

Modelling Level 1 Situation Awareness in Driving: A Cognitive Architecture Approach

by

Umair Rehman

A thesis
presented to the University of Waterloo
in fulfillment of the
thesis requirement for the degree of
Doctor of Philosophy
in
Systems Design Engineering

Waterloo, Ontario, Canada, 2020

© Umair Rehman 2020

Examining Committee Membership

The following served on the Examining Committee for this thesis. The decision of the Examining Committee is by majority vote.

External Examiner

Dr. Birsen Donmez
Associate Professor

Supervisors

Dr. Shi Cao
Assistant Professor

Dr. Carolyn MacGregor
Associate Professor

Internal Member

Dr. Siby Samuel
Assistant Professor

Internal Member

Dr. Nasser Lashgarian Azad
Associate Professor

Internal-external

Dr. Plinio Morita
Assistant Professor

This thesis consists of material all of which I authored or co-authored. Please see the statement of contributions included in the thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Statement of Contribution

Papers Published This following paper [1] is incorporated in Chapter 3 of this dissertation.

- Rehman, U., Cao, S., & MacGregor, C. (2019, November). Using an Integrated Cognitive Architecture to Model the Effect of Environmental Complexity on Drivers' Situation Awareness. In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting* (Vol. 63, No. 1, pp. 812-816). Sage CA: Los Angeles, CA: SAGE Publications.

Contributor	Statement of Contribution
Rehman,U. (Candidate)	Conceptual design (80%)
	Data collection and analysis (100%)
	Writing and editing (80%)
Cao, S.	Conceptual design (10%)
	Writing and editing (10%)
MacGregor, C.	Conceptual design (10%)
	Writing and editing (10%)

Papers Under Preparation Three manuscripts are currently under preparation and would be soon submitted to Journals in the field.

This following manuscript is also incorporated in Chapter 3 of this dissertation.

- Rehman, U., Cao, S., & MacGregor, C. (To be submitted to IEEE Access). Modelling Situation Awareness in Driving: A Cognitive Architecture Approach.

Contributor	Statement of Contribution
Rehman,U. (Candidate)	Conceptual design (80%)
	Data collection and analysis (100%)
	Writing and editing (80%)
Cao, S.	Conceptual design (10%)
	Writing and editing (10%)
MacGregor, C.	Conceptual design (10%)
	Writing and editing (10%)

This following manuscript is incorporated in Chapter 4 of this dissertation.

- Rehman, U., Cao, S., & MacGregor, C. (To be submitted to Transportation Research Part F: Traffic Psychology and Behaviour). Modelling Situation Awareness Using an Integrated Cognitive Architecture: Simulating Brake Perception-Response Time to On-Road vs. Roadside Hazards.

Contributor	Statement of Contribution
Rehman,U. (Candidate)	Conceptual design (80%)
	Data collection and analysis (100%)
	Writing and editing (90%)
Cao, S.	Conceptual design (10%)
	Writing and editing (5%)
MacGregor, C.	Conceptual design (10%)
	Writing and editing (5%)

This following manuscript is incorporated in Chapter 5 of this dissertation.

- Rehman, U., Cao, S., & MacGregor, C. (To be submitted to Transportation Research Record). Predicting the Effects of Automation and Distraction on Drivers Situation Awareness: A Cognitive Architecture Approach.

Contributor	Statement of Contribution
Rehman,U. (Candidate)	Conceptual design (80%)
	Data collection and analysis (100%)
	Writing and editing (90%)
Cao, S.	Conceptual design (10%)
	Writing and editing (5%)
MacGregor, C.	Conceptual design (10%)
	Writing and editing (5%)

Abstract

The goal of this research is to computationally model and simulate the collective drivers' Level I Situation Awareness (SA)¹. I developed a computational model in a cognitive architecture that can interact with a driving simulator to infer quantitative predictions of drivers' SA. I demonstrate theoretical application of modelling and predicting SA from the lens of human cognition utilizing the Queueing Network-Adaptive Control of Thought-Rational (QN-ACT-R) framework as a foundation. I integrated a dynamic visual sampling model (SEEV) with QN-ACT-R to create QN-ACT-R-SA which simulates realistic attention allocation patterns of human drivers at SA Level 1 (i.e. perception of critical elements). QN-ACT-R-SA also incorporates a driver model that can simulate human driving behaviors by interacting with a driving simulator. Three validation studies (Study I, II and III) were conducted to determine whether Level 1 SA results produced with the QN-ACT-R-SA model correspond to empirical data collected from human drivers for the same tasks. In Study I, QN-ACT-R-SA model was validated against probe-based SA measures and in Study II, the model was validated against a hazard perception-based SA measure. In Study III, model's predictive power was assessed by comparing model results to a previously conducted empirical experiment.

In Study I, two types of probe-based SA measures were used: within-task queries using Situation Awareness Global Assessment Technique (SAGAT), and post-experiment questions. A comparative assessment demonstrated that QN-ACT-R-SA could reasonably simulate drivers' Level 1 SA for two driving conditions: easy (with few vehicles and signboards) and complex (with dense traffic and signboards). QN-ACT-R-SA fit for human SAGAT scores resulted in mean absolute percentage error (MAPE) of 5.02%, and the root mean square error (RMSE) of 3.47. Model fit for post-experiment human SA results were MAPE of 6.73%, and RMSE of 6.13. The RMSE of 3.47 for SAGAT responses indicate a small error difference between the average human and modelling results since the average SAGAT scores (measured on a scale of 0-100) for the easy and complex driving condition is around 71.9 (SD: 21.1). Similarly, the RMSE of 6.13 for post-experiment SA questionnaire also indicates a small error difference since the average post-experiment SA questionnaire score (on a scale of 0-100) for the easy and complex driving condition is around 73.8 (SD: 16.2).

In Study II, Brake Perception Response Time (BPRT) was used as a hazard perception test to further assess the model's ability to simulate drivers' SA at Level 1. An empirical study was designed mainly for model validation purposes. In the trials runs, the participants encountered two major types of hazards: on-road hazards in the forward view of the driver and roadside hazard which originated from the driver's periphery. The two contrasting conditions were selected to explore the difference in driver's BPRT. The results demonstrated that BPRT was significantly shorter for on-road hazards as compared to roadside hazards. The overall model fitness for empirical BPRT results indicated an MAPE of 9.4 % and the RMSE of 0.13 seconds. The RMSE value in Study II indicates a

¹The model developed in this research does not model a specific individual driver's Level I SA, but rather models aggregated Level I SA across drivers.

small error difference between the average human and modelling results since the average BPRT for the two on-road and roadside hazard conditions is around 1.49 seconds (SD: 0.54).

Study III involved extending the same modelling approach towards assessing the predictive power of QN-ACT-R-SA. The empirical data was taken from a previously conducted research study that had examined the effects of Adaptive Cruise Control (ACC) and cell-phone use on drivers' SA using SAGAT tests. QN-ACT-R-SA fit for predicting the effects of ACC and cellphone use on drivers' Level 1 SA resulted in a MAPE of 5.6%, and the RMSE of 4.9. The RMSE of 4.9 for SAGAT responses indicates a small error difference between the average human and modelling results since the average SAGAT scores for the different driving conditions in Study III is around 72 (SD: 4.76).

Both absolute (MAPE) and relative (RMSE) measures of goodness-of-fit confirm models efficacy in reasonably simulating human SA across the three studies. The MAPE value of less than 10% across the three studies show that the model's deviation from the empirical results in terms of percentage error is relatively small. The graphical analysis of the average model versus average human plots further indicate that the model was able to successfully map the changes in SA scores across the different experimental conditions tested in the three studies.

In summary, this research presents: 1) a model of collective drivers' Level 1 SA that is grounded in cognitive and perceptual mechanisms of human information processing; 2) a real-time programmable implementation of the model as a simulation software; 3) validation of the model using empirical results drawn from established SA measures; and 4) new ideas towards modelling Level 2/3 SA and improving the existing modelling paradigm.

*We have seen that computer programming is an art,
because it applies accumulated knowledge to the world,
because it requires skill and ingenuity, and especially
because it produces objects of beauty.*

— Donald E. Knuth [2]

Acknowledgments

Foremost, I would like to express my sincere gratitude to my supervisors, Dr. Shi Cao and Dr. Carolyn MacGregor. I am grateful for their insights and support that refined this research. Their guidance over the years has been critical in helping me become a better researcher. I would also like to extend my most sincere gratitude to my committee members for their encouragement and invaluable feedback. I am also thankful to Dr. Catherine Burns since her coursework contributed significantly to my experience at University of Waterloo.

I thank all my friends, especially: Adil Ashraf, Moazam Murtaza, Ali Arslan, Gohram Baloch, Talha Qadeer, Haris Zahid and Umair Shah. My friends made sure that my life outside the lab was fun-packed and exciting. I would specially thank my cricket team (Waterloo Titans) which I captained in my final semester. It was a competitive season and I am glad that we were able to win the intramurals right before I graduate.

I would like to convey my appreciation to my in-laws and my grandfather who were both an invaluable source of support during this academic journey. Also I thank my late grandmother for raising me in the finest of ways and inspiring me to accept bigger challenges in life. A special note of appreciation to my parents, Ami and Abu for supporting me through thick and thin. I owe my successes to your encouragement and prayers. I would also like to thank my son Ibrahim. His delightful presence has been a source of serenity in an otherwise hectic routine. Most importantly, I would like to thank my wife Amna. I am blessed to have a partner who is exceptionally supportive and comforting. I am grateful for her unfaltering love and encouragement during the course of this work.

Dedication

Ohana means family.
Family means nobody gets left behind, or forgotten.
— Lilo & Stitch

Dedicated to Ami, Abu, Ibrahim & Amna

Table of Contents

List of Tables	xii
List of Figures	xiii
Abbreviations	xiv
1 Modelling Situation Awareness in Driving	1
1.1 Human Performance Modelling	2
1.2 Motivation	2
1.3 Research Problems	3
1.4 Contributions	5
1.5 Dissertation Outline	7
2 Theoretical Foundations of Situation Awareness in Driving	8
2.1 General Models of Situation Awareness	8
2.1.1 Endsley (1995)	8
2.1.2 Bedny and Meister (1999)	9
2.1.3 Smith and Hancock's (1995)	9
2.1.4 Sarter and Woods (1991)	10
2.1.5 Taylor (1990)	10
2.1.6 Adams et al. (1995)	10
2.1.7 Summary of General Models of Situation Awareness	10
2.2 Driving Specific Models of Situation Awareness	11
2.3 Situation Awareness and Cognitive Processing	12
2.3.1 Situation Awareness and Memory	12
2.3.2 Situation Awareness and Visual Attention Allocation	13
3 QN-ACT-R-SA Model Development and Initial Validation	14
3.1 Introduction to Study I	14
3.2 Background of Cognitive Architecture	16
3.3 Development of QN-ACT-R-SA	19
3.3.1 Modelling Visual Attention Allocation	20
3.3.2 Modelling Information Retrieval for Answering SA Probes	23
3.3.3 Information Processing within QN-ACT-R-SA	24
3.4 QN-ACT-R-SA Parameters	27

3.5	Methodology Study I	28
3.5.1	Participants	28
3.5.2	Driving Simulator	29
3.5.3	Scenario	29
3.5.4	Experiment Design and Measures	30
3.5.5	Procedure	31
3.5.6	Results	31
3.6	Discussion Study I	34
3.6.1	Empirical Study	34
3.6.2	QN-ACT-R-SA Model	35
4	Modelling Brake-Perception Response Time	37
4.1	Introduction to Study II	37
4.2	Methodology Study II	39
4.2.1	Participants	39
4.2.2	Scenario	40
4.2.3	Experimental Design and Measures	41
4.2.4	Procedure	41
4.2.5	Modelling and Simulation	43
4.2.6	Results Study II	43
4.3	Discussion Study II	45
4.3.1	Empirical Study	45
4.3.2	QN-ACT-R-SA Model	46
5	Modelling the Effects of Automation and Distraction	48
5.1	Introduction to Study III	48
5.2	Methodology Study III	49
5.2.1	Empirical Experiment	49
5.2.2	Modelling and Simulation	50
5.2.3	Results Study III	54
5.3	Discussion Study III	56
6	Conclusion	58
6.1	Limitations of QN-ACT-R-SA	58
6.2	Future Work	59
6.2.1	Expanding Current Empirical Research Using QN-ACT-R-SA	59
6.2.2	Modelling Level 2 and Level 3 Situation Awareness	60
6.2.3	Application of Model in Other Areas	62
6.3	Thesis Contribution Highlights	64
	References	66
	APPENDICES	81

A	Data from Study I	82
A.1	Empirical Results SAGAT	82
A.2	QN-ACT-R-SA Simulation Results SAGAT	84
A.3	Empirical Result Post Experiment SA Questionnaire	86
A.4	Model Result Post Experiment SA Questionnaire	87
B	Data from Study II	88
B.1	Empirical Results Brake Perception Response Time	88
B.2	QN-ACT-R-SA Results Brake Perception Response Time	89
C	Data from Study III	90
C.1	QN-ACT-R-SA Responses to SAGAT Probes	90

List of Tables

3.1	SEEV parameters for easy and complex driving conditions.	23
3.2	Description, values and sources of parameters.	28
5.1	SEEV parameters for conditions without cellphone task.	52
5.2	SEEV parameters for conditions with cellphone task.	53
A.1	Participants responses to SAGAT - Study I complex condition.	82
A.2	Participants responses to SAGAT - Study I easy condition.	83
A.3	QN-ACT-R-SA simulation of SAGAT - Study I complex condition.	84
A.4	QN-ACT-R-SA simulation of SAGAT - Study I easy condition.	85
A.5	Empirical Results Post Experiment Questionnaire - Study I.	86
A.6	QN-ACT-R-SA Post Experiment Questionnaire Results - Study I.	87
B.1	Empirical BPRT results - Study II	88
B.2	QN-ACT-R-SA BPRT results - Study II	89
C.1	QN-ACT-R-SA responses to SAGAT probes - Study III.	91

List of Figures

3.1	QN-ACT-R cognitive structure from Cao and Liu [3].	17
3.2	The QN-ACT-R-SA framework.	20
3.3	Information processing within QN-ACT-R-SA.	25
3.4	Screenshot of the driving simulation.	30
3.5	SAGAT scores of model and human in Study I.	32
3.6	Post Experiment SA scores of model and human in Study I.	34
4.1	The figure represents scenario 1-4 tested in Study II.	42
4.2	BPRT scores of model and human.	45
5.1	Model results across experimental conditions in Study III.	55
5.2	SAGAT scores for both human and model trials in Study III.	56

Abbreviations

SA	Situation Awareness
AI	Artificial Intelligence
QN-ACT-R-SA	Queueing Network-Adaptive Control of Thought-Rational-SA
UDP	User Datagram Protocol
MAPE	Mean Absolute Percentage Error
RMSE	Root Mean Square Error
BPRT	Brake Perception Response Time
ACC	Adaptive Cruise Control
HPRT	Hazard Perception Response Time
SPRT	Steering Perception Response Time
AOIs	Areas-of-Interests
TTC	Time-To-Collision
THW	Time Headway
QN-ACT-R	Queueing Network-Adaptive Control of Thought-Rational
SART	Situation Awareness Rating Technique
QN	Queueing Networks

Chapter 1

Modelling Situation Awareness in Driving

Situation Awareness (SA) theory describes how operators in complex environments acquire and maintain awareness of ‘what is going on’ [4]. Formally, SA is described as an internally held cognitive construct consisting of three main levels: perception (Level 1); comprehension (Level 2); and projection (Level 3) [5]¹. Studying SA is important because it allows investigators to gather diagnostic information about the nature and relative role of situational factors influencing human performance and decision-making in complex systems. Identifying the level of SA that is compromised in a task can help with the selection of appropriate human factor countermeasures.

