazard. The speed limit sign in the construction zone also represented the maximum speed of the roadway (70 km/h); therefore, the participants did not carry an inclination to disengage the cruise control in the segment of the track that represented the construction zone. These measures ensured that participants maintained cruise control while driving and disengaged only when encountering a hazardous situation. The hazardous obstacles used in the on-road and

roadside scenarios are described in the following sections. Time-to-Collision (TTC) was set at 3.6 s for all scenarios; TTC was computed based on the time it would take the front of the participant's vehicle to reach the anticipated collision point had it continued at a constant speed without braking.

a) On-road Scenarios

Two lead-vehicle braking events were designed as on-road scenarios, categorized as *On-road condition-scenario 1* (Fig.2. a) and *On-road condition-scenario 2* (Fig.2. b). In Scenario 1, the lead-vehicle braking event occurred on the right-side lane with the left side representing a construction zone, and in Scenario 2, the lead-vehicle braking event occurred on the left-side lane with the right side representing a construction zone. In Scenario 1, the lead vehicle drove with a Time Headway (THW) of 1.54 s at a constant speed of 50 km/h. The lead vehicle then suddenly applied brakes at a predefined location with a deceleration of -1.54 m/s^2 and continued to brake until it came to a complete halt. In Scenario 2, the lead vehicle drove at a THW of 2.32 s at a constant speed of 50 km/h. The lead vehicle then suddenly applied sharp brakes at a predefined location with a deceleration of -3.86 m/s^2 and continued to brake until it came to a complete halt.

b) Roadside Scenarios

We also designed two roadside scenarios, categorized as *Roadside condition-scenario 3* (Fig.2. c) and *Roadside condition-scenario 4* (Fig.2. d). Scenario 3 depicted an incursion by a right-turning vehicle at an intersection, and in Scenario 4, a car suddenly came in front of the driver's vehicle from a merging lane. The roadside scenarios were unexpected as the incursive vehicles were programmed to violate traffic laws. In Scenario 3, the hazardous vehicle disregarded a stop sign, and in Scenario 4, the hazardous vehicle disregarded a yield sign. In Scenarios 3 and 4, the programmed traffic vehicle accelerated from rest at 1.54 m/s^2.

Each scenario in Fig.2. (a-d) has a diagrammatic view that illustrates the properties (e.g., speed, THW, TTC) of the different vehicles in the scenario. Next, the diagrammatic view is the panoramic illustration of the scenarios. Three markers are also added in the diagrammatic view to illustrate the TTC calculation process. Markers A and B reflect the relative position of the participant's vehicle and programmed traffic vehicle, and Marker C in the figure denotes the collision point.

3) EXPERIMENTAL DESIGN AND MEASURES

A within-subject design was employed in this experiment. The independent variable in this experiment was a hazard location with two levels: roadside hazards vs. on-road hazards. The dependent variable in this experiment was BPRT, individually measured for each model and human run. BPRT was defined as the time duration between the onset of the hazard and the first brake response received at the simulator. For scenarios 1(a) and 1(b), the onset is the moment when the lead car initiates braking and for scenarios 1(c) and 1 (d), the onset is when the programmed traffic vehicle accelerates from rest. In both cases, the BPRT involves two key components: perception-reaction time (PRT) and mechanical reaction time (MRT). The PRT refers to the time taken to perceive the threat and decide on the appropriate response, while the MRT refers to the time taken to physically move the foot from the accelerator to the brake pedal and press it. The measure of BPRT in this way provides an empirical measure of how long it takes for a driver to respond to an imminent hazard, whether that's another vehicle braking in front of a vehicle suddenly encroaching on the driver's path.

4) PROCEDURE

Upon the arrival of the participants, the research study was explained by the experimenter in the experiment room. Participants were then required to fill out the consent form and background questionnaire. An overview of the experiment and driving simulator was provided prior to the formal experiment. Participants were also acquainted with the driving simulator in an eight-minute practice drive. For the formal experiment, participants were instructed to reach the maximum speed of the roadway (70 km/h) and then engage the cruise control. Participants were allowed to disengage the cruise control wherever necessary by pressing the brake pedal. Participants were still required to manage vehicle lateral control via steering inputs. Participants were instructed to finish the track as early as possible by changing lanes wherever necessary but were told to always maintain safe driving behavior. The participants were also informed prior to the formal experimentation that they were allowed to maintain the speed limit of 70 km/h in construction zones, and they should consider disengaging cruise control only in hazardous scenarios.

B. MODELLING AND SIMULATION

Our goal in this research is to describe how BPRT could be modelled using QN-ACTR-SA. QN-ACTR-SA describes the cognitive processes essential in the acquisition and maintenance of SA using two complementary theories, called SEEV and QN-ACTR, which are explained in the following sections.

1) CRITICAL ELEMENTS

To facilitate the simulation of BPRT, we proposed using the concept of critical elements [52]. Critical elements are situational elements that are critical in supporting the operator to perceive and understand the situation at hand. The human visual system is initially engaged with the goal to identify the relevant critical elements in different Areas-of-Interests (AOIs) in the task environment. These elements serve as cues to draw the operator's attention for subsequent cognitive processing. Certain critical elements are better than others at drawing human attention.

In the case of driving, examples of critical elements include pedestrians, traffic signs, and traffic vehicles. Drivers need to be aware of them for tasks such as lane-keeping, speed control, and hazard avoidance. Drivers undertake precautionary actions such as braking or steering in response to critical elements that demonstrate unsafe behaviour, such as the risky intrusion of a vehicle at an intersection. Timely perception of hazardous critical elements can be categorized as having good Level 1 SA.

2) QN-ACTR-SA

The QN-ACTR-SA model is a discrete event simulation model designed to simulate different aspects of human cognitive performance. The model's input includes production rules, declarative chunks, and model parameters, which allow it to interact with a driving simulator and produce simulated behavi-

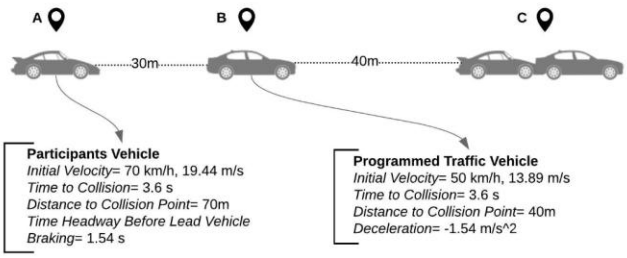
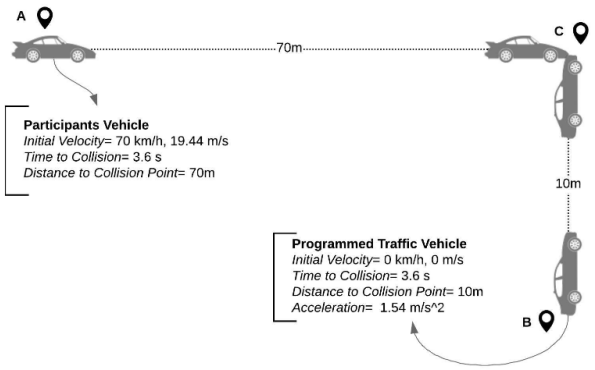




FIG.2. (a) This figure represents On-road condition-scenario 1. The red car (closer) represents the participant's vehicle, and the maroon car (farther) represents the traffic vehicle programmed to be the hazard.



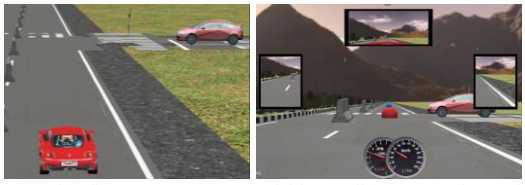


FIG.2. (c)This figure represents Roadside condition-scenario 3. The red car (left) represents the participant's vehicle, and the pink car (right) towards the intersection represents the traffic vehicle programmed to be the hazard.

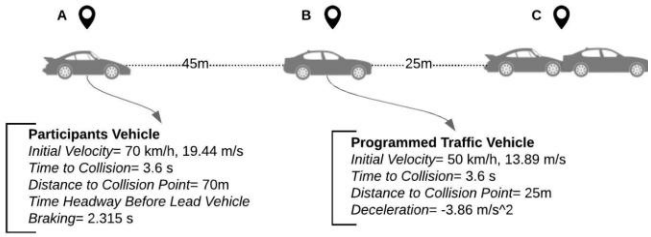




FIG.2. (b) This figure represents the On-road condition-scenario 2. The red car (closer) represents the participant's vehicle, and the maroon car (farther) represents the traffic vehicle programmed to be the hazard.

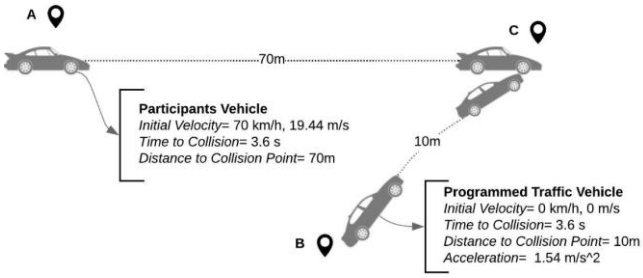




FIG.2. (d) This figure represents Roadside condition-scenario 4. The red car (left) represents the participant's vehicle, and the grey car (right) represents the traffic vehicle programmed to be the hazard.

FIG.2. This figure shows four different scenarios, labeled (a) through (d), with a diagrammatic view of each scenario. The diagrams illustrate the properties, such as speed, time headway, and time-to-collision, of the vehicles involved in each scenario. The egocentric image depicts the perspective observed by both the driver and the model from within the car during experimental conditions. Conversely, the image on the left provides an exocentric view, included to assist the modeler in comprehending the scenario.

-or as model output. These outputs might include acceleration commands, steering control, brake response, and other cognitive aspects of driving behavior.

Queuing Networks are used to model the order in which tasks are processed in a cognitive system [69]. It allows the system to handle multiple goals simultaneously, and information flows through the network, facing queuing mechanisms when there are cognitive bottlenecks [69].

ACT-R, on the other hand, is a production rule system with symbolic representations of both declarative and procedural memory [55]. Declarative knowledge in the QN-ACTR-SA model is represented as chunks of information stored in the declarative memory [70], [71]. Each of these chunks has a base-level activation value B_i, which represents the memory strength of the chunk. The base-level activation is determined by the frequency and recency of chunk usage, according to the following equation by Anderson et al. [71]:

$$B_i = \ln\left(\sum_{k=1}^{n} t_k^{-d}\right) \quad (1)$$

In this equation, n is the number of times chunk i has been used, t_k is the time passed since the kth use of the chunk, and d is the decay factor. The model also calculates the probability of successfully recalling a chunk, $Pr(recall)$, using a sigmoid function of the chunk's activation level A_i and a retrieval threshold τ. The parameter s controls the level of random noise. Refer to the following equation by Anderson et al. [71]:

$$Pr(recall) = \frac{1}{1 + e^{-\left(\frac{A_i - \tau}{s}\right)}} \quad (2)$$

Critical elements are stored as chunks in the model's declarative memory. These equations enable the model to simulate human-like memory retrieval, accounting for factors such as decay over time and strengthening with rehearsal or retrieval. Retrieval of chunks can be used to model probe-based measures of SA, such as SAGAT [52], however, the current research focuses on performance-based measures of Level 1 SA, mainly BPRT.

Production rules in the model serve as psychologically plausible procedures that decompose overall tasks into smaller operational goals. These rules process task-specific knowledge to produce actions that simulate human behavior. The model uses the rules stored in its procedural memory to make decisions about actions, with the decision influenced by the expected utility values of the rules. The utility of a specific production i, U_i, is calculated as follows [71]::

$$U_i = P_i G + C_i \quad (3)$$

In this equation, P_i is the probability that a specific production i would be chosen, G is the goal, and C_i is the estimated cost of the rule.

If n productions have their condition parts match the current state at the same time, only one production can be selected to use in this same processing cycle (50 ms by default). The model calculates the probability of selecting a particular production rule using the following softmax function [71]:

$$Pr = \frac{e^{(U_i/t)}}{\sum_{j=1}^{n} e^{(U_j/t)}} \quad (4)$$

Production rules and declarative chunks interact in the model to simulate how humans process information to achieve operational goals. A production rule might stipulate an action based on certain conditions, while a declarative chunk represents specific information in memory. When a condition in a production rule matches a chunk in memory, the model executes the corresponding action. The model determines which rule to execute based on its knowledge base and external inputs, simulating functions such as memory retrieval, perception, and motor processes.