SA has been investigated across multiple domains of application, including: aviation [6], air traffic control systems [7], railway operation [8], process control [9], and healthcare [10]. In particular, there exist a comprehensive body of empirical research that has employed SA methods to address critical research problems within driving safety research. For instance, SA has been used to assess driver training programs [11], explore driver-automation interaction [12], explain individual differences in driving skill [13], investigate the effects of driver distraction [14], and improve the design of in-vehicle interfaces [15].

As typical approaches for understanding SA are experiential in nature, they tend to lack rigorous computational representations, thereby, limiting most SA results to being descriptive rather than predictive. In the field of human factors, other human performance constructs such as time performance, memory recall, attention allocation, and mental workload have been actively investigated in the wider facet of computational modelling research; however, attempts to model SA using computational approaches have been limited in comparison. This research is motivated by the lack of computational representations of SA, particularly for the driving domain where running multiple comparative simulations without the need to put drivers into high risk situations is preferable to participant-based experiments. This dissertation presents the development and evaluation of a computational human performance model that can support SA simulation and testing using driving as the domain of demonstration.

¹A theoretical review of different models of SA is presented in Section 2.1.

1.1 Human Performance Modelling

Human performance modelling is a method used by human factors researchers to infer quantifiable predictions of human-machine interactions in early stages of the systems design process. Most human performance models are computational in nature however they are built upon qualitative theories of human behavior and cognition. Human performance modelling is not intended to construct ‘intelligent systems’ as that lies under the domain of artificial intelligence (AI). There are certainly cases where AI concepts have been incorporated into human performance modelling research, yet these two disciplines are inherently distinct [16]. AI research seeks to develop systems that produces intelligent behavior irrespective of the fact that behavior replicates human performance or not; whereas human performance models are primarily developed to predict and explain human-system interactions.

Human performance models could be categorized by their characteristics, such as: output versus process models, top-down versus bottom-up models, and single-task versus multitask models [16]. Individual models of human performance, such as models of perception, attention, locomotion, gait analysis, to name a few, have been the focus of research for a considerable amount of time. Some early models of human performance include: Fitts’ law [17], Hick–Hyman law [18], stimulus-response compatibility [19] etc. Integrated models are also becoming prevalent. There exist different types of integrated models, such as: task network models [20, 21], cognitive architectures [22, 23, 24], models of anthropometrics and biomechanics [25] etc.

I propose an approach based in cognitive architecture to develop a computational model of SA. A cognitive architecture represents multiple computational models of human cognition integrated within a unified framework. The interaction of different cognitive components within a cognitive architecture can be represented in a computer program. Cognitive architectures are able to directly interact with the task environment by means of simulated visual and motor modules. The performance output from a cognitive architecture takes the form of a time-stamped sequence of actions that replicates quantitative human performance results [26].

1.2 Motivation

I explain below why developing a simulation and prediction model of collective drivers’ Level 1 SA in a computational cognitive architecture is a valuable contribution to human factors research and therefore an important undertaking.

Modelling drivers’ SA in a cognitive architecture can yield consistent and precise predictions of driver behavior. This process can allow researchers to observe and test drivers’ SA in real time. Cognitive architectures are able to directly interact with the task environment by means of simulated visual and motor modules. Using cognitive architectures as surrogate users can facilitate researchers to explore minor nuances in driver performance that would have otherwise been difficult to capture. Model-based evaluations can provide explanatory accounts of drivers’ SA results that are independent of modeller bias.

Using predictive modelling in lieu of empirical testing can equip researchers with pre-

dictive capacity early on in the research lifecycle. This can save system designers and researchers significant time and money. The process can also minimize the number of end users needed in an experiment. Predictive modelling can also account for tests that were initially ruled out on human participants due to safety concerns. Leveraging early-stage predictive modelling can aid human factor engineers to discern between initial prototypes such as deciding between two categories of in-vehicle interfaces or evaluating the impact of different roadway designs on drivers' SA. Predictive modelling therefore empowers researchers to test important hypotheses prior to formal experimentation. This not only reduces the testing phases needed for a study but also allows researchers to conduct user studies on issues that are pertinent and necessitate further testing.

Computational simulation models can complement commonly used methods in human factors research such as direct empirical evaluation, experience-based heuristics, expert guidelines etc. Therefore, there is a need to advance the quantitative foundation in human factors engineering. In many engineering disciplines, researchers routinely create models to analyse competing designs or assess trade-offs [27]. Investigators in these fields have access to a range of quantitative tools that assist them in making informed decisions. The predictive value and widespread applicability of such modelling tools are appreciated in many disciplines and considered central to professional practice. By creating a predictive model of drivers' SA, I hope to further advance the same approach in human factors research.

Synthesis of different individual models of human performance can be best expressed in a cognitive architecture. Theoretically-grounded cognitive architectures can now be applied to real-world tasks. Researchers can leverage these architectures to support human factors design and evaluation. The goal of this research is to equip cognitive architectures to model and predict drivers' SA. The need for empirical SA testing will not disappear, but its role will evolve. Although, more complex problems will continue to be identified through user studies, SA modelling can compliment user testing and reduce research dependency on empirical data.

Human factors rely on practical concepts to advance the understanding of human behavior in complex environments. A looked-for aspect in human factors research is that these concepts could be quantifiable in the form of mathematical or computational models; however, attempts to model and predict SA using computational models have been limited. Moreover, the theoretical foundations of SA have also been a focus of much debate within human factors research. Therefore, I aim to distill the misconceptions and misrepresentations that are common in SA theories and provide a computational account of the construct that can be modelled and simulated within an integrated cognitive architecture.

1.3 Research Problems

In the research literature, a few studies have developed SA models and demonstrated the application of modelling techniques including fuzzy cognitive maps, used to predict SA in military decision making [28]; machine learning, used in aviation games [29]; granular computing methods, used for automated air surveillance applications [30]; and probabilistic models of visual scanning (attention-situation awareness model), and used in aviation [31].

These techniques, however, are limited in terms of full operationalization of SA modelling. With the exception of the attention-situation awareness model [31], most computational models lack the explanation of SA in terms of perceptual and cognitive mechanisms that are established in descriptive models of SA (e.g. visual attention and memory). The attention-situation awareness model [31] does represent computational instantiation of visual attention allocation mechanisms, but it does not take into account other important cognitive components such as memory. Moreover, the research cited have not included empirical comparisons using common SA measures, such as Situation Awareness Global Assessment Technique (SAGAT), thereby lacking a connection to SA measures that can be applied to models of human operators. Furthermore, most of these models were constructed using a priori data from expert-probes making them intrinsically domain dependent. Lastly, these models cannot be connected directly to task environments (e.g. driving simulators) to run real-time simulations of SA. Based on the above discussion, the following four research problems are identified and later addressed as part of this research:

1. The first goal of this research is to develop a computational model that is grounded in cognitive and perceptual mechanisms that explain drivers' SA. There seems to be an apparent gap present between the theoretical models of SA and computational modelling work validated thus far. It's important to develop psychologically plausible models of SA since such models provide mechanisms for understanding how different cognitive components individually influence SA.
2. The second goal of this research is to develop a computational model of drivers' SA that is capable of directly interacting with the same task environment as human participants. Computational models lacking direct access to the task environment do not abide by the same input/output confines and environmental constraints as experienced by human participants and are, therefore, less likely to model actual human performance.
3. The third goal of this research is to validate the model results against empirical methods that capture the core characteristics of operator SA in driving. Previous computational models of SA were not rigorously evaluated against established SA measures such as SAGAT and hazard perception tests.
4. Our fourth goal is to show that the model fits empirical data using a cohort of goodness-of-fit measures. A quantitative performance evaluation of model and human results across conditions would determine the model's robustness and widespread applicability. A good model fit would demonstrate that the model is capable of simulating human results across experimental conditions.

The area of modelling drivers' SA is quite vast and it's important to detail the extent to which this topic will be investigated in this research. The current work is limited to modelling, simulation and prediction of Level 1 SA (i.e. perception only). While there are new ideas presented that offer insights into how higher levels of SA could be simulated using the cognitive architecture approach (Chapter 6), modelling of higher levels of SA is well beyond the scope of this work and the core focus of this project is on Level 1 SA only.

Perception is a complex construct that has been investigated across different disciplines. For instance, human perception has been explored from the lens of sensory neuroscience [32], evolutionary psychology [33] and philosophy [34]. In this research, I view perception from the context of SA rather than as an independent theory carrying its own nuances and complexities. Investigating perception from the perspective of SA can aid researchers to formulate testable recommendations for understanding and improving human-system performance [35]. In addition to the prescriptive attributes, the SA model is inherently a psychological construct and facilitates investigation of perception from the lens of human psychology [36]. Also, perception when viewed as a subcomponent of SA becomes a well operationalized concept since different methods (subjective measures [37], physiological measures [38] etc.) can be applied to assess the construct in a quantifiable fashion. There exists credible and acceptable evidence indicating that SA methods can capture Level 1 SA (i.e. perception across different domains, including driving [36]). This extensive body of work offers valuable research concepts and data that can be handy in developing and validating the computational model of drivers' Level 1 SA. Furthermore, research demonstrates that perception affects other aspects of cognition in systematic ways [39]; therefore, a computational investigation of perception from the context of SA could open doors for a deeper analysis on higher levels of SA. By this criterion, it appears that investigating perception in the context of SA would ensure tactical relevancy and effectiveness in addressing the devised research questions.

1.4 Contributions

This research takes the initial steps towards the development of a psychologically plausible computational model of drivers' SA. The computational modelling method discussed in this thesis develops an algorithmic approach to SA modelling by extending the widely accepted qualitative description of SA presented by Endsley [5] into a computational model that can be characterized within a cognitive architecture.

The main contribution is the development of Queueing Network-Adaptive Control of Thought-Rational-Situation Awareness QN-ACT-R-SA (Section 3.3). QN-ACT-R-SA is an integrated cognitive architecture capable of modelling and simulating Level 1 SA. QN-ACT-R-SA takes into account different human abilities (such as memory storage and recall, learning, perception, and motor action etc.) as well as constraints (such as memory decay, visual attention allocation limitations etc.) in order to represent human behavior.

Since the domain of this research is limited to driving, a previously validated driving-control model is implemented within QN-ACT-R-SA to simulate lateral and longitudinal control maneuvers (3.3.3). The model's control movements follow a steering control law adopted from Salvucci and Gray [40]. QN-ACT-R-SA is also embedded with a computational theory of visual attention allocation, called Saliency-Effort-Expectancy-Value (SEEV) [31] that enables it to simulate drivers' attention allocation patterns (3.3.1).

QN-ACT-R-SA is connected to a simulated driving environment and programmed to directly perceive situational elements from this environment and implement corresponding driving-control decisions. The driving environments tested in this research are developed in OpenDS driving simulator [41]. QN-ACT-R-SA is equipped to communicate with OpenDS

by means of a User Datagram Protocol (UDP) connection (3.3.3).

A twofold approach is adopted for validating QN-ACT-R-SA in simulating drivers' SA. Two empirical studies (Study I and Study II) are first designed to determine whether Level 1 SA results construed from the QN-ACT-R-SA model correspond to empirical data collected from human participants. The two studies assess drivers' SA using two different SA measures, SAGAT and post-experiment SA questionnaire, respectively. In the two studies, the same driving environment is used by both the QN-ACT-R-SA model and human participants. To garner evidence of the model's predictive capacity, a third research study (Study III) examines the model's ability to map empirical data that has been collected in a different test setting. Study III provides confirmatory evidence to show that QN-ACT-R-SA could be applied to generate predictions of drivers' SA without the need for excessive model fitting or parameter tweaking.

In Study I, QN-ACT-R-SA and human participants are probed for SA using two approaches: within-task queries using SAGAT and post-experiment questions (Chapter 3). A comparative assessment reveals that QN-ACT-R-SA can reasonably simulate drivers' Level 1 SA for two driving conditions: easy (with few vehicles and signboards) and complex (with dense traffic and signboards). QN-ACT-R-SA fit for human SAGAT scores resulted in Mean Absolute Percentage Error (MAPE) of 5.02%, and the Root Mean Square Error (RMSE) of 3.47. The RMSE of 3.47 for SAGAT responses indicate a small error difference between the average human and modelling results since the average SAGAT scores (measured on a scale of 0-100) for the easy and complex driving condition was around 71.9 (SD: 21.1). Model fit for post-experiment human SA results indicated a MAPE of 6.73%, and a RMSE of 6.13. Similarly, the RMSE of 6.13 for post experiment SA questionnaire also indicates a small error difference since the average post experiment SA questionnaire score (on a scale of 0-100) for the easy and complex driving condition is around 73.8 (SD: 16.2).