In the current study, we are interested in testing how the QN-ACTR-SA model will respond to dynamic critical elements that eventually develop into materialized hazards. We run a comparative study investigating hazards originating in the front of the driver, called on-road hazards vs. hazards originating from the peripheral environment, called roadside hazards. The model is programmed to execute a braking action in response to materialized hazards. This is similar to how hazard perception tests are conducted on human participants. The primary dependent variable we are interested in comparing between model and human data is the BPRT.

The visual module of QN-ACTR-SA attends a critical element in one of the AOIs. AOIs defined in this study include on-road frontal view, mirrors (center, left, and right mirror), and the speedometer. The visual module decides to render attention towards a specific AOI based on its attention allocation probability, which is determined by the dynamic SEEV model.

3) SEEV: Modelling Visual Attention Allocation

SEEV mechanics embedded within QN-ACTR-SA account for the visual attention allocation processes required in scanning different Areas-of-Interests (AOIs). SEEV is a probabilistic model of scanning behavior that explains how humans allocate visual attention toward different critical elements in an external environment [62]. SEEV classifies four major factors that influence attention allocation. These factors include Saliency, Effort, Expectancy, and Value. The Value parameter is computationally expressed as the product of Relevance and Priority for a given task.

The SEEV model relies on specific parameters and divisions of the visual scene into AOIs. The mentioned parameters in the context are as follows (Table 1):

AOIs: These are specific parts of the visual scene where a person might focus their attention. In a driving scenario, they include:

1) FV (RS): Forward View Roadside, which refers to the visual scene on the sides of the road ahead.
2) FV (OR): Forward View On Road, which refers to the direct road view in front of the vehicle.
3) Mirrors: This refers to the Left, Right, and Center mirrors in the vehicle.
4) Dash: This refers to the Dashboard, specifically focusing on the Speedometer.

Tasks: These are the tasks the person (or the model) is performing, which include:

1) T1: Task 1 (Lateral Control), which is about maintaining the vehicle in the center of the lane.
2) T2: Task 2 (Longitudinal Control), which involves maintaining speed and a safe distance from the vehicle in front.
3) T3: Task 3 (Situational Monitoring), which is about hazard monitoring and ensuring the destination lane is clear before changing lanes.

SEEV Parameters: These are used in the SEEV model to calculate attention allocation. They include:

1) EX_t: Expectancy, which characterizes how a person would anticipate new information in a specific AOI.
2) R_t: Relevance, which is about how relevant a specific AOI is for a given task.
3) P_t: Priority, which determines the importance of a specific task.

TABLE 1.
THE TABLE REPRESENTS AOIS, TASKS, AND SEEV PARAMETERS.

	T1			*T2*			*T3*				
AOI	EX_1	R_1	P_1	EX_2	R_2	P_2	EX_3	R_3	P_3	VA_{AOI}	P(AOI)%
FV (RS)	0.333	0.666	0.6	0.333	0.333	0.3	0.333	0.333	0.1	0.144	19.6
FV (OR)	0.666	1	0.6	0.666	0.333	0.3	0.666	1	0.1	0.474	64.5
Mirror	0.333	0.333	0.6	0.333	0.333	0.3	0.333	0.333	0.1	0.09	12.2
Dash	0.333	0	0.6	0.333	0.333	0.3	0.333	0	0.1	0.027	3.67

4) VA_{AOI}: Raw Visual Attention score, which is a raw measure of attention directed at an AOI.
5) $P(AOI)$%: This is the Percentage Normalized Score for each AOI, which represents the probability of scanning an AOI.

In our current study, we have adopted SEEV parameters from a previous study that had an identical environmental setup [52]. The previous study, focusing on recall-based probes, involved simulation pauses to gather responses, a technique not employed in our current performance-based approach. This methodological variation, however, does not diminish the SEEV parameters' applicability, given the identical nature of situational elements and traffic conditions in both studies. Our findings offer a foundation for future research to compare these modeling approaches in terms of their accuracy and effectiveness in different experimental setups.

Expectancy characterizes how a person would anticipate new information in a specific AOI. If an AOI has a high bandwidth, then it would be sampled more frequently and, therefore, would be assigned a higher expectancy weight. For instance, drivers can expect more activity in the forward view as compared to other AOIs; thus, on-road objects will be assigned the highest expectancy weight. Value considers the importance of processing information within a given AOI, and it is computationally expressed as the product of relevance and priority. Amongst the different tasks carried out by the model, lateral control [72], [73] is the most important task, and therefore AOIs associated with this task were assigned the highest priority value.

Saliency describes the conspicuity of visual information presented in an AOI, and Effort represents the workload required to shift attention to the AOI. Salience is broadly understood to shape attention within a singular AOI. Despite its acknowledged influence, Salience is not typically factored into models that distribute attention across multiple AOIs [72]. The reasoning behind this omission can be traced back to the observation that the salience of elements within various AOIs does not manifest significant differentiation. In the context of singular AOIs, salience can profoundly impact attention allocation. However, when attention is distributed across multiple AOIs—as is the case with multi-area scanning models (SEEV)—the influence of this variable appears to diminish. In our current study, critical elements within a single AOI did not display significantly varying levels of salience, and the effort required to attend to these elements remains comparatively consistent. Building on prior research that applied the SEEV model to driving scenarios [72], the current study does not take into account the factors of Salience and Effort. This decision is based on the findings of Horrey et al. [72], where they discovered the impact of these two elements to be minimal in driving simulation scenarios.

As mentioned, for AOI-AOI transitions, the likelihood of shifting attention to a specific AOI is dynamically determined by a combination of Expectancy, Relevance, and Priority. This approach realistically mimics how human attention transitions in similar situations. To model attention allocation accurately, the model employs Monte Carlo simulations, creating probabilistic distributions that reflect the dynamic and stochastic nature of human attention. Transition targets within the model are determined probabilistically, allowing for the possibility of revisiting the source AOI, which mirrors human behavior of rechecking areas for additional information.