In Study II, Brake Perception Response Time (BPRT) is used as a hazard perception test to further assess the model's ability to simulate drivers' SA at Level 1 (Chapter 4). An empirical study is first designed mainly for model validation purposes. In the trials runs, the participants encounter two major types of hazards: on-road hazards in the forward view of the driver, and roadside hazards which originate from the driver's periphery. The two contrasting conditions are selected to explore the difference in drivers' BPRT. Not surprisingly, the results reveal that BPRT is significantly shorter for on-road hazards as compared to roadside hazards. The overall model fitness for empirical BPRT results indicate a MAPE of 9.4 % and a RMSE of 0.13 seconds. The RMSE value in Study II indicates a small error difference between the average human and modelling results since the average BPRT for the two on-road and roadside hazard conditions is around 1.49 seconds (SD: 0.54).

Study III investigates the predictive power of QN-ACT-R-SA in simulating Level 1 SA results (Chapter 5). The empirical data is taken from a previously conducted research study that examined the effects of Adaptive Cruise Control (ACC) and cellphone use on drivers' SA using SAGAT tests [42]. QN-ACT-R-SA fit for predicting the effects of ACC and cellphone use on drivers' Level 1 SA resulted in a MAPE of 5.6%, and a RMSE of 4.9. The RMSE of 4.9 for SAGAT responses indicates a small error difference between the average human and modelling results since the average SAGAT scores for the different driving conditions in Study III is around 72 (SD: 4.76).

The MAPE score of less than 10% further signify that the relative error between the average human and model results is very small for the three studies [43, 3]. Furthermore the visual analysis of the model versus human graphs confirm the model’s efficacy in successfully matching human results across experimental conditions tested in the three studies.

In summary, the main contributions of this research involves developing a computational cognitive model of drivers’ SA in a cognitive architecture; implementing the model as a runnable software program; and validating the results produced by the model in relation to empirical findings across different experimental conditions. The limitations of QN-ACT-R-SA model, as well as areas of future research are also discussed in detail in this dissertation (Chapter 6).

1.5 Dissertation Outline

Chapter 3 details the development of QN-ACT-R-SA; and, explains the algorithmic approach towards modelling and simulating Level 1 SA using QN-ACT-R-SA. The chapter also reports an empirical study (Study I) designed for model validation purposes that measures participants’ SA using probe-based techniques in easy and complex driving conditions.

Chapter 4 reports on a driving experiment (Study II) and a corresponding model simulation conducted to assess QN-ACT-R-SA’s ability to simulate participants’ BPRT for on-road and roadside hazards. The model and empirical data is compared using goodness-of-fit approaches to evaluate the efficacy of QN-ACT-R-SA in simulating Level 1 SA.

Chapter 5 reports a model simulation study (Study III) that examines the predictive ability of QN-ACT-R-SA in modelling the ACC and cellphone use on drivers’ SA using SAGAT tests. The empirical data is taken from a study conducted by Ma and Kaber [42].

Chapter 6 discusses the limitations of QN-ACT-R-SA, and highlights the strengths of the model to date. The chapter also details areas of future work, specifically with respect to modelling higher levels of SA.

Chapter 2

Theoretical Foundations of Situation Awareness in Driving

2.1 General Models of Situation Awareness

2.1.1 Endsley (1995)

Endsley [5] describes SA as an internally held cognitive phenomena comprised of three main levels that include perception (Level 1), comprehension (Level 2) and projection (Level 3). Level 1 SA represents the perception of different elements in the task environment. The model credits a range of factors that can influence which elements get perceived. Major factors that influence perception of critical elements include the nature of the task being performed; individual's goals and expectations; and system considerations, such as interface design, level of complexity and automation. Level 2 SA depends on how an individual comprehends the present situation with regards to the relevant tasks and goals. It primarily involves making sense of different elements in the task environment and forming a coherent understanding of the current situation. Level 3 SA involves forecasting future events. Individuals combine Level 1 and Level 2 SA knowledge as well as prior information from mental models, in order to develop Level 3 SA. According to Endsley [5], SA is a cognitive product and exists in an operator's memory. The process used to achieve SA is categorized as situation assessment.

Mental models play a key role in the development and acquisition of SA as environmental artifacts are characterized within the mental models. Mental models assist individuals in disseminating attentional resources to the critical elements within the task environment (Level 1). Mental models also support individuals with comprehending the present situation (Level 2) as well as forecasting likely future events (Level 3).

Attention span and working memory capacity are two limitations in the development and maintenance of SA. Well-developed long term memory stores that exist in the forms of schemata are able to overcome some of these constraints even when critical information is lacking or obscure. Pattern matching is another key constituent of Endsley's model. Pattern matching between critical elements in the environment and components in the mental model follows a recurrent cycle. Individual goals and expectations also impact SA as these constructs explain how attention is dispersed and environmental elements are

identified and understood.

Endsley [5] also explains how automaticity assists in minimizing attention constraints but can also cause unintended loss of SA. As actions become routine and habitual, individuals tend to overlook unique elements in the environment thereby compromising SA.

2.1.2 Bedny and Meister (1999)

Bedny and Meister [44] explain the concept of SA using the theory of activity approach. This theory asserts that individuals contain goals that can allow them to achieve a particular desired state by carrying out series of activities. The difference between the current condition and the desired state prompts an individual to take actions that can assist them in achieving the desired state. Activity consists of three stages: the orientation stage, the executive stage, and the evaluative stage. The first step involves the development of an internal characterization of the current environment. The understanding of information coming from the environment is affected by goals and the individual's mental representation (conceptual model) of the present environment. Key elements of the surroundings are subsequently recognized depending on their relative importance in achieving the desired state. The second stage requires the individual to undertake necessary decisions and perform actions that are focused towards achieving the desired state. The final stage involves evaluating the situation through information feedback, as well as updating the executive and orientation stage constituents of the model accordingly. This model is different from approaches deeply rooted in cognitive psychology as the model does not classify the different cognitive processes (perception, working memory, pattern matching etc.) required in acquisition of SA. The model is primarily grounded on the theory that describes how SA is contingent on the nature of the task and pre-ordained goals of the individual.

2.1.3 Smith and Hancock's (1995)

Smith and Hancock's [45] ecological approach defines SA as a “generative process of knowledge creation and informed action taking”. Their description draws on **Neisser's** [46] perceptual cycle model that illustrates how human thought is coupled closely with experiences and interaction with the environment. Existing knowledge of how the critical elements in an environment function develops an individual's expectations that lead to informed actions. One's interaction with the environment is, therefore, influenced by internally held schemata. The knowledge from prior experiences changes the original schemata and this process repeats itself infinitely. Thus, SA can only be found in an individual's back and forth interaction with the environment rather than residing in either of the two permanently. Therefore **Smith and Hancock's** [45] model describes SA as: “externally, directed consciousness” that is an “invariant component in an adaptive cycle of knowledge, action and information”. The acquisition of SA is due to internal mental models that carry all the necessary information. These models prepare an individual for situational stimuli, influencing where the individual directs their attention. Unlike the three stage model introduced by **Endsley** [5], SA here is viewed as both, a process and a product.

2.1.4 Sarter and Woods (1991)

Research by [Sarter and Woods \[47\]](#) research is focused towards the different cognitive processes necessary in the development of SA. They explain that terms like situation assessment and mental models are related to SA but inherently different. Mental models comprise of a structured set of knowledge that develops to become the foundation for SA. Situation assessment is described as a process of perception and pattern matching that aids in development of SA. [Sarter and Woods \[47\]](#), therefore define SA as “the accessibility of a comprehensive and coherent situation representation which is continuously being updated in accordance with the results of situation assessments”. [Sarter and Woods \[47\]](#) also accentuate the importance of temporal aspects of SA. They emphasise that attentiveness to system changes is necessary to maintain SA as delicate variations can subsequently become major events over time.

2.1.5 Taylor (1990)

[Taylor \[48\]](#) conducted interviews with pilots in order to discover the different aspects necessary in the development of SA. [Taylor \[48\]](#) proposed that the construct of SA could be divided into three major levels. The first level deals with the amount of attentional resources needed in a specific scenario. The second level expands on the allocation of attentional resources in response to the situational circumstances and the last level deals with the understanding of the current situation. Taylor also shortlists ten major theoretical constructs that explain the concept of SA. These include: familiarity, focusing, information quantity, instability, concentration, complexity, variability, arousal, information quality and spare capacity. [Taylor \[48\]](#) therefore defines SA as “the knowledge, cognition and anticipation of events, factors and variables affecting the safe, expedient and effective conduct of a mission”.

2.1.6 Adams et al. (1995)

[Adams et al. \[49\]](#) expand the perceptual cycle model by mapping the relevant cognitive constructs on it; mainly working memory (explicit and implicit memory) and long term memory (episodic and semantic memory), in order to explain the mechanism of SA. [Adams et al. \[49\]](#) explains how SA can exist as a product and a process simultaneously at any given instance. The state of active schema would explain how SA exists as a product and the periodic nature of the perceptual cycle would describe how SA exists as a process. [Adams et al. \[49\]](#) also clarify how on a perceptual cycle diagram, components of working memory could be characterized in place of the “schema of present environment” and components of long term memory can be represented as “cognitive map of the world and its possibilities”.

2.1.7 Summary of General Models of Situation Awareness

All the models have important details that improve our understanding of SA. [Smith and Hancock \[45\]](#) use the perceptual cycle model to demonstrate the dynamic nature of SA explaining in detail how SA exists as a process that entails continuous sampling of the

environment and how SA can also be characterized as a product, represented by the continually activated schema. Similarly, [Adams et al. \[49\]](#) further expanded this concept and mapped the relevant components of working memory and long term memory into the perceptual cycle model in order to explain the inner workings of SA. [Bedny and Meister \[44\]](#) employ concepts from the activity theory to specify the underlying functional blocks necessary in the development of SA. [Sarter and Woods's \[47\]](#) contribution provides insights into the temporal dimensions of SA. They also offer details that help us distinguish between SA and other related constructs such as mental models and situation assessment. The most popular model of SA has been the three-level model of SA introduced by [Endsley \[5\]](#). The model takes into account the different cognitive constructs that are necessary in the development of SA. The model also caters to different individual, task and system related factors that can influence SA. The simple three level characterization offers researchers additional granularity during SA measurement and allows practitioners to design simplified training techniques and design guidelines.

2.2 Driving Specific Models of Situation Awareness

Driving is a complicated activity that requires the distribution of attention across various Areas-of-Interests (AOIs). Drivers need to maintain a high degree of SA across a range of processes since driving requires perception, identification, and interpretation of road elements such as traffic vehicles, road signs, pedestrians etc. There are three simultaneous tasks involved in driving: vehicle control, hazard monitoring and mitigation and route navigation [\[50\]](#). All three tasks require drivers to maintain SA for safe driving operations. The driver may also indulge in additional tasks, legal or illegal, such as operating centre console, texting etc. Given the combination of tasks, driving is considered as a multi-task activity. As with any multi-task activity, certain tasks will take precedence over others; and these task prioritizations vary over time.

This research primarily focuses on developing a predictive model of driver behavior that can allow researchers to analyse how external factors, such as roadway hazards and traffic complexity influence drivers SA. These objectives have not been previously addressed in the literature; however, researchers have utilized existing theoretical models of SA to further explain the concept of SA in driving.

For instance, [Matthews et al. \[51\]](#) developed an information processing model that linked [Michon's \[52\]](#) description of driver behaviour (strategic, tactical, and operational) to [Endsley \[5\]](#) three level model. [Matthews et al. \[51\]](#) proposed that an operational driver functions at SA Level 1, a tactical driver functions at SA Level 2, and a strategic driver functions at all three SA levels, with a significant contribution of SA Level 3 that could assist the driver in projecting future system states. [Ward \[53\]](#) however rebutted explaining that all three levels of SA could be required at the strategic, tactical and operational level, respectively. [Ma and Kaber \[54\]](#) proposed a related concept that incorporated [Endsley \[5\]](#) three level model to explain driver SA. They suggested that at any given time, drivers' SA comprises of navigational, environmental, spatial and vehicle knowledge. Applying a similar framework, [Gugerty and others \[55\]](#) defined driver 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”. Stanton et al. [56] took a systems approach rather than a cognitive stance to explain driver SA. They characterized SA as the ability of the driver to understand the relation between driving goals, the car’s current state, the environmental conditions, the surrounding infrastructure and the actions of other road users.

2.3 Situation Awareness and Cognitive Processing

There are three stages of cognitive processing [55]: a) the unconscious level of processing that renders minimal demand on mental resources; this is involuntary, pre-attentive cognition; b) the limited-conscious level that occurs for transitory periods and places slightly more demand on mental resources; this is categorized as recognition-primed cognition; c) and the full-conscious level that places the most stress on mental resources; this is categorized as controlled cognition.

Regarding visual perception, the involuntary cognition is mostly using ambient vision; whereas the recognition-primed cognition and controlled cognition are using focal vision [57]. Two methods of vision have been outlined by Schneider [58] and others: focal vision, which controls object identification and conscious awareness by means of foveal input and sequential processing; and ambient vision, which directs unconscious involuntary movement by means of foveal retinal input and parallel processing.

It was proposed by Leibowitz and Owens [57] that vehicle control, the primary sub-task of vehicle operation, demands ambient vision; whereas subtasks such as recognizing potential hazards requires focal vision. In the light of Endsley [5] three-stage model, SA is mostly maintained through focal vision and caters to recognition-primed, and controlled stages of cognition and excludes involuntary or sub-perceptual processes.

2.3.1 Situation Awareness and Memory

While different cognitive constructs affect SA, we primarily discuss the role of memory and attention in shaping driver SA. Endsley [5] three-stage classification proves to be a valuable scaffold for explaining the connection between working memory and SA. Level 1 SA often requires selective attention towards certain environmental stimulus, and it is presumed that working memory, and more specifically the central executive, is involved in activating selective attention [59].

Eye movement studies indicate that traffic input collected from drivers front-facing view is frequently updated in the visuospatial sketchpad, a component of working memory responsible for visual and spatial information [60]. It can therefore be assumed that the visuospatial sketchpad plays an integral role in supporting drivers’ SA of spatial orientation tasks such as identifying location of proximal vehicles. Gugerty et al. [61] discovered that drivers’ performance on recall of nearby traffic vehicles decreased when they were instructed to complete a concurrent verbal task; indicating a decline in SA due to an increase in working memory load.