The probability of attention allocation towards a certain AOI is calculated using the following formula (Equation 5), cited from the work by Wickens et al. [74]. The probability of scanning an AOI, $P(AOI)$, can be calculated by normalizing all VA_{AOI} values so that the $P(AOI)$ values for different AOIs add up to 100%. VA_{AOI} is the raw visual attention score of an AOI, t is a number of tasks, n in this study equals to three (tasks Lateral Control, Longitudinal Control, and Situational Monitoring), EX_t is the Expectancy of an AOI for a given task, R_t is the relevance for a given task, and P_t is the priority of a specific task. R_t and P_t together represent Value [74]. Since the driving scenario is adopted from the previous study [52], therefore, the same SEEV parameters are adopted. For further detail, refer to Table 1.

$$VA_{AOI} = \sum_{t=Tasks}^{n} (EX_t)(R_t)\,(P_t) \qquad (5)$$

Based on the final attention allocation weightings, Monte-Carlo simulations [64] are performed in real-time. This results in a probabilistic distribution of transitions as well as a distribution of fixations within each AOI and between all pairs of AOIs. A dynamic Monte Carlo simulation version of SEEV [75] can forecast a moment-by-moment measure of attention distribution. Thus, given the transitory characteristics of attention allocation, the coefficients of this model determine the probability of attention allocation to each AOI. When the model is repeated multiple times, these coefficients produce a probabilistic distribution of transitions.

Refer to Fig.3. to understand the weighted random selection process used in Monte Carlo simulations for the SEEV model. Each AOI is represented as a horizontal bar, with its length corresponding to the P(AOI)% value. These bars are aligned on a probability scale from 0 to 100. The AOIs shown are FV (RS) at 19.6%, FV (OR) at 64.5%, Mirror at 12.2%, and Dash at 3.7%. A dashed red line indicates a randomly generated number

on the probability scale, exemplifying how the model selects an AOI based on this number. For instance, if the random number falls within the range of an AOI's probability (cumulative range on the scale), that AOI is selected.

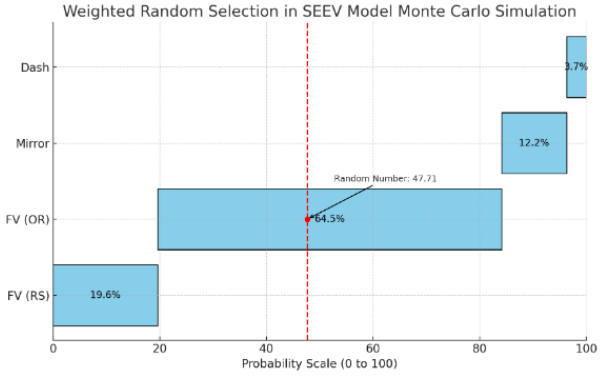


FIG.3. This figure represents the stochastic nature of attention allocation in the SEEV model, highlighting the influence of each AOI's probability on where attention is likely to be allocated.

While the current SEEV model effectively simulates pre-hazard detection scanning behavior and as a result the model initiates appropriate mitigative responses if a hazard is detected, such as braking upon hazard identification, it does not currently encompass the phenomenon of hazard fixation observed in drivers post-hazard detection.

4) Information Processing within QN-ACTR-SA

Information processing within QN-ACTR-SA is instituted on three important characteristics: the use of environmental elements that simulate road objects and hazards; the representation of human limitations on memory, cognitive processing speed, and attention allocation built in the cognitive architecture; and a series of production rules that describe driving behavior. The model simulates the following three major aspects of driver behavior, including (1) lateral and longitudinal control, (2) monitoring the environment, and (3) undertaking high-level decisions (refer to Fig.4).

a) Lateral and longitudinal control

The driving model follows the work of Salvucci et al. [76], [77]. The performance of the vehicle control loop occurs within a timeframe of 150 milliseconds, which represents the firing of the relevant production rules [78]. The model communicates with a driving simulator (OpenDS) by means of a User Datagram Protocol connection. This allows for the BPRT of the model to be computed in the same way as for human participants. This is because our model was integrated with the driving simulator (OpenDS), enabling it to execute realistic braking and steering commands, analogous to human responses. This mutual process ensures consistency and allows for a direct comparison of human and model responses.

The model applies a basic control paradigm to simulate the behavior of a driver centering their vehicle between two perceptual targets at different distances: a near point and a far point. The near point, set at 10 meters ahead of the vehicle's center, represents the vehicle's current lane position. The far point, representing road curvature anticipation, has three potential targets: the lane center point on a straight road, the tangent point on the inner lane edge when approaching a curve, or the point representing a lead vehicle.

These two points work together to allow for subtle driving adjustments that mimic human driving behavior. The near point influences immediate lane-center adjustments, while the far point informs future positioning. This dual approach forms the basis for steering control principles, aiming for stable near and far point angles and maintaining the vehicle in the lane's center.

A steering control law is applied based on the near and far points. The control law for steering angle φ can be represented as follows, adopted from Salvucci & Gray [77]:

$$\Delta\varphi = k_{far}\,\Delta\theta_{far} + k_{near}\,\Delta\theta_{near} + k_I \min(\theta_{near}, \theta_{nmax})\Delta t \qquad (6)$$

The control law places three constraints: a stable far point ($\Delta\theta_{far} = 0$), a stable near point ($\Delta\theta_{near} = 0$) and a near point in the middle of the lane ($\theta_{near} = 0$). Three constants (k_{far}, k_{near}, k_I) control the weights of the components in the equation. In Equation (6), θ_{nmax} (set to 0.07) controls the maximum of θ_{near}, whereas the duration of a control cycle is represented by Δt. Our steering model, inspired by the work of Salvucci & Gray [77], utilizes a variety of far points for navigation: the vanishing Point on straight roads where the lanes seem to merge in the distance; the tangent Point on curves, marked by the lane's inner edge meeting the curve; and the lead car, which acts as a guiding element and offers crucial control information when present.

b) Monitoring the environment:

The model monitors critical elements in the external environment. Lane-keeping and hazard avoidance are aspects of this situational monitoring, where the model periodically assesses the environment and becomes aware of the other vehicles around it. The SEEV framework is applied in this model as a means of distributing attention to different AOIs, such as the speedometer, the rear-view, and side mirrors, and events happening directly in front of the windshield.

c) Undertaking high-level decisions

The model undertakes driving control decisions in two circumstances: a situation that necessitates a hazard mitigation response from the model as a reaction to a perceived hazard; or in lane-changing situations as the model attempts to overtake slower vehicles ahead. The lane-changing ability of the model has been validated against empirical data in previous studies [79]. The current version of QN-ACTR-SA still lacks certain key components in its decision-making framework. While the model is equipped to make lane-changing decisions, it falls short in the necessary production rules that would permit prioritizing between lane changes and brake application upon encountering an imminent hazard. In light of these limitations, the scope of the current experiment is narrowed down to focus primarily on brake perception response. This allows for a deep, focused exploration of one aspect of the model's decision making capabilities while acknowledging the known limitations.