2.3.2 Situation Awareness and Visual Attention Allocation

Drivers allocate visual attention to elements in the environment in order to maintain SA of both regular and potentially dangerous events. Allocating visual attention across multiple AOIs while driving represents a critical constituent of driver behaviour. Focal vision is a requirement of two of the three primary subtasks that are involved in driving: detection and mitigation of risk, and route awareness. Drivers' ability to monitor the environment and remain cognizant of the surrounding traffic enables them to avoid hazards. Many studies in naturalistic and experimental scenarios reveal the significance of visual attention on driving safety. [Dingus et al. \[62\]](#) discovered that drivers' inability to attend visual events in front of the vehicle contributed to 78% of all traffic incidents and 93% of all rear-end collisions. A German car accident study [\[63\]](#) revealed that most accidents occur because roughly 65% of drivers identify critical information too late or fail to recognize it altogether. Visual scanning models [\[64\]](#) can predict drivers' dwell time percentages and gaze behaviour in different driving scenarios. These predictive models can, therefore, determine how vulnerable drivers are when they fail to attend safety critical information in the environment.

Chapter 3

QN-ACT-R-SA Model Development and Initial Validation

3.1 Introduction to Study I

In empirical studies, a driver's SA is usually assessed by probing the driver's recall of situational elements that are critical in accomplishing the main driving tasks (e.g., pedestrians, traffic vehicles, and traffic signboards). A driver's knowledge of these elements is typically captured by means of probe-based SA measures. Probe-based SA measures include Situation Awareness Global Assessment Technique (SAGAT) [65] and post-experiment SA questionnaires [54]. SAGAT requires participants to respond to SA queries during simulation freezes. Incorrect SAGAT responses reflect limitations in the awareness of relevant information in the task environment. Since queries are probed immediately after each freeze, and usually only one query is used in each freeze, the effect of memory decay is minimal. On the other hand, a post-experiment SA questionnaire requires participants to respond to scenario-based SA queries at task completion. In comparison to SAGAT, post-experiment SA avoids interrupting the flow of the main task by not using simulation freezes, but it introduces a time delay between a situation and its query question. As a result, post-experiment SA measures are affected by memory decay and interfering events that occur during the task [66]. Probe-based SA measures are evidence-based description techniques requiring real-time experiential data. The fundamental limitation of such measures is the inability to predict SA in a new situation. In contrast, computational models aim at capturing the quantitative relationship between SA and the factors affecting it; and, therefore can be used as predictive tools.

I propose an approach based in cognitive architecture to develop a computational model of SA. This new model can simulate human responses to established SA measures such as SAGAT; and, is based on the perceptual and cognitive mechanisms that formulate the SA construct. The main contribution is the development of QN-ACT-R-SA: an integrated cognitive architecture capable of modelling and simulating SA. This architecture is an extension and improvement to the Queueing Network and Adaptive Control of Thought-Rational (QN-ACT-R) framework [3]. As the first stage in the SA model development process, the current study focuses on the modelling and simulation of Level 1 SA (i.e.

perception). Driving is selected as the domain of focus because previous models within the cognitive architecture have simulated drivers’ steering control, multitasking, and hazard response behaviors [67, 68, 69], thereby providing foundation for this work.

QN-ACT-R integrates two previously isolated but complementary cognitive architectures – Queueing Network (QN) [70] and Adaptive Control of Thought-Rational (ACT-R) [71]. QN-ACT-R is essentially a production rule system with queues for scheduling multiple resource demands. Production rules represent procedural knowledge or skills, whereas chunks represent declarative knowledge. QN-ACT-R can represent human behavior by interacting with simulated task environments (e.g., driving simulator) using its perceptual and motor modules. Details regarding QN-ACT-R are described further in Section 3.2

To facilitate the simulation of Level 1 SA (i.e. perception), I propose using the concept of critical elements. Critical elements are situational elements that are ‘critical’ for the operator to accomplish the primary task. Drivers must visually attend different critical elements (e.g., pedestrians, traffic signs, and speedometer) in the environment to dynamically maintain SA. Optimal SA at Level 1 depends on the perception of critical elements in the task environment. The mental representations of these elements can be stored as declarative chunks [71]. During SA probes, response outcomes depend on memory retrieval of the chunks, which is affected by factors such as whether a critical element was perceived, how many times it was observed, and the delay between perception and query.

To capture Level 1 SA in our model, I integrate Saliency-Effort-Expectancy-Value (SEEV) attention model into QN-ACT-R [31]. The current visual attention mechanisms in ACT-R as well as QN-ACT-R are relatively simple (i.e. focus on top-down mechanisms directing attention) and cannot account for priority and distribution of attention among multiple visual targets. Factors such as expectancy and value of situational elements in different Areas-of-Interests (AOIs) are not represented in QN-ACT-R’s attention allocation processes. The default visual attention mechanisms in QN-ACT-R and ACT-R rely on the procedural module to carry out the central executive role of directing visual attention in a top-down manner. It lacks a probabilistic model of visual attention allocation that could explain driver scanning patterns for different stimuli in the driving environment. Attention allocation plays a crucial role in characterizing drivers’ SA. Researchers have discussed the benefits of integrating visual attention allocation models with ACT-R [72, 73]. Therefore, I have integrated the QN-ACT-R driving model with SEEV to create QN-ACT-R-SA. SEEV is a well-tested and widely used model of attention allocation [31]. SEEV classifies four major factors that influence attention allocation: saliency, effort, expectancy and value. Within QN-ACT-R-SA, the SEEV model explains the attention allocation process in scanning different AOIs present in the driving environment, whereas QN-ACT-R explains the internal cognitive processes necessary for the acquisition and maintenance of SA (e.g. multitasking, declarative memory, and production rules). Combined QN-ACT-R and SEEV provide complementary capabilities for SA modelling. Further details related to QN-ACT-R-SA integration are described in Section 3.3.

To evaluate and validate the model, I compare SA results generated by the model against empirical data from human participants. To collect human data, I conducted an experiment in a driving simulator, whereby participants drove on a highway with different road-environment complexity in terms of traffic volume and the number of road signs. Driving environment complexity is known to influence a driver’s ability to perceive elements

in the environment, such as identifying road signs, detecting changes in nearby traffic, observing the current speed, and sensing hazards [62]. Excessive information present in a complex driving environment may exceed a driver’s attention capacity threshold and as a result degrade the driver’s SA scores on SAGAT probes [74, 62]. In the current experiment, SA was measured using both SAGAT and post-experiment SA questionnaires. The QN-ACT-R-SA model was connected to the same driving simulator in which human results were collected. The model and human participants were, therefore, exposed to the same experimental conditions; and the model was probed with SA queries in a manner similar to human participants. Details of the comparative assessment is presented in Section 3.5.

In the described study, I expect drivers’ SA to be lower in complex driving (increased traffic and signs) conditions due to over-occupation of attentional resources resulting in poorer response rates to probe questions concerning situational elements. Furthermore, I expect SA of critical elements in the central forward view (e.g., cars ahead) to be better than SA of critical elements in the driver’s periphery (e.g., roadside vehicles, in-vehicle devices, and objects in mirrors), since objects in the central forward view are considered more central to driving control and safety [75]. A simulator-based experiment was designed to validate the efficacy of the computational model of SA.

3.2 Background of Cognitive Architecture

In order to understand the process of modelling SA using QN-ACT-R-SA, I provide an overview of how the cognitive processes within QN-ACT-R function (Figure 3.1). Within the QN-ACT-R cognitive architecture, the queuing networks (i.e., QN) components carry the capacity for multi-task performance modelling [76], and ACT-R components maintain the ability to simulate cognitive processes [71]. Integrating both architectures provides the capability to model complex cognitive and multi-task scenarios. QN-ACT-R has previously been employed in different domains including driving [77] and multitasking [78]. Although queuing networks and queuing theory [79] have been extensively applied in complex engineering systems (e.g., communications networks and manufacturing), the adoption for modelling human performance has been fairly recent [76]. The mathematical formulations of QN and queuing theory provide useful tools for modelling reaction time and multitasking performance [76]. For instance, models have been created to simulate the psychological refractory period that occurs when performing two simultaneous tasks [80] and for concurrent driving tasks [81]. Neurological evidence at both the neuron and cortex levels reveal that queues likely exist within the perceptual system. It’s been discovered that movement of the synaptic vesicles happens in a sequential order [82], with certain vesicles receiving higher priority over others [82]. Motor commands from the cerebral cortex are also thought to form queues for coordination of sensory data prior to execution of motor responses.

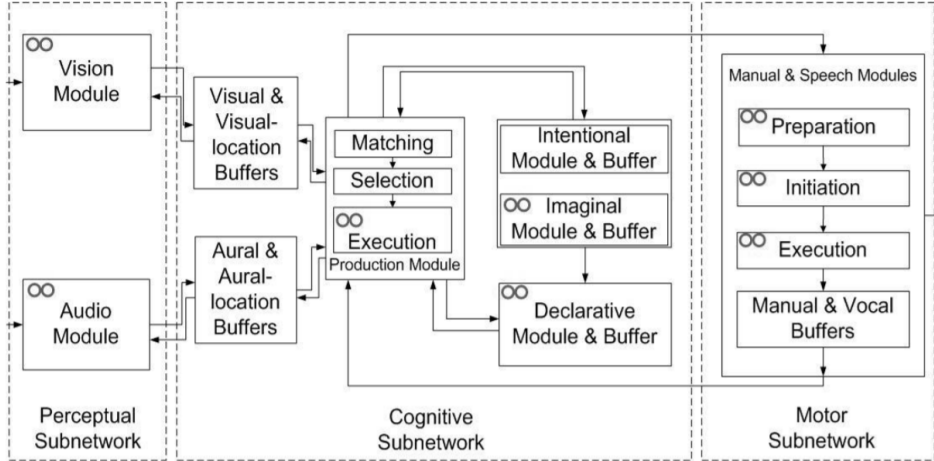


Figure 3.1: QN-ACT-R cognitive structure as the combination of QN and ACT-R frameworks. QN-ACT-R’s servers represent ACT-R’s modules and buffers. Information that travels between these servers represents ACT-R’s buffer demands, chunks and production rules. Source: reproduced by UR (author) from Cao [83].

In contrast, ACT-R is a production rule system with symbolic representations of both declarative memory and procedural memory [71]. The declarative memory is represented by chunks, while the recall rate and retrieval time of chunks are processed based on chunk activation values. The procedural memory is represented by production rules, and the selection and acquisition of production rules is based on rule utility values. In each processing cycle, ACT-R determines which production rule to execute based on information from the declarative knowledge base and inputs from the external environment (e.g., visual and aural). Execution of production rules either triggers the model to perform a specific action or results in modification of the internal state of the model (e.g. forming new knowledge or goals). ACT-R’s architecture contains modules that perform different functions such as memory retrieval, perception, and motor processes. The mechanism of these modules is grounded in established mathematical formulations which have been empirically validated for different contexts [84, 85]. The core of these modules is the procedural module that handles the cognitive processing of production rules. All other modules in ACT-R carry an associated buffer system that allows production rules to communicate, back and forth, with the declarative memory as well as with the external environment via perceptual and motor modules. Neurological evidence indicates that the modules of ACT-R can be anatomically mapped to corresponding brain regions [86, 87, 88].

A major benefit of an integrated QN-ACT-R architecture is its capacity to simulate multitasking. The ACT-R architecture has certain limitations in dual-task scenarios since each buffer is only capable of holding a single chunk at a time, and the procedural module can only process one production rule at a time. While these assumptions are used to represent human cognitive limitations, it is not clear how multiple task demands should be scheduled. In contrast, the QN architecture allows the goal buffer to hold several goals at a time thereby allowing multi-task performance. Multiple information streams can flow

though the network and follow queueing mechanisms when facing cognitive bottlenecks. With a queueing structure in place, requests that arrive at busy modules can wait in sequence until the module is available, thereby resolving issues of module jamming. Previous studies have demonstrated the benefit of this approach in predicting drivers' direction sign reading reaction time [89] and take-over reaction time [77].

QN-ACT-R, like ACT-R, has two types of knowledge representation: procedural knowledge processed in the procedural module and declarative knowledge processed in the declarative module. Procedural knowledge can be characterized as implicit knowledge, applied directly to a task for problem solving purposes. Procedural knowledge is programmed as production rules, which are condition-action statements (i.e., if-then rules) that yield precise actions if certain conditions are met. The procedural module serves as a central executive to send requests to and synthesize information from other modules. It observes the processes in different buffers and searches for patterns that may match a condition specified in a production rule. If conditions are met, then a rule is selected and fired, generating a specific action, such as a motor response.

Production rules have a sub symbolic parameter associated with it called the expected utility value. Expected utilities can be learned with time and are underpinned by a reinforcement learning model. Expected utility helps the model to control rule matching, selection and execution. Since multiple production rules can compete with each other, a utility value indicates the relative probability for a specific rule to be implemented.

With every production rule, ACT-R has two main parameters. The estimated cost of the rule and estimated probability of success. The utility equation is represented below (Equation 3.1), cited from Anderson et al. [90]:

$$U_i = P_i G - C_i \quad (3.1)$$

P_i is an approximation of the probability that a specific production i would be chosen in order to accomplish a goal G with an estimate cost of C_i . The probability of selecting a production rule (Production choice equation P_i) is calculated using the formula below (Equation 3.2), cited from Anderson et al. [90]:

$$Probability = \frac{e^{U_i/t}}{\sum_j e^{U_j/t}} \quad (3.2)$$

Equation 3.2 states that n productions that match and the probability of selecting the i th production is related to utilities U_i of the n production rules.

Declarative knowledge in ACT-R represents explicit information that is stored as chunks in the declarative memory. Chunks are small logical units comprised of static knowledge such as simple facts, current goals, and perceptual information [90]. Each chunk has a parameter called chunk activation, reflecting the memory strength of the chunk. The change of chunk activation imitates the human learning process that decays with the passage of time, and yet can strengthen with rehearsal and retrieval. The declarative module caters to memory retrieval requests by finding the chunk that matches the properties set in the request. The retrieval time for a specific chunk from the declarative memory directly corresponds to its activation value [91].

Chunk activation is mainly determined by base-level activation, which reflects both learning and forgetting. Base-level activation is calculated following the formula below (Equation 3.3), cited from Anderson et al. [90]:

$$B_i(t) = \ln \left(\sum_{k=1}^n (t_k)^{-d} \right) \quad (3.3)$$

In Equation 3.3, n represents the number of times chunk i has been used, t_k is the time passed since the k th use of the chunk, and d is the decay factor. Equation 3.3 implies that base-level activation B_i increases with the recency and frequency of use of chunk i .

The probability of successfully recalling a chunk, $Pr(recall)$, can be calculated using the following formula (Equation 3.4), cited from Anderson et al. [90]:

$$Pr(recall) = \frac{1}{1 + e^{-\left(\frac{A_i - \tau}{s}\right)}} \quad (3.4)$$

In Equation 3.4, τ is the retrieval threshold, and s is a noise parameter.

The visual module allows the model to perceive elements in the environment, and it contains both ‘where’ and ‘what’ mechanisms for identifying visual location of objects and encoding the relevant visual content. The model first identifies the location of a visual element in the environment and then focuses visual attention on that specific location. Usually, a production rule would request the location of the visual element with a second production rule matching the location in the visual location buffer to activate the encoding process. A third production rule harvests the encoded content for further cognitive processing. The shift of attention due to a sequence of visual encoding results in a series of eye movements [92].

3.3 Development of QN-ACT-R-SA

In this section, I provide an introduction to QN-ACT-R-SA (Figure 3.2), which is an extension of QN-ACT-R with additional methods for the simulation and prediction of SA. As mentioned in the introduction section, QN-ACT-R-SA models the cognitive processes required in acquisition and maintenance of SA using two independent computational theories of human attention allocation and cognition, called SEEV and QN-ACT-R respectively. QN-ACT-R-SA perceives critical elements in the visual environment and stores the underlying information related to these elements in its declarative memory. Critical elements are essentially situational components important for drivers to successfully accomplish driving tasks. In the case of driving, examples of critical elements include pedestrians, traffic signs, and traffic vehicles. Drivers need to be cognizant of critical elements in order to make appropriate decisions for tasks such as lane keeping, speed control, and hazard avoidance. A drivers SA is measured as the percentage of correct responses to probes concerning critical elements within the driving environment.

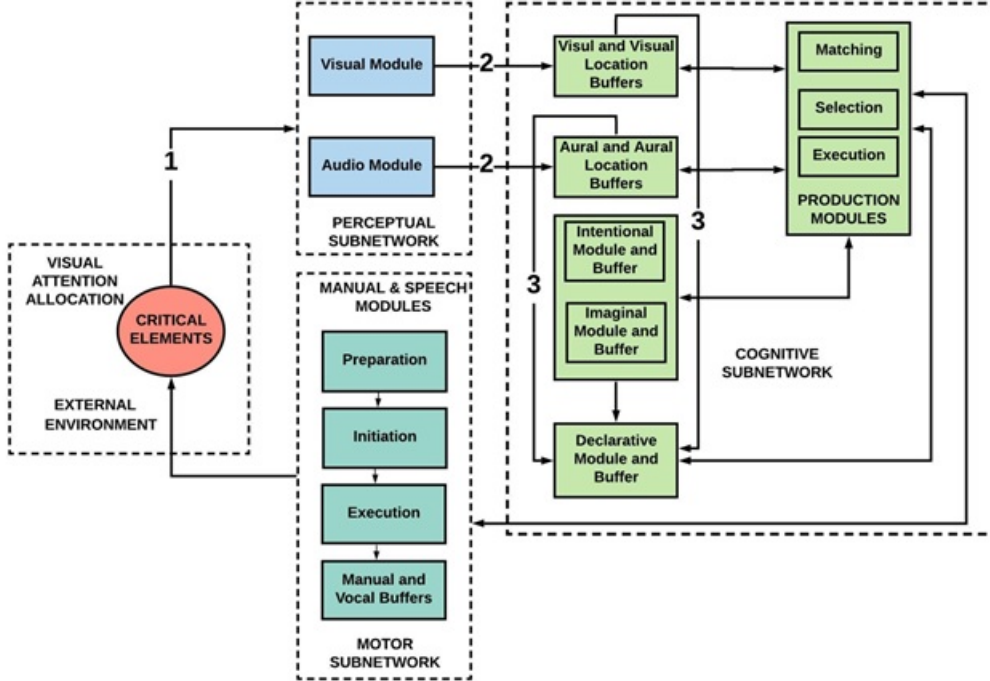


Figure 3.2: The QN-ACT-R-SA framework. Stages 1-3 (marked on the lines in the figure and explained in the main text) signify the different cognitive processes necessary in the acquisition and maintenance of Level 1 SA. Source: original, UR (author).

Probe-based SA techniques, such as SAGAT and post-experiment SA questionnaires, are set up as queries to capture the outcome of attention distribution among multiple critical elements. A similar query-based approach can be used with the QN-ACT-R-SA model. QN-ACT-R-SA's visual and memory modules play important roles in acquiring and maintaining Level 1 SA during driving. QN-ACT-R-SA simulates visual attention distribution with the aid of SEEV theory. SEEV mechanics embedded within QN-ACT-R-SA manages the visual attention allocation processes required in scanning different AOIs. The model's declarative memory mechanisms are used to imitate typical human memory decay processes on queries concerning critical elements that may have been forgotten due to time delay.

3.3.1 Modelling Visual Attention Allocation

The QN-ACT-R-SA model has three stages of processing (Figure 3.2). For the purposes of explanation, the QN-ACT-R-SA model is described as it has been generally applied in our empirical study. In Stage 1, the visual module attends to a critical element located in one of the AOIs. AOIs defined in this study include on-road frontal view, mirrors (centre, left and right mirror), and the vehicle speedometer. The selection of an AOI is based on the probability of scanning different AOIs as computed by the SEEV model [93]. A simplified SEEV method to calculate the probability of attending an AOI is described by

Gore et al. [94], wherein the probability to select an AOI is associated with the weighted average of the AOI’s property values including Saliency, Effort, Expectancy, and Value. I deduced the weights for SEEV coefficients a priori by means of the lowest ordinal heuristic approach [95]. Different task conditions and AOIs were ranked along the model parameters as described by Gore et al. [94]. This score was then weighted against the sum of all tasks and conditions and used as a percentage of the total dwell time. Two major AOIs were shortlisted for this experiment that include the driver’s peripheral environment (left mirror, right mirror, and centre mirror, speedometer, roadside view) and the driver’s front view of the road. The tasks carried out by the QN-ACT-R-SA model include: (1) lateral control (maintain vehicle in centre lane), (2) longitudinal control (maintaining speed limit and safe distance from vehicle in the front or rear) and (3) situational monitoring (hazard monitoring and ensuring destination lane is clear before lane changes). The probability of attention allocation towards a certain AOI is calculated using the following formula (Equation 3.5), cited from Wickens et al. [93]:

$$VA_{AOI} = \sum_{t=Tasks}^n (Ex_t) (R_t) (P_t) \quad (3.5)$$

where VA_{AOI} is the raw visual attention score of an AOI, t is a number of tasks, n in this study equals to three, 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 [93]. The probability of scanning an AOI, $P(AOI)$, can be calculated by normalizing all values so that the $P(AOI)$ values for different AOIs add up to 100%.

The saliency and effort factors have been rounded off to zero to account for a simpler model. Effort parameter was nullified because its effect on driver’s attention allocation has been found to be negligible in simulator studies [64]. Effort factor is influenced by the size of visual angle between two distinct visual targets and in simulator settings this size is minimal therefore the factor is often discounted [64]. In the current experimental setup, all visual targets were within the LCD display and the visual angle between them was small therefore following existing research protocol, a decision was made to nullify the effort parameter in the SEEV modelling paradigm [64]. The model was further simplified to not account for saliency parameter because the model focuses on simulating driver’s visual attention allocation across different AOIs rather than across individual critical elements. In the SEEV model, saliency is a property of an AOI (information channel) rather than a property of individual elements in the driving environment [31]. Had the model been programmed to simulate attention across different critical elements, the modeller would be expected to assign saliency parameter weights to each critical element in the driving environment, making modelling attention allocation extremely complex and impractical. A strong model fit without saliency and effort parameters has been found in previous studies [31, 96] and model results have been robust when validated against eye tracking data [64].

Within the SEEV model, Expectancy refers to the information frequency in a specific AOI. Expectancy has also been called bandwidth [93]. If an AOI has a high bandwidth, then it would be sampled more frequently and assigned a higher expectancy weight. For instance, drivers can expect more activity in the forward view as compared to other AOIs, thus on-road areas are assigned the highest expectancy weight. The expectancy coefficient

should be different for complex and easy driving conditions because a driver’s expectancy changes as visual clutter increases in the driving environment [94]. Following the lowest ordinal heuristic approach [95], Expectancy for each information channel was set as one of four values, those being none (0), low (0.333), moderate (0.666), and high (1.0) [94], as shown in Table 3.1.

Value, within SEEV, is a measure of the objective usefulness of information contained in a specific AOI. Value considers the cost of failing to process important information within a given channel. It is computationally expressed as the product of relevance and priority. Relevance for each task in each driving condition was also set following the lowest ordinal heuristic approach, as shown in Table 3.1. Regarding priority of the three task components of driving (i.e., lateral control, longitudinal control, and situational monitoring), lateral control is the most important task component and therefore assigned the highest priority value, following Horrey et al. [64] and Wortelen and Ludtke [73]. Situational monitoring should have the lowest priority in comparison to lateral control and longitudinal control [73]. The priority values determined for each task component are shown in Table 3.1. To ease weighted score calculations, the priority values were normalized so that all priority values for the same AOI add up to one [94]. Table 3.1 presents the values used in calculating the probability of scanning each AOI in the driving task used in our empirical study. Based on the probability distribution, Monte-Carlo simulations [97] were performed to determine which AOI would receive visual attention at a given period of time.

Table 3.1: SEEV parameters for easy and complex driving conditions.

Easy Condition											
	T1 ^a			T2 ^b			T3 ^c				
AOI ^d	EX_1 ⁱ	R_1 ^j	P_1 ^k	EX_2	R_2	P_2	EX_3	R_3	P_3	VA_{AOI} ^l	P(AOI)% ^m
FV (RS) ^e	0.333	0.666	0.6	0.333	0.333	0.3	0.333	0.333	0.1	0.144	19.6
FV (OR) ^f	0.666	1	0.6	0.666	0.333	0.3	0.666	1	0.1	0.474	64.5
Mirror ^g	0.333	0.333	0.6	0.333	0.333	0.3	0.333	0.333	0.1	0.09	12.2
Dash ^h	0.333	0	0.6	0.333	0.333	0.3	0.333	0	0.1	0.027	3.67

Complex Condition											
	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	13.7
FV (OR)	1	1	0.6	1	0.333	0.3	1	1	0.1	0.79	75.2
Mirror	0.333	0.333	0.6	0.333	0.333	0.3	0.333	0.333	0.1	0.09	8.6
Dash	0.333	0	0.6	0.333	0.333	0.3	0.333	0	0.1	0.027	2.6

^aT1: Task 1 (Lateral Control); ^bT2: Task 2 (Longitudinal Control); ^cT3: Task 3 (Situational Monitoring); ^dAOI: Areas-of-Interests; ^eFV (RS): Forward View Roadside; ^fFV (OR): Forward View On Road; ^gMirrors: Mirrors (Left, Right, Center); ^hDash: Dashboard (Speedometer); ⁱ EX_t : Expectancy; ^j R_t : Relevance; ^k P_t : Priority; ^l VA_{AOI} : Raw Visual Attention score; ^mP(AOI)%: Percentage Normalized Score for each AOI representing probability of scanning an AOI.

Using the expected limitations in driver attention allocation patterns, QN-ACT-R-SA provides a sound approach for modelling and simulating SA. A distinguishing factor is that decisions on whether to store critical elements in the declarative memory are based on attention allocation to identified AOIs. The less visual attention put on an AOI, the greater the probability that the critical element will not be stored, and the more likely that answers to SA query will be incorrect.

3.3.2 Modelling Information Retrieval for Answering SA Probes

While SEEV accounts for SA based on whether a critical element was seen (i.e. visual attention allocation), the declarative memory in ACT-R contributes to SA based on memory. Even if a critical element was seen, the answer to the SA probe may be incorrect due to memory decay. According to ACT-R, the retrieval success depends on both how many times the same critical element is attended and how long the delay is between perception of critical elements and the SA probe. In Stage 2 of the QN-ACT-R-SA model, the visual buffer acquires the visual content of the critical element in the environment from the visual module (see Figure 3.2). In Stage 3 of the QN-ACT-R-SA model, the visual buffers extract

the corresponding information from the declarative memory resulting in cognitive activation of the critical element using Equation 3.4. As such, Level 1 SA only comes into effect when the activation value of a chunk representing the critical element in the environment is over a certain threshold. Thus, QN-ACT-R-SA covers both the attention and memory mechanisms for Level 1 SA.

3.3.3 Information Processing within QN-ACT-R-SA

In this section, I explain how the different components of the model function in an integrated manner. QN-ACT-R-SA is a discrete event simulation model and its input includes production rules, declarative chunks and model parameters¹. These components explain how human cognition processes information. This cognitive model is capable of interacting with a task model (driving simulator) to produce simulated behavior as model output (e.g., steering control, brake reaction time, SA query results etc.). Production rules, as previously defined, represent psychologically plausible input-procedures (discreet sequential steps) that divide overall tasks into smaller operational goals. Production rules explain task details and task-specific information. Processing a production rule results in QN-ACT-R-SA to output actions that simulate human performance and therefore represent a realistic portrayal of human cognitive capabilities and limitations.

The QN-ACT-R-SA cognitive architecture already encompasses a standard cognitive framework that details non-task-specific information processing abilities. As mentioned previously, QN-ACT-R-SA comprises several independent modules that cater to different cognitive functionalities such as memory processes, perception, and motor actions. These modules are responsible for performing a wide variety of general-purpose cognitive tasks. The modeler provides the task specific knowledge based on the theoretical understanding of the task under analysis (e.g. how lane changing is typically performed by a driver). Within QN-ACT-R-SA architecture, this knowledge is computationally programmed and encoded in terms of production rules.