5) Model Parameters

QN-ACTR-SA model offers certain parameters that can be preset by the modeler. These parameters serve to fine-tune the behavior of the model and regulate distinct facets of the model's

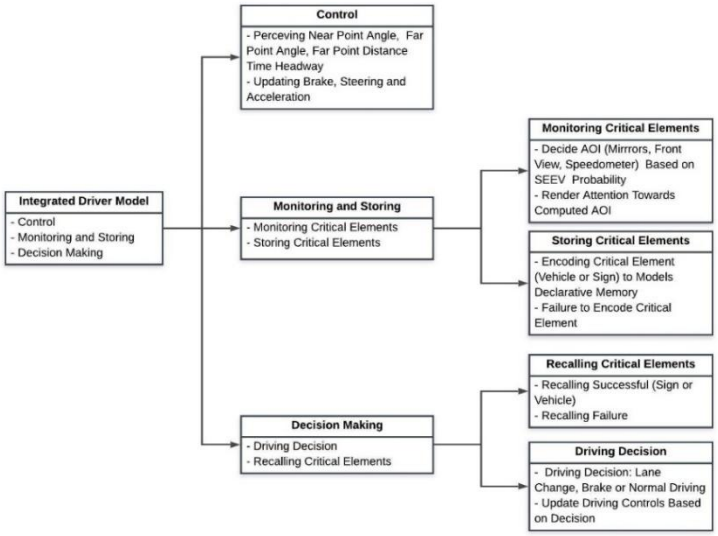


FIG.4. The figure above represents information processing with QN-ACTR-SA.

functionality. In our implementation of the QN-ACTR-SA model, a conscientious effort was made to ensure transparency and precision in the selection and application of model parameters. The primary parameters employed were derived from the foundational work of Anderson et al. [71] in the development of ACT-R, reflecting a robust theoretical and empirical basis. These parameters, including :dat, :imaginal-delay, and :visual-attention-latency, were utilized in their default configurations as specified in the ACT-R 6.0 reference manual by Dan Bothell [80]. This approach guarantees a consistent and replicable foundation, leveraging the established efficacy of these parameters. Simultaneously, for aspects of the model requiring specialized attention related to driving, such as the steering control model, parameters were chosen from relevant research, specifically the works of Salvucci & Gray [77] and Cao [81]. These selections were motivated by the necessity to adapt the model specifically to the complex aspects of agent-based driving requirements. Visual attention allocation within our model is governed by the SEEV parameters (Table 1), which dictate how attention is distributed across different Areas of Interest (AOIs), including how different factors would influence scanning behavior. Our balanced integration of default and customized parameters enhances the model's applicability and reliability, reduces overfitting, and ensures consistency and reproducibility. Table 2 in our manuscript comprehensively details all parameters of the QN-ACTR-SA model, ensuring transparency and clarity on factors influencing our study's outcomes, while Table 1 specifically addresses the SEEV parameters.

III. Results

SPSS was utilized to conduct a Repeated Measures ANOVA in order to examine the impact of hazard location on drivers' BPRT. The absence of outliers and the normal distribution of the data were confirmed through boxplot analysis and the Shapiro-Wilk test ($p > .05$), respectively. Moreover, Mauchly's test of sphericity indicated that the assumption of sphericity had

TABLE 2
THE TABLE PRESENTS VARIOUS PARAMETERS ALONG WITH THEIR DESCRIPTIONS, VALUES, AND THE SOURCES FROM WHICH THEY WERE ADOPTED.

Parameter	Description	Value	Source
:dat	:dat is defined as the production rule default action time. The parameter signifies the default time required to execute a production.	0.05s	Dan Bothell, ACT-R 6.0 reference manual [80]
:imaginal-delay	The parameter signifies the time (in seconds) needed to form a chunk for imaginal representation.	0.2s	Dan Bothell, ACT-R 6.0 reference manual [80]
:visual-attention-latency	The parameter specifies the time (in seconds) needed for a shift in visual attention.	0.085s	Dan Bothell, ACT-R 6.0 reference manual [80]
d	*d* represents the time-based decay parameter (Equation 1).	0.5	Dan Bothell, ACT-R 6.0 reference manual [80]
τ	τ represents the retrieval threshold and signifies the minimum activation level required for chunk retrieval (Equation 2).	-1.5	Dan Bothell, ACT-R 6.0 reference manual [80]
s	*s* represents the instantaneous noise that is added to the activation value of a chunk (Equation 2).	0.4	Dan Bothell, ACT-R 6.0 reference manual [80]
k far	Parameter used in steering control model (Equation 6).	20	Salvucci & Gray [77]
k near	Parameter used in the steering control model (Equation 6).	9	Salvucci & Gray [77]
k I	Parameter used in the steering control model (Equation 6).	1.5	Cao [81]

not been violated, $\chi 2(2) = 4.487, p = .484$. The main effect of hazard location on drivers' BPRT was statistically significant, $F(3, 30) = 261.019, p < 0.005, \eta^2 = 0.96310226$. Pairwise comparisons were conducted (with Bonferroni correction) for further analysis. The results revealed that BPRTs for the on-road condition-scenario 1 ($M = .8425$, $SD = .13445\ s$) and on-road condition-scenario 2 ($M = 1.126$, $SD = .07112\ s$) was statistically significant ($M = .284$ (95% $CI, .126\ to\ .441$) $s, p = .001$) (refer to Fig.4.).

However, the BPRTs for roadside condition-scenario 3 ($M = 2.0434$, $SD = .09337\ s$) and roadside condition-scenario 4 ($M = 1.959$, $SD = .15785\ s$) did not elicit a statistically significant difference ($M = .084$ (95% $CI, -.088\ to\ .256$) $s, p = .838$) (refer to fig.5.). Furthermore, a statistically significant difference existed between the on-road condition-scenario 1 and roadside condition-scenario 3 ($M = -1.201$ (95% $CI, -1.394\ to\ -1.008$)s, $p < .0005$); on-road condition-scenario 1 and roadside condition-scenario 4 ($M = -1.117$ (95% $CI, -1.337\ to\ -.896$) s, $p < .0005$); on-road condition-scenario 2 and roadside condition-scenario 3 ($M = -.917$ (95% $CI, -1.037\ to\ -.797$) s, $p < .0005$); and lastly, on-road condition-scenario 2 and roadside condition-scenario 4 ($M = -.833$ (95% $CI, -.984\ to\ -.682$) s, $p < .0005$) (refer to Fig.5.).

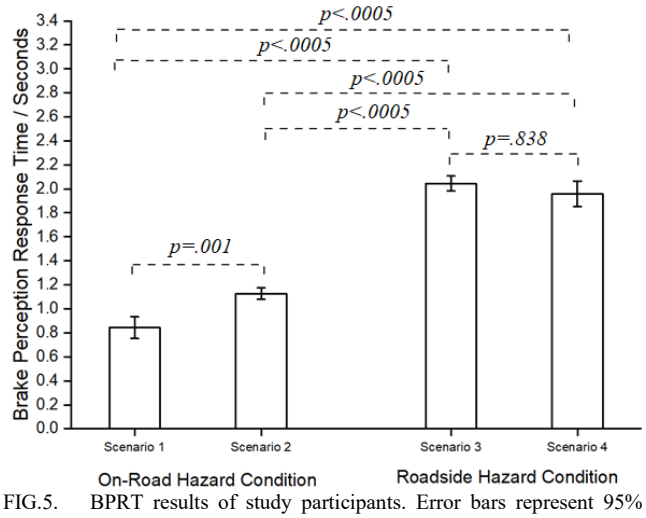


FIG.5. BPRT results of study participants. Error bars represent 95% confidence intervals.

To determine model fitness, root means squared error (RMSE) and mean absolute percentage error (MAPE) was calculated for model and human results. RMSE (Equation 6) represents the differences between values predicted by QN-ACTR-SA and the values observed in the empirical study; MAPE is calculated as in Equation 7. In both equations, $X_{human,i}$ represents the average value from human in condition i, $X_{model,i}$ represents the average value from the model in condition i, and n represents the total number of conditions.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(X_{human,i} - X_{model,i})^2}{n}} \quad (6)$$

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{X_{human,i} - X_{model,i}}{X_{human,i}}\right| \% \quad (7)$$

QN-ACTR-SA model simulation runs were carried out eleven times to evaluate the model's ability to simulate drivers' BPRT in various driving environments (on-road hazards, roadside hazards). The simulation was repeated multiple times until the averaged results reached a steady state. The stopping criterion was that the widths of the 95% confidence intervals for BPRT in all test conditions were within 100 ms because this was considered to provide enough precision and was also similar to the confidence intervals from the human data. This method for determining the number of simulation runs is frequently used in the research field [82]. The overall model fitness for BPRT results is illustrated in Fig.6. The MAPE was 9.4 %, and the RMSE was 0.13 s.

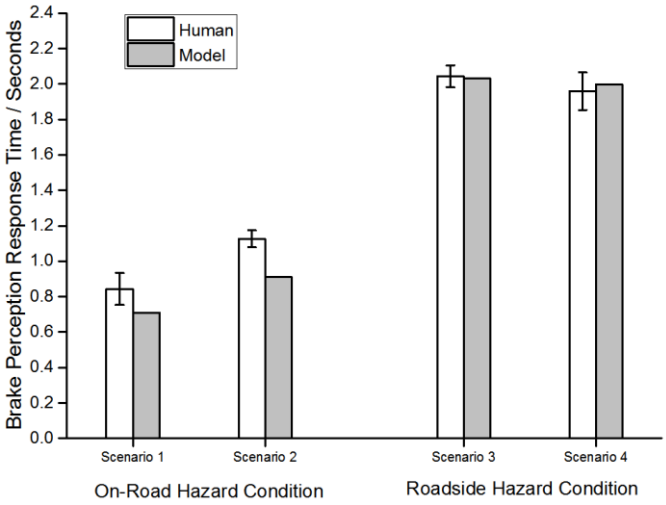


FIG.6. BPRT results of model and human. Error bars represent 95% confidence intervals. The QN-ACTR-SA focuses on modelling average results rather than variance, so the model's variance is not shown.

Both absolute (MAPE) and relative (RMSE) goodness-of-fit measures confirm QN-ACTR-SA's ability in simulating BPRT. The RMSE of 0.13 seconds indicates a small error difference between the average human and modelling results given that the average human BPRT for the on-road and roadside hazard conditions was around 1.49 seconds (SD: 0.54). The MAPE value of less than 10% also demonstrates that the model deviation from the empirical results in terms of percentage error was relatively small. The graphical analysis of the average model versus average human plots further indicates that the model was able to successfully map the changes in BPRT across the different experimental conditions in the study. A linear regression established that the overall model BPRT could statistically predict Human BPRT performance results, $R^2 = 0.992$ (the regression was significant), $F(1, 2) = 262.1584062$, $p < .0005$. The resultant regression equation was the following:

$$Model = -0.325 + 1.163\,(Human) \qquad (8)$$

IV. DISCUSSION

Cognitive architecture-based modelling is a valuable tool for simulating driver hazard perception skills. The present study adds a quantitative foundation to BPRT modelling by demonstrating a real-time simulation of empirical results. The empirical study was designed mainly for model validation purposes. In the trial runs the participants encountered two major types of hazards: on-road hazards in the forward view of the driver, and roadside hazards, which originated from the driver's periphery. The contrasting conditions were mainly selected to explore the difference in BPRT. Not surprisingly, the results demonstrated that BPRT was significantly shorter for on-road hazards as compared to roadside hazards.