Production rules are processed when the knowledge chunks from the declarative memory match a pre-condition set by the modeller. For instance, a potential production rule could direct the model to output a braking action in response to a series of preconditions such as vehicle intrusions, stop signs etc. The stop signs or the intruding vehicle here would represent the chunk in the architecture’s declarative memory. At times multiple production rules are matched; however, the production rule with the highest utility value is fired. Utility values, as previously described, are underpinned by a computational model that simulates how humans administer cost and reward processes for different decision paths. In this research, we propose three sets of production rules that function in an integrated fashion with the overall goal to simulate human driving and SA. Each set of production rules represents a specific cognitive model. The model simulates the following set of production rules by means of its production system: (1) maintaining lateral and longitudinal control, (2) monitoring the environment, and (3) undertaking high-level decisions. Figure 3.3 represents the information processing within QN-ACT-R-SA. The model communicates with a driving simulator (OpenDS) by means of a User Datagram Protocol (UDP) connec-

¹Table 3.2 details the parameters used in the current study.

tion. The performance of the entire loop occurs within a timeframe of 150 milliseconds, which represents the firing of the three relevant production rules [69].

To maintain lateral control, a steering control law is implemented based on the work of [Salvucci and Gray \[98\]](#). A similar control law is also implemented to maintain a stable speed or car-following distance following the work of [Salvucci \[99\]](#). For monitoring the environment, the model scans different AOIs to perceive and store information, including the road heading direction, front car leading distance, traffic signs, traffic vehicles, and other road users. The model scans different AOIs based on the SEEV parameters as described in earlier [3.3.1](#). The model then uses this information to determine steering and pedal commands that are eventually sent to the driving simulator to control the simulated car. This aspect of the model is geared to simulate QN-ACT-R-SA’s decision making capacity. The model can also be probed to recall critical elements that it has stored in its declarative memory while monitoring the environment. Further details on the model’s production system are discussed in the following subsections.

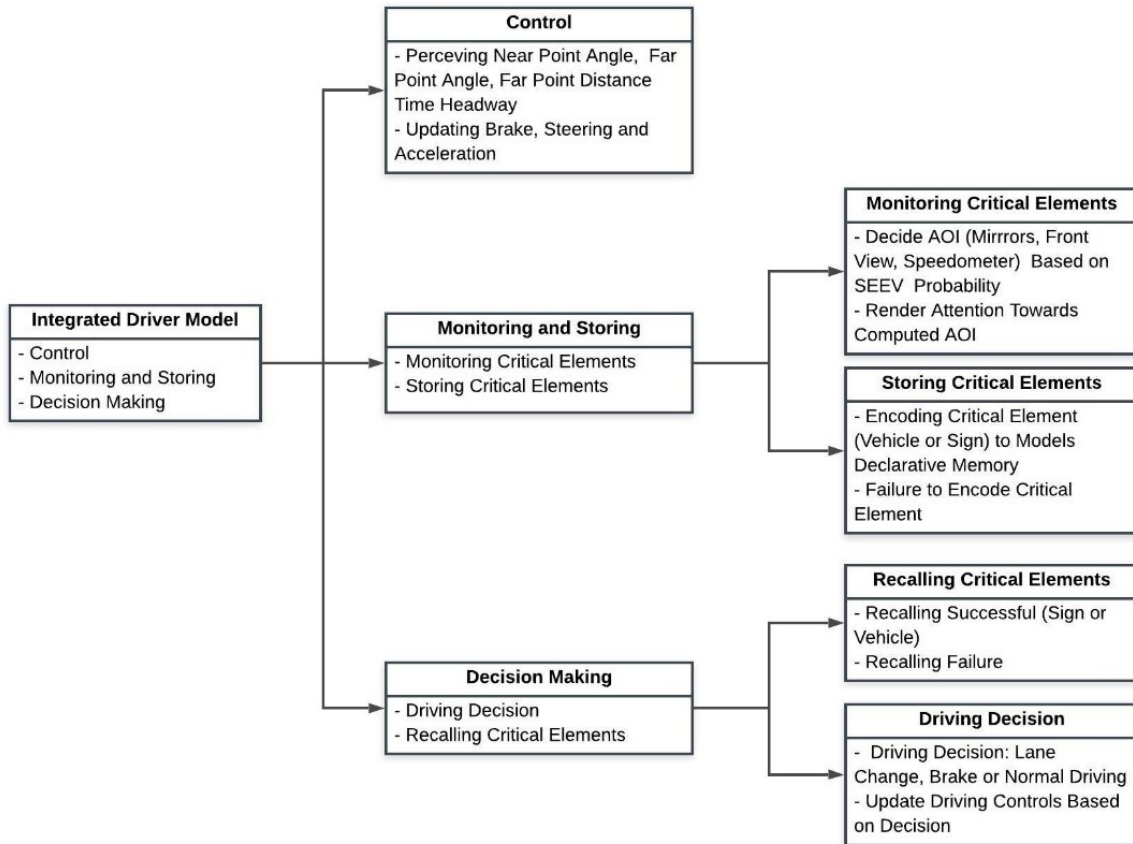


Figure 3.3: A schematic display of information processing within QN-ACT-R-SA. Source: original, UR (author).

Driving Control

A basic control paradigm is applied in the model that enables the driver’s vehicle to centre on two perceptually distinct targets at different distances: a near point and a far point. The model is adopted from the work conducted by [Salvucci and Gray \[40\]](#). First, the near point represents how close the vehicle is to the centre of the road, thus representing the vehicle’s current lane position. As per [Salvucci and Gray \[40\]](#), the near point is set at 10 meters ahead of the vehicle’s centre and is positioned at the mid-point of the lane viewable from the front of the vehicle. The far point represents how a driver should anticipate a bend or a curvature on the road. There exists three types of far point targets: (1) the vanishing point that represents an imaginary point characterising a time headway of 2 seconds on a straight road; (2) the tangent point that is at the vertex of an approaching curve [\[100\]](#); and (3) the lead vehicle point that represents the vehicle directly in front of the driver’s view. When the near and far points are used in tandem, they allow minor driving adjustment to be made that simulates human driving behavior. For instance, the near point allows for present lane-centre modifications, while the far point determines how the model adapts for future positioning.

A steering control law is applied based on the near and the far points. The control law for steering angle Φ , as adopted from [Salvucci and Gray \[40\]](#), can be represented as following (Equation 3.6):

$$\Delta\Phi = k_{far}\Delta\theta_{far} + k_{near}\Delta\theta_{near} + k_1(\theta_{near}\theta_{nmax})\Delta t \quad (3.6)$$

$\Delta\Phi$ is the change of steering angle. 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_{near} , k_{far} , k_1) control the weights of the components in the equation. In Equation 3.6, θ_{nmax} (set to 0.07) controls the maximum of θ_{near} whereas the duration of a control cycle is represented by Δt .

Essentially, the procedural system employs one rule to identify the near point, one to identify the far point, and one to issue the motor commands. Within the architecture, perception occurs through shifts of visual attention via ACT-R’s visual module [\[101\]](#). The model utilizes the steering control equation (Equation 3.6), for lane changing. To perform a lane change, the model uses the near and far points of the target lane.

Monitoring and Storing

The model monitors critical elements in the external environment. Lane keeping and hazard avoidance is an aspect of this situational monitoring, where drivers periodically assess the environment and become aware of the other vehicles around them. The SEEV framework is applied in this model as a means of distributing attention to the key AOIs such as the speedometer, the rear-view and side mirrors, and objects in the front view. In essence, the model looks at an AOI and encodes critical elements presented within that AOI, storing both the location and other pertinent information in the declarative memory (e.g., for vehicle, its color, lane, direction, and distance; for signs, its type; for pedestrian, its location, and for billboard, the type of billboard).

Decision Making

The model undertakes lane changing when necessary. The model is given a goal to reach the destination as fast as possible while maintaining the speed limit. This lane changing ability has been validated against empirical data in previous studies [102]. Each time the model glances at the previously viewed critical element, the activation value increases, its representation is strengthened in the memory, and the likelihood of efficient recall is increased. Activation value, however, decreases with time and causes these memories to fade as time passes. To extract SA probes, the QN-ACT-R-SA model is programmed to recall critical elements at designated simulation clock times corresponding with query timing used with human participants.

3.4 QN-ACT-R-SA Parameters

As mentioned previously, QN-ACT-R-SA has certain parameters that can be pre-set by the modeller. These parameters are employed to adapt the behavior of the model and control specific aspects of the model's functionality. All parameters employed in the current study either used values from previous studies or were set at their default values. Table 3.2 presents further details on the parameters used in this research. The parameters employed in the SEEV model of visual attention allocation are explained in 3.3.1.

Table 3.2: The table shows the description, values and sources of parameters used in this research.

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.	0.05	Anderson et al. (1997) [103]
:imaginal-delay	The parameter signifies the time (in seconds) needed by the imaginal module to form a chunk of imaginal representation.	0.2s	Anderson et al. (1997) [103]
:visual-attention-latency	The parameter specifies the time (in seconds) needed for a shift in visual attention.	0.085s	Anderson et al. (1997) [103]
d	d represents the time based decay parameter (Equation 3.3).	0.5	Anderson et al. (1997) [103]
τ	τ represents retrieval threshold and signifies the minimum activation level required for chunk retrieval (Equation 3.4).	-1.5	Anderson et al. (2001) [103]
s	s represents the instantaneous noise that is added to the activation value of a chunk (Equation 3.4).	0.4	Anderson et al (1997) [103]
k_{far}	Parameter used in steering control model (Equation 3.6).	20	Salvucci & Gray (2004) [40]
k_{near}	Parameter used in the steering control model (Equation 3.6).	9	Salvucci & Gray (2004) [40]
k_1	Parameter used in the steering control model (Equation 3.6).	1.5	Cao (2013) [40]

3.5 Methodology Study I

To evaluate the QN-ACT-R-SA model, an empirical study was designed to test whether the model’s simulation of SA reasonably corresponds to human empirical data. This study received ethics approval from Office of Research, University of Waterloo.

3.5.1 Participants

For sample size estimation, a preliminary study was conducted and a power analysis was performed using G*power 3 software [104]. The effect sizes were determined from the mean

values construed from the preliminary study. The effect sizes indicated a large effect based on partial eta squared [105] and Cohen's d [106] criteria². The power analysis indicated a sample size of $N=5$ for an $\alpha = .05$ and power = 0.8. Thus, our proposed sample size of $N=14$ is adequate to achieve the main objective of the study. A total of 14 participants (9 males and 2 females) ages 22 to 26 years were recruited for this study. The lack of gender balance is a limitation of the current experiment design, however, previous studies show an insignificant effect of gender on SA scores [107, 108, 109]. The mean age of participants was 22.2 (SD: 1.1) years, with mean driving experience of 3.4 (SD: 1.1) years. All participants reported normal or corrected-to-normal visual and auditory acuities.

3.5.2 Driving Simulator

The participants had control of the steering wheel, brake pedals, and accelerator pedal as main driving controls. The simulator used for this experiment was a customized fixed-base driving simulator with a 2004 Toyota Corolla seat mounted on a wooden platform. Driver controls included a Logitech Driving Force GT steering wheel and pedals. Driving simulator software called OpenDS was used in this study [41]. The simulated driving task was displayed on a Samsung (55 inch) LCD television, with a resolution of 1080 by 1920 degrees and a refresh rate of 60 Hz. The visual angle of the viewable driving scene is approximately 15.3 by 10.2 degrees.

3.5.3 Scenario

Participants drove on a simulated highway situated in a lowland rural landscape. The highway is one straight path of 3300 m with no curve and consists of four lanes, two in each direction (Figure 3.4). The visual elements in the head-on-display include speedometer, side view mirrors, and rear centre mirror. In this experiment, the participant's car is initially located at the centre of the right lane. There are two conditions in the experiment: an easy driving condition (low traffic density and less visual clutter) and a complex driving condition (high traffic density and more visual clutter). Low traffic density represents two vehicles in a car following distance of 600m and 1000m respectively. High traffic density represents five vehicles with a car following distance of 300m, 600m, 900m, 1200m and 1400m respectively. To allow for reasonable driving control in the simulator, the traffic vehicles are artificially programmed to maintain the speed of 50 km/h, which is lower than the speed limit on the roadway (70 km/h). The traffic also follows a pattern that allows participants to easily overtake vehicles and perform lane changes where appropriate; however, lane changing is more difficult when the traffic density is higher. Critical elements present on the highway include traffic signs, billboards with distinct messages, potential roadside hazards such as pedestrians, and nearby traffic vehicles. I envisage the simplified driving environment to naturally increase SA due to lowered cognitive load and less visual clutter. Easy driving condition is, therefore, intentionally set up to see if the model could also map the trend in SA scores across the easy versus complex driving conditions.

²Repeated measures ANOVA and paired samples t-test were used as statistical tests in Study I.



Figure 3.4: Screenshot of the driving simulation showing the driver’s view. The driver’s view of 2-lanes going in the same direction (i.e. no on-coming traffic). Source: original, UR (author).

3.5.4 Experiment Design and Measures

A 2x2 within-subject design was applied for this experiment. The first independent variable was the driving condition with two levels: easy driving condition and complex driving condition. The second independent variable was the visual AOI with two levels: the front view (on-road) and the peripheral view (combining roadside, mirror, and speedometer). Simple counterbalancing of conditions was used since there were only two conditions (easy and complex). The dependent variables were SAGAT and post-experiment SA question scores.

SAGAT was administered by querying the participants at pre-determined time intervals while they were undertaking the driving task. The driving simulation was frozen, and the driving scene was blanked during the probe question. The simulation was promptly resumed once the participant’s response was recorded. The participants were probed on road signs, latent hazards, pedestrians, and presence of nearby traffic. The responses to SA probes could only be provided in a "yes" or "no" binary format. For example, “did you just see a speed limit sign of 70 km/h?” would generate a yes/no answer. A SAGAT score was calculated as the percent of correct answers to all probe questions for the same condition. The score represented the driver’s Level 1 SA (i.e., perception of critical elements). There was a total of six probes for each condition. The SAGAT score essentially represented the correct response rate converted to a scale ranging from 0 to 100.

A post-experiment SA questionnaire was also employed at task completion. The participants were probed on their ability to accurately identify billboards that were present during the driving scene in a multiple question quiz with a true/false format. A total of 12 distinct billboards were present during the driving scene with 6 in the complex condition and 6 in the easy condition; the questionnaire, however, also had 6 distractors that were not part of the experiment. The post-experiment SA score reflected the correct response rate converted to a scale from 0 to 100.