While there is a general agreement between the model results and empirical data, the model's BPRT prediction for on-road hazard condition scenario 2 fell noticeably outside of the confidence interval established from the empirical experiment. While the difference isn't substantial, it seems to suggest a lack of precision when replicating human responses to specific complex driving situations. In scenario 2, the on-road hazard condition was relatively common - a lead vehicle braking - which is a situation most drivers are accustomed to and therefore shows a smaller variability in response. This could be a factor leading to the tight confidence interval in the empirical data. This highlights the need for further model refinement to better account for common on-road hazards and human drivers' anticipation of such scenarios.

Furthermore, it is plausible that other factors, such as the initial distance to the lead vehicle and its deceleration rate, have a more profound impact on influencing BPRT. This perspective implies that the BPRT might be influenced by the drivers' perception of the hazard's urgency, which is shaped by the specific conditions of the scenario, rather than solely by the familiarity of the scenario. For instance, in scenario 2, the lead vehicle's sudden braking creates a sense of urgency for the following drivers, as they need to react quickly to avoid a collision. The initial distance between the vehicles and the deceleration rate of the lead vehicle can significantly affect the drivers' perception of the hazard's urgency. A shorter initial distance or a faster deceleration rate can make the hazard appear more imminent, leading to a shorter BPRT. Conversely, a longer initial distance or a slower deceleration rate can make the hazard appear less urgent, resulting in a longer BPRT. Therefore, it is essential to consider these factors when developing models that aim to predict BPRT. By incorporating data on the initial distance to the lead vehicle and its deceleration rate, as well as other relevant factors, the model can better account for the complexities of real-world driving scenarios and provide more accurate predictions of BPRT.

Effective visual attention allocation plays a critical role in hazard perception. To mimic human visual scanning processes, the visual attention allocation mechanisms embedded within QN-ACTR-SA are dependent on the SEEV parameters. The modelling results indicate that QN-ACTR-SA can reasonably simulate and predict BPRT as the results are in line with empirical findings conducted under the same driving conditions. The model also demonstrates that BPRT would be shorter for on-road hazards when compared to roadside hazards. The significantly faster BPRT for on-road hazards compared to roadside hazards and the significant difference between the two on-road conditions can primarily be attributed to the following reasons.

Frequency of Scanning AOI: Front AOI is most actively scanned by the driver since it significantly affects the main driving tasks of lateral and longitudinal control. For the lead vehicle braking scenario, the cues for safely judging the lead vehicle as an imminent hazard are present in the front AOI. On the other hand, roadside hazards are present in the peripheral environment, which is not actively scanned, and as a result, human drivers are slower to identify roadside hazards.

The SEEV parameters within QN-ACTR-SA allow effective simulation of human drivers' visual attention distribution patterns. The model scans for hazards in the front view more frequently than in the peripheral environment. The major driving tasks carried out by the model, including lateral control and longitudinal control, rely on visual information perceived in the front AOI. As a result, the R_t (Relevance) and P_t(Priority) of the front AOI is weighted significantly more in comparison to peripheral AOI, and therefore on-road hazards are identified much faster by the model in comparison to roadside hazards.

Perception of Hazardous Cues: For the on-road condition, as the lead vehicle slows down, the drivers view the brake lights in conjunction with an instant change in time headway and optical expansion of the lead vehicle. These cues function as an alerting signal that a braking response may be required and therefore, the participants are better prepared for emergency braking. Furthermore, the significant difference in BPRT for the two on-road conditions can be attributed to the difference in deceleration intensities of the two on-road scenarios tested in this study. In one of the designed scenarios, the lead vehicle brakes with a shorter time headway and stronger deceleration in the right lane, whereas in the other scenario, the lead vehicle brakes with a longer time headway and comparatively lighter deceleration in the left lane. For roadside conditions, the hazardous vehicle is not instantly identified by drivers due to delayed perception of hazardous cues, which results in slower BPRT. The roadside hazards, merge and intersection scenarios, were relatively similar since both were highly unexpected, and the acceleration of the programmed traffic vehicle was the same for both scenarios, therefore we don't see a significant difference in the BPRT of the two roadside scenarios.

Based on the probability of attending allocation, the model continuously monitors different AOIs to identify hazardous cues and potential road threats. The model protects itself through a safety boundary, which is essentially the tolerance level beyond which an object is categorized as an imminent threat. The model executes brake action in response to approaching objects. For on-road conditions, the BPRT is shorter for hazards with shorter time headways and faster decelerations since such hazards are immediately identified by

the model. The magnitude of the deceleration influences the model's perceived criticality of the situation. For roadside scenarios, the model's BPRT is slower due to delayed perception of hazardous cues; these cues inform the model that the safety boundary has been violated.

Expectancy of Hazards: Expectancy around different types of visual stimuli plays a role in how attention is dispersed across AOIs. Drivers expect more activity in the forward view as compared to other AOIs. In the current experimental setup, for on-road scenarios, there is a construction zone blocking one lane of the roadway, and as a result, most drivers are expecting traffic in the front to slow down. On the contrary, for roadside conditions, the probability that a traffic vehicle accelerating from the driver's periphery would violate yield and stop signs and intrude in the traffic next to a construction zone is very low. Therefore, the roadside hazard condition carries a significantly lower collision probability when compared to on-road hazard conditions.

E_t (Expectancy) of information plays a critical role in administering models' attention allocation patterns. The front AOI has higher bandwidth in terms of road clutter and therefore it is assigned a higher expectancy weight, and as a result, the model attends to it more frequently. In comparison, the peripheral AOI is assigned a lower expectancy weight since drivers do not expect vehicles to violate road signs and merge or intersect from the roadside. Therefore, the model's BPRT is faster for on-road hazards in comparison to roadside hazards.

A. FUTURE WORK, LIMITATIONS, AND CONCLUSIONS

The eventual goal of this research is to allow transportation researchers to simulate and predict hazard perception outcomes from various road and driver conditions. This approach can further support research towards understanding minor nuances in different driving conditions, for example, analyzing how other variables such as TTC influence drivers' hazard perception for roadside hazards vs. on-road hazards. Such modelling tools can play a crucial role in improving driving safety research since modelling using cognitive architectures is a cheaper and time-effective option that can complement early-stage hypothesis testing with quantitative results and real-time simulations.