3.5.5 Procedure

The research study was explained to the participants upon arrival in the experiment room. Participants completed the consent form and background questionnaire. All participants had a 10-minute practice session with the driving simulator before the start of the formal experiment. Participants were tasked to reach the end of the track as quickly as possible while following the speed limit of 70 km/h. They were permitted to alter their speed, change lanes, and take over other cars when necessary, provided safe driving behavior was always exhibited. The two experimental trials lasted 30 minutes and the entire experiment lasted an hour including the practice session and time spent towards filling out information consent for and background questionnaire.

3.5.6 Results

SAGAT Results

Repeated measures ANOVA was performed using SPSS on the empirical data to determine the effect of driving environment and visual area on drivers' SA. Mean SA in the easy driving condition for on-road objects was 95.24% (with 95% confidence interval of 88.25 to 100 max); whereas SA for peripheral objects was 70.00% (with 95% confidence interval, 61.23 to 78.77). In the more complex driving condition, mean SA for on-road objects remained high at 90.48% (with 95% confidence interval, 81.45 to 99.49); however, SA for peripheral objects was noticeably lower at 48.57% (95 % confidence interval, 35.99 to 61.15). No statistically significant two-way interaction was found between driving environment and visual area for drivers' SA, $F(1, 13) = 2.67$, $p = 0.13$, $\eta^2 = 0.032$. The main effect of driving environment on drivers' SA was statistically significant, $F(1, 13) = 11.86$, $p = 0.001$, $\eta^2 = 0.079$. The main effect of visual area on drivers' SA was also statistically significant, $F(1, 13) = 52.31$, $p < 0.001$, $\eta^2 = 0.518$.

In efforts to determine model fitness, root mean squared error (RMSE) and mean absolute percentage error (MAPE) were calculated for model and human results. RMSE (Equation 3.7) represents the differences between values predicted by QN-ACT-R-SA and the values observed in empirical study. MAPE (Equation 3.8) is a time series estimate of the mean of the absolute percentage errors present within model and human data. Coefficient of determination (r-squared) was also measured in order to evaluate the model's ability to predict the changes present in human data for different experimental conditions.

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (X_{human,i} - X_{model,i})^2}{n}} \quad (3.7)$$

$$MAPE = \frac{100}{n} \sum_{i=1}^n \left| \frac{X_{human,i} - X_{model,i}}{X_{human,i}} \right| \quad (3.8)$$

Where X_{human} represents data from human, X_{model} represents data from model, i represents the condition and n represents the sample size.

QN-ACT-R-SA model simulation runs, using a priori weights in a stochastic system, were carried out 14 times in order to evaluate the model's ability to simulate drivers'

SAGAT response accuracy for the two driving environments (easy, complex), and the two visual conditions (on road, peripheral). The fourteen simulation runs reached the criterion that the widths of 95% confidence interval of model SA scores in the four test conditions were all within 15, which is less than the average of the four human participant conditions. The overall model fitness for SA results is illustrated in Figure 3.5³. The MAPE was 5.02%, the RMSE was 3.47, and the coefficient of determination (r-squared) was 0.98. A further analysis revealed that all the errors in the model’s SAGAT responses were due to limitations in visual attention allocation.

Both absolute (MAPE) and relative (RMSE) goodness-of-fit measures confirm QN-ACT-R-SA’s efficacy in mapping empirical SAGAT results. The RMSE of 3.47 for SAGAT responses indicates a small error difference between the average human and modelling results given the average SAGAT scores (measured on a scale of 0-100) for the easy and complex driving condition was around 71.9 (SD: 21.1). The MAPE value of less than 10% also demonstrates that the model’s deviation from the empirical results in terms of percentage error was relatively small [43, 3]. The graphical analysis of the average model versus average human plots further indicate that the model was able to successfully map the changes in SAGAT scores across the different experimental conditions in the study.

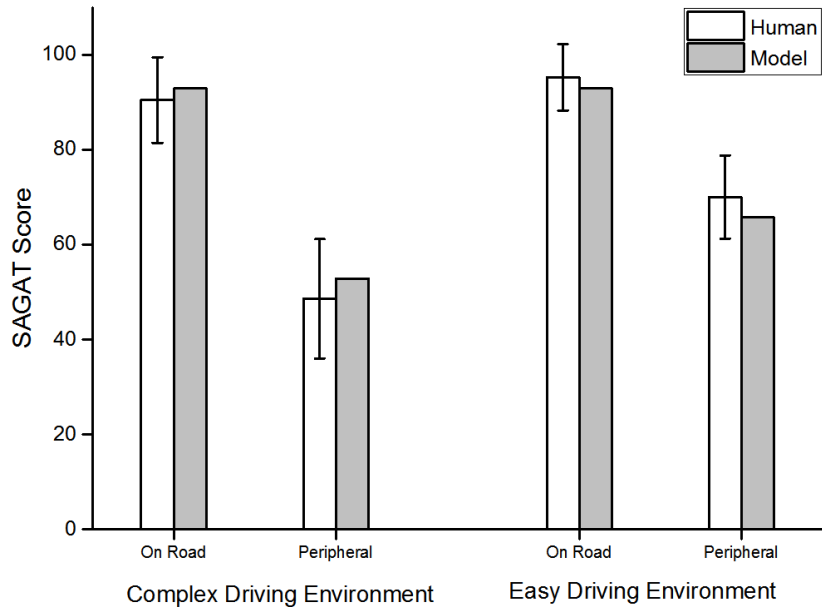


Figure 3.5: SAGAT scores of model and human. Error bars represent 95% confidence intervals. The model focuses on simulating average results rather than variance, so the model’s variance is not shown. Source: original, UR (author).

³Human and Model data is presented in Section A.1 and Section A.2 respectively.

Post Experiment SA Questionnaire Results

A paired-samples t-test was performed using SPSS on the empirical data to determine whether there was a statistically significant mean difference between the post-experiment SA results in the easy condition compared to post-experiment SA results in the complex condition. Descriptive statistics are mean \pm standard deviation, unless otherwise stated. There were no outliers in the data, as assessed by inspection of a boxplot for values greater than 1.5 box-lengths from the edge of the box. The assumption of normality was not violated, as assessed by Shapiro-Wilk's test ($p = .339$). Participants' SA was higher in the easy driving condition (88.10 ± 16.57) as opposed to the complex driving condition (59.52 ± 19.30), a statistically significant increase of 28.57 (with 95% confidence interval, 12.81 to 44.33), $t(13) = 3.917$, $p = .002$, $d = 1.05$. QN-ACT-R-SA model simulation runs were carried out 14 times in order to evaluate the model's ability to simulate drivers' post-experiment SA for the two driving environments (easy, complex). The fourteen simulation runs reached the criterion that the widths of 95% confidence interval of model SA scores in the four test conditions were all within 15. The overall model fitness for SA results is illustrated in Figure 3.5.6⁴. MAPE was 6.73%, and RMSE was 6.13. A further analysis revealed that only 4.16 % of the model's probe errors to post-experiment SA questions were due to limitations in visual attention allocation whereas 94.86 % of the errors were due to memory retrieval failures.

Both absolute (MAPE) and relative (RMSE) goodness-of-fit measures confirm QN-ACT-R-SA's efficacy in mapping post-experiment SA results. The RMSE of 6.13 for post-experiment SA questionnaire indicates a small error difference between the average human and modelling results given the average post-experiment SA questionnaire scores (on a scale of 0-100) for the easy and complex driving condition was around 73.8 (SD: 16.2). The MAPE value of less 10% also demonstrates that the model deviation from the empirical results in terms of percentage error was relatively small [43, 3]. The graphical analysis of the average model versus average human plots further indicate that the model was able to successfully map the changes in post-experiment SA scores across the different experimental conditions in the study.

⁴Human and Model data is presented in Section A.3 and Section A.4 respectively.

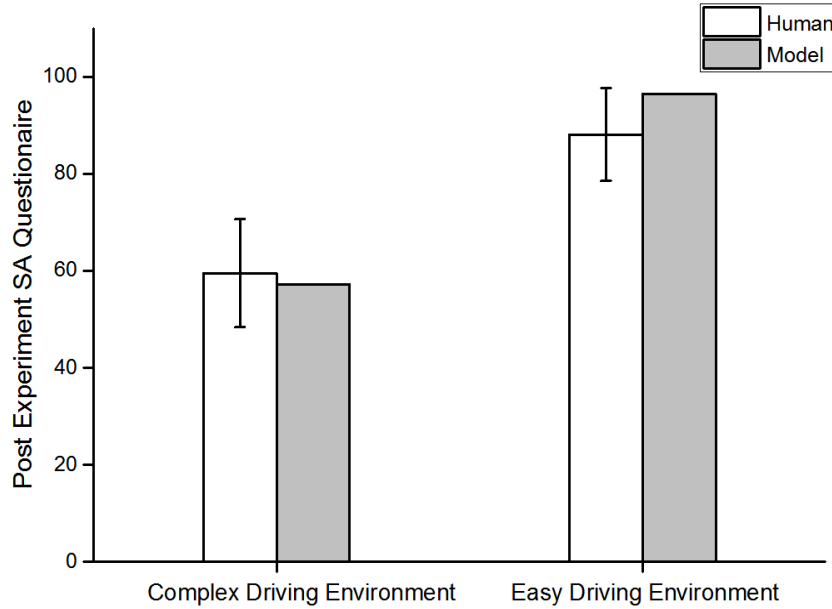


Figure 3.6: Post Experiment SA scores of model and human. Error bars represent 95% confidence intervals. The model focuses on simulating average results rather than variance, so the model’s variance is not shown. Source: original, UR (author).

3.6 Discussion Study I

Computational modelling is an important instrument for addressing the need for automating human factors evaluation. More specifically, cognitive architectures are being increasingly used by researchers to infer quantitative predictions of human factors measures such as SA. The current study contributes to this field of research by developing and examining a simulation model for Level 1 SA based on an integrated cognitive architecture approach.

3.6.1 Empirical Study

An empirical study was conducted to collect human data for model validation. I selected the driving tasks with two levels of environmental complexity to contrast drivers’ SA in the two conditions. SA measures included both SAGAT and post-experiment SA questions. Not surprisingly, the results showed that SA was reduced in the complex condition with more visual critical elements. In addition, SA of critical elements in the peripheral AOI (i.e. secondary AOI) was worse than SA of critical elements in the front view on-road area (i.e. primary AOI). The reduced SA in the complex condition may be due to structural interference or capacity interference. Structural interference refers to visual obstruction that blocks the detection of other elements [110]. This is unlikely to be the case in the current study because the number of visual objects used was not large enough to cause

significant obstruction. On the other hand, capacity interference [111] refers to the limitations of human visual attention. Complex driving conditions require additional attention resources to manage increased information processing. Facing limited attention resources, drivers tend to focus on the front view area and sacrifice the peripheral area. Therefore, the probability of missing a visual object, especially one in the peripheral area, becomes greater in the complex driving condition. While visual allocation of limited attention resources may explain the SAGAT results, it is insufficient to explain the post-experiment SA results which seemed more prone to memory decay. Due to the delay between the perception of a critical element and its post-experiment SA probe, the participant could have perceived the critical element but had forgotten the information by the time of query. Both the visual attention mechanism and the memory decay mechanism were built into the QN-ACT-R-SA model.

3.6.2 QN-ACT-R-SA Model

As a framework, QN-ACT-R-SA considers both attention and memory limitations in modelling drivers' SA. The overall model is grounded in established cognitive mechanisms, production rules, and default parameters within the cognitive architecture. The modelling results validated QN-ACT-R-SA's capability to reasonably simulate human-like Level 1 SA (i.e. perception of critical elements). Similar to assumptions around human information processing, the model's attention allocation mechanism only stores a critical element as a chunk in the declarative memory of the model if attention had been directed towards that element (i.e. if attention was not allocated by the model to the element, then the element was considered as not perceived). The likelihood of ignoring a specific element increases for those elements located in an AOI that is insufficiently scanned by the model. It was expected that retrieval failures during SA probe questions would be more common during complex driving conditions. Errors due to visual attention allocation limitations were found during both post-experiment SA questions and SAGAT; however, visual attention-based errors were more common for SAGAT responses. The SAGAT queries focused on immediate driving elements (e.g. traffic sign, vehicle on side of road). SA post-questions focused on billboard signs that were conspicuously designed to capture full attention of participants since they were visible from far away and were comparatively larger than the traffic signs and on road vehicles. Even with higher conspicuity of the billboard signs, SA errors due to limitations in attention allocation were observed in post experiment SA questionnaire results.

The memory related SA mechanism relies on activation level for retention of critical elements. Memory related explanations for retrieval errors can be attributed to the model's declarative threshold value and activation level of chunks representing critical elements. Activation level increased based on the number of times a critical element was viewed by the model's perceptual module. Due to the higher density of visual clutter present in the complex driving condition, the temporal timeline in which a critical element could be perceived by the model in the complex condition was limited. The probability of chunk retrieval from the model's declarative memory was dependent on the activation value of a chunk. Low activation values of critical elements in complex conditions lead to retrieval failures and subsequent poorer SA scores. Memory-based SA errors occurred only during

the post-experiment SA questionnaire since those responses reflected the effects of memory decay.

Chapter 4

Modelling Brake-Perception Response Time

4.1 Introduction to Study II

Driver error due to poor Situation Awareness (SA) is one the leading reasons for motor-vehicle collisions [112, 113, 114]. Lack of SA resulting from delayed or missed hazard perception can lead to decision errors increasing the risk of traffic collisions [112, 115, 116]. According to a recent 100-car naturalistic driving study [62], a major contributing factor of traffic accidents is inattention due to improper perception of roadway risks. Therefore, the driver’s ability to perceive possible hazards and respond appropriately to critical events is vital for traffic safety.

Hazard perception is officially defined as the driver’s ability to identify and respond to roadway hazards [117]. Hazard perception is often used to indicate the different perceptual processes necessary for hazard avoidance [117, 118]. Previous research has demonstrated that the concept of hazard perception captures the essence of the three stage model of SA [115, 119]. The three stage model indicates that the perception of potential hazards precedes comprehension of possible response selection maneuvers and projection of future state of the environment [120].