There are many different avenues where cognitive-architecture-based modelling can be exploited to tremendous effect—for instance, using modelling to investigate the effects of distraction on drivers' hazard perception ability. As we know that while driving, multiple pieces of information compete for drivers' attention; this information is related to the primary task of vehicle control as well as other non-driving activities such as operating vehicles, media consoles, texting, etc. With limited cognitive resources, if drivers' task demands exceed a certain threshold at any given time, it can lead to a lack of SA, poor hazard perception, and possible motor-vehicle collisions. More work is also needed to investigate how cognitive architecture-based modelling can simulate the effects of distraction on BPRT.

While our model incorporates SEEV to simulate visual scanning behavior, we recognize that this approach may not be the only way to model BPRT. In future studies, it would be valuable to compare the performance of our SEEV-based model with these simpler models to determine the extent to which they differ in their predictions of BPRT. Such a comparison would provide insights into the unique contributions of SEEV to BPRT modeling and help to identify the situations in which a more complex model is necessary. Additionally, it would allow researchers to consider alternative modeling approaches that may be more appropriate for certain driving scenarios or populations.

The current SEEV model effectively simulates pre-hazard detection and initiates mitigative responses, but does not account for post-hazard detection behavior, such as 'target fixation.' Future enhancements should include this aspect, where the model would simulate the shift in attention between fixating on a hazard and scanning other AOIs. This addition aims to improve the model's alignment with real-world driving behaviors and enhance its predictive capabilities in hazardous situations.

It is important to note that our design decision to block one side of the roadway could potentially impact the ecological validity of the task. The use of concrete bollards to simulate a construction zone, while effective in creating a controlled environment, does not fully represent the wide variety of scenarios drivers may encounter in real-world driving situations. This approach might limit the generalizability of our findings. In retrospect, alternative methods, such as confining the action to a single lane only, could present a more "naturalistic" constraint, enhancing the ecological validity of the study. We acknowledge this shortcoming and recommend that future research considers more naturalistic roadway constraints to further improve the representativeness and applicability of the findings.

Another limitation of our experiment is related to the fidelity of the driving simulator with only one display in the front without showing the roadside scenarios on the left and the right areas. Although a similar setup has been used in many driving studies, the limitation may affect the realism and accuracy of the driving behavior captured in our study. Future improvements should consider incorporating more screens displaying a wider field of view. Another limitation is that we have restricted the modelling to simple reaction time and have not investigated choice-based response times. This was done since QN-ACTR-SA is currently not advanced enough to dynamically take into account the different factors representing differential choices (steering and brake) in an expected utility fashion and, as a result, cannot simulate BPRT and SPRT concurrently. Future studies are needed to expand the current modelling paradigm so that it can take into account choice reaction times. Moreover, further work is needed to develop the current modelling approach into a usable tool that can be employed by researchers so that they can benefit from simulations easily without the need to learn the technical details of the modelling and simulation method.

Our study also recognizes and acknowledges the limitations that arise from the small sample size and the demographic skew towards young participants. While the model successfully

replicated the differences in BPRT between roadside and on-road scenarios within this sample, this study represents an important first step in modelling Level 1 SA. It is important to note that the study participants are best characterized as young adult drivers. A larger sample that is more representative of the driving population would extend the accuracy of the empirical data to reflect the range of human responses more accurately. We advise caution in generalizing this study to other driver demographics (e.g., older drivers) results, particularly considering the well-established variations in hazard perception performance across different demographics [37]. More nuanced studies are needed to test the model's effectiveness in simulating the reactions of other demographics, such as older adults, individuals with impairments, etc.

Our study used a practical approach by applying default or previously researched values for model parameters, which limited our exploration of different parameter settings on outcomes. Recognizing this as a key limitation, future research should focus on varied parameter settings and larger, diverse samples for a thorough sensitivity analysis. This will enhance the model's validity and robustness in predicting BPRT across various driving scenarios.

The present study primarily centers on the validation of the QN-ACTR-SA model's efficacy in evaluating the hazard perception skill of drivers. This objective is achieved through the utilization of a performance-based approach, wherein the model is employed to simulate BPRT. To achieve a more nuanced understanding of the relationship between the model and hazard perception skill, future research should explore the effectiveness of the modelling approach in relation to other forms of measures. Specifically, researchers should explore physiological methodologies, such as eye-tracking behavior, with a particular emphasis on analyzing the average duration of fixations across various AOIs. By incorporating a broader array of assessment methods, scholars can attain a more comprehensive understanding of the model's performance and its correspondence with driver's hazard perception skill.

Cognitive modelling research has mainly focused on simulating the average performance of human operators while omitting variability caused by individual differences. Nevertheless, predicting mean values from different task conditions is valuable to theoretical research and practical applications of design evaluation by explaining and evaluating task, design, and environmental factors that may affect human performance. Further research needs to model individual differences as well. The challenge is that there are many factors contributing to individual differences, such as the speed of perception and motor responses, cognitive capacities and abilities, knowledge, and strategies. A cognitive model needs to explain what causes individual differences. Some research, for example, has used the difference in production rule knowledge to model the difference between novice and experienced drivers [57]. However, individual differences were not the focus of the current study and therefore were not modelled.

In conclusion, we have presented and evaluated QN-ACTR-SA as a rigorous computational modelling method capable of simulating and predicting drivers BPRT for on-road and roadside hazards. While there exist countless pieces of literature exploring BPRT in simulated and naturalistic settings, research studies demonstrating the simulation and modelling of BPRT are rare in comparison. Although it seems obvious that drivers must carry a shorter BPRT for on-road hazards vs. roadside hazards, we currently did not come across any study that has provided an empirical account of this premise. Most research has either examined the factors that influence BPRT or investigated BPRT to different types of hazards in different driving conditions. Moreover, the modelling and simulation work in this area is very limited and comes with a set of confines. Therefore, this study carries applied value for practitioners exploring tools that can simulate HPRT and theoretical value for researchers investigating how drivers' perception changes when encountering different types of roadway hazards.

V. References

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