Hazard perception tests have been used in the last five decades to investigate human factors within driving safety research¹. The driver’s reaction time to critical events is used as a measure to assess the driver’s hazard perception ability since it influences the success-rate of evading emergency scenarios [121]. In formal terms, the time bracket for a driver to perceive and respond to a hazard is alluded to as hazard-perception response time (HPRT) [122, 123]. HPRT could further be broken into brake-perception response time (BPRT) or steering-perception response time (SPRT) when capturing individual brake or steering response latencies. Most studies have focused on evaluating BPRT [124], whereas a few studies have also reported SPRT [125, 126, 127]

There has been extensive research that has investigated the effect of different factors that influence drivers HPRT [124, 128, 129]. Factors commonly investigated include: age and experience of drivers [122, 130], peculiarity of hazards [131, 132], effects of distraction

¹Refer to Moran et al. [116] for review.

[133, 134, 135], and scenarios involving transfer of control from automated driving [136]. HPRT has been used to assess road design safety [137] and also utilized as evidence in court hearings linked to motor vehicle accidents [121]. HPRT related to different types of roadway hazards has been investigated, including: static objects on the road [137]; signalized intersections [138], lead vehicle braking scenarios [139], auditory stimuli [140], pedestrian incursions [141, 142], and intruding vehicles at intersections and merges etc.[143, 144]. Most of these studies have been conducted in simulated settings using driving simulators, while other studies were conducted on actual roadways and test tracks. A few studies have reported measuring hazard perception skill based on reactions to video clips that require participants to push a button in response to hazardous events on visual displays [145].

Despite the rigorous work in the domain, most hazard perception theories are conceptual in nature and lack rigorous mathematical formulations or computational implementations. Hazard perception results have mostly been construed from participant-based controlled experiments. There is a paucity of research that attempts to model and simulate drivers' hazard perception skills since standard methods for assessing hazard perception are either experimental or through the analysis of driver data from naturalistic settings.

Computational modelling can facilitate simulation of HPRT and can allow researchers to forecast HPRT for different driving conditions. Such modelling endeavors can reduce dependency on empirical experimentation and decrease the overall research expenditure [146]. 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 data. This research is therefore motivated by the lack of computational models that can be employed for simulation and prediction of HPRT.

In the research literature, a limited number of studies have introduced computational models that have been successful in capturing HPRT in different conditions. These include microsimulation models that follow a stimulus-response paradigm and are built using a standard two-stage process. First, a causal relationship between perception-response times and some other variable is established (e.g. deceleration rate, time headway etc.). The second stage involves developing a predictive model using a statistical technique to match human driving data. Usually techniques such as log-normal modelling [147, 148, 149] or regression [150, 151, 152] are employed. While this work is effective at addressing traffic-level phenomena, it fails to account for the underlying cognitive mechanisms that explain drivers' hazard perception skills. These models are lacking 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 that lack psychological underpinnings, cognitive architectures based simulation research takes into account human cognitive processes by unifying psychologically plausible models of human perception and attentional mechanisms, memory resources and motor functionality [26]. A cognitive architecture represents a cohort computational cognitive model 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 [153]. Cognitive architecture-based models are inherently stochastic in nature and flexible enough to cater to different test cases and driving scenarios. I propose a cognitive

architecture-based approach to address the need for modelling HPRT to visual roadway hazards that require emergency avoidance response. In this section, I demonstrate the use of QN-ACT-R-SA (Queuing Network – Adaptive Control of Thought-Rational – Situation Awareness) to model and simulate HPRT.

4.2 Methodology Study II

The focus of the current study is to investigate QN-ACT-R-SA’s ability to simulate HPRT. For validation, I compare HPRT results generated by QN-ACT-R-SA against empirical data from human participants. To collect empirical data, I conduct an experiment in a driving simulator where participants encounter different types of hazards. The QN-ACT-R-SA model is 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, I 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.

The simple reaction time is when a participant can exercise only one possible response action [154]. The information processing for such tasks directly shifts from perception to response action without deciphering the nature of the hazard or the type of response. Choice reaction time accounts for the time needed to identify the type of hazard and response needed in a given situation. Choice reaction time delves into higher levels of SA that include comprehension and projection. As the current cognitive architecture is limited to Level 1 SA, and the mechanisms are not advanced enough to simulate human decision choices, this study is limited to simple reaction time for brake responses.

Drivers’ BPRT to four surprise road-way hazards was measured in this research: two on-road conditions and two roadside conditions. The hazards were designed such that they required emergency avoidance maneuvers. The two on-road conditions include lead vehicle braking scenarios on either side of the dual carriageway. The two roadside condition include unexpected intrusion from an intersection and a car suddenly coming in front of the driver’s vehicle from the merge lane. I hypothesize that drivers’ BPRT to on-road hazards would be faster since drivers dedicate the majority of their visual attention in front of the road rather than the periphery. An experiment was designed on the above stated hypothesis.

4.2.1 Participants

For sample size estimation, a preliminary study was conducted and a power analysis was performed using G*power 3 software [104]. The effect sizes were determined from the mean values construed from the preliminary study. The effect sizes indicated a large effect based on partial eta squared values [105]. The power analysis indicated a sample size of N=4 for an alpha = .05 and power = 0.8. Thus, our proposed sample size of N=11 is adequate to achieve the main objective of the study. A total of 11 participants (7 males and 4 females) aged 21 to 26 years (M = 24, SD = 1.1) took part in this research study. The lack of gender balance is a limitation of the current experiment design, however, previous studies show an insignificant effect of gender on SA results [107, 108, 109]. All participants had

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.

4.2.2 Scenario

The experiment was conducted on a simulated dual carriage way, located in a lowland rural landscape, with two lanes in each direction. The maximum speed of the track was 70 km/hrs. 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 manoeuvre and the remaining four tracks did not present any hazard. The order of experiencing the hazardous tracks was randomized across subjects using a latin square design.

To limit the driver's response actions to brake-response only, a few experimental controls were adopted. The segment where the hazardous event materialises was designed to be a single lane event only. This was done to ensure that participants did not consider steering as an evasive response manoeuvre. The tangential lane was purposely closed with a construction sign to indicate that it is an active work zone. Also, the drivers were instructed to engage cruise control after reaching the maximum speed limit of the roadway. This ensured that the first brake-response received was an evasive maneuver when the drivers were actually attempting to disengage the cruise control to avoid the collision. This also made certain that brake responses generally expected while driving were not interfering with the BPRT measurement process since the driver's vehicle was on cruise control.

Apart from the presence of hazards, the driving environment was adopted from one of the conditions (easy condition) investigated in Section 3.5. 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 in order to facilitate participants to perform lane changing and overtaking during the trials. The lane changing was designed in such a way that it did not require active brake responses since traffic vehicles were far apart. Furthermore, the participants were also 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/hr) 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. Time-to-Collision (TTC) is set at 3.6 seconds for both on-road and roadside 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.

On-road Scenarios

Two lead vehicle braking events were designed as on-road scenarios, categorised as On-road condition-scenario 1 (Figure 4.1a) and On-road condition-scenario 2 (Figure 4.1b). In scenario 1, the lead vehicle braking event occurs on the right side lane with the left side representing a construction zone; and in scenario 2, the lead vehicle braking event occurs

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 seconds at a constant speed of 50 *km/h*. The lead vehicle then suddenly applies brakes at a predefined location with a deceleration of -1.54 m/s^2 and continues to brake until it comes to a complete halt. In scenario 2, the lead vehicle drives at a THW of 2.315 seconds at a constant speed of 50 *km/h*. The lead vehicle then suddenly applies sharp brakes at a predefined location with a deceleration of -3.86 m/s^2 and continues to brake until it comes to a complete halt.

Roadside Scenarios

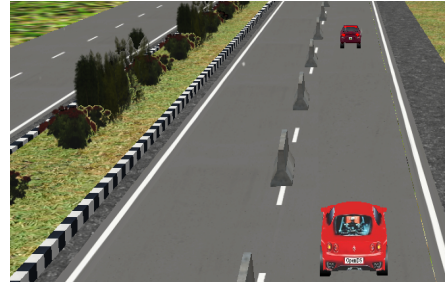
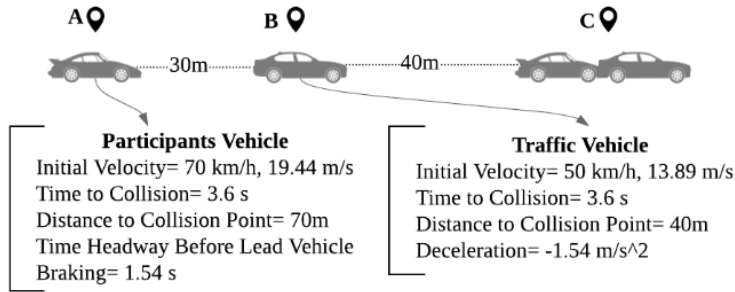
I also designed two roadside scenarios, categorised as Roadside condition-scenario 3 (Figure 4.1c) and Roadside condition-scenario 4 (Figure 4.1d). Scenario 3 depicts an incursion by a right turning vehicle at an intersection; and in scenario 4 a car suddenly comes in front of the driver's vehicle from the merge lane. The roadside scenarios are also unexpected in nature as the incursive vehicles are programmed to violate traffic laws. In scenario 3 the hazardous vehicle disregards a stop sign and in scenario 4 the hazardous vehicle disregards a yield sign. In scenario 3 and 4, the programmed traffic vehicle accelerates from rest at 1.54 m/s^2 .

4.2.3 Experimental Design and Measures

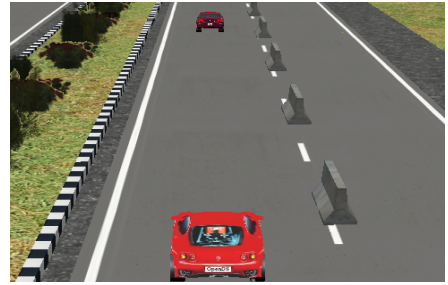
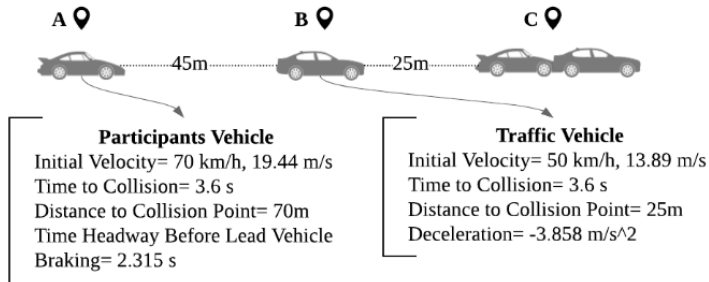
A within-subject design was employed in this experiment. Independent variable in this experiment was hazard location with two levels: roadside hazards and on-road hazards. Dependent variable in this experiment was BPRT, individually measured for each model and human run. BPRT was defined as the time frame between the onset of the hazard until the first brake response was received at the simulator.

4.2.4 Procedure

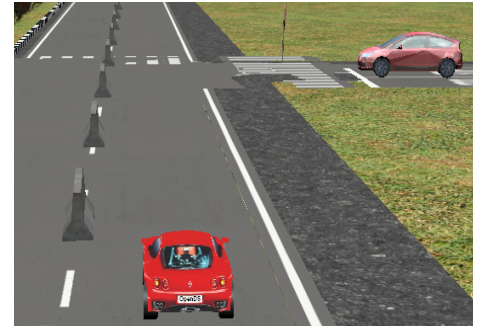
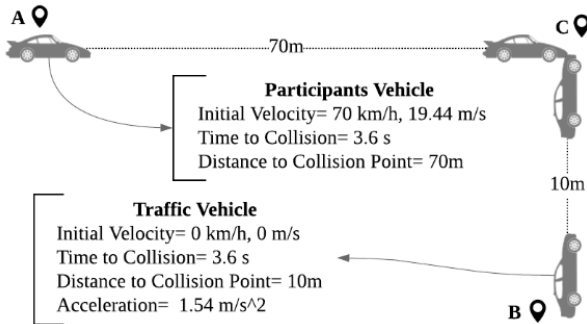
Upon arrival of the participants, the research study was explained by the experimenter in the experiment room. Participants were then required to fill the consent form and background questionnaire. An overview of the experiment and driving simulator was provided prior to the formal experiment. Participants were also acquainted with the driving simulator in an 8-minute practice drive. For the formal experiment, participants were instructed to reach the maximum speed of the roadway (70 *km/hr*) 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 whenever necessary but were told to maintain safe driving behavior at all times. 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.



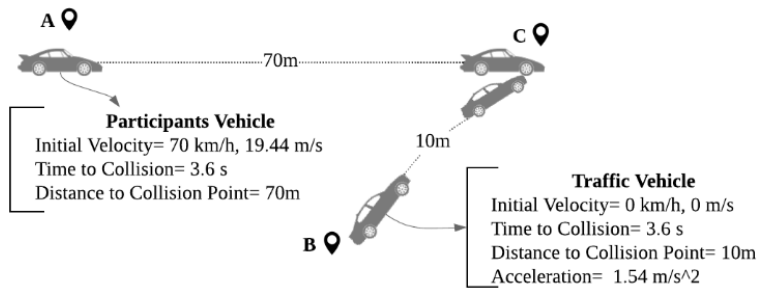
(a) This figure represents On-road condition-scenario 1.



(b) This figure represents On-road condition-scenario 2.



(c) This figure represents Roadside condition-scenario 3.



(d) This figure represents Roadside condition-scenario 4.

Figure 4.1: The figure represents scenario 1-4, respectively. Each scenario has a diagrammatic view that illustrates the properties (speed, THW, TTC etc.) of the different vehicles in the scenario. Next, to the diagrammatic view is the panoramic illustration of the scenario. The red

car represents the participant’s vehicle. Three markers (a-c) are also added in the diagrammatic view to illustrate the TTC calculation process. Markers a and b reflect the relative position of the participants vehicle and programmed traffic vehicle respectively and Marker c in the figure denotes the collision point. Source: original, UR (author).

4.2.5 Modelling and Simulation

I am interested in testing how QN-ACT-R-SA model will respond to dynamic critical elements that eventually develop into materialized hazards. I ran a comparative study investigating hazards originating in the front of the driver, called on-road hazards versus 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 I am interested in comparing between model and human data is the BPRT.

The visual module of QN-ACT-R-SA attends a critical element in one of the AOIs. AOIs defined in this study include on-road frontal view, mirrors (centre, left and right mirror), and 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. Since the driving scenario is adopted from Section 3.5, therefore the same SEEV parameters (3.3.1) are adopted.

The driving model monitors critical elements in the external environment. Lane keeping and hazard avoidance is an aspect of this situational monitoring, where the model periodically assesses the environment and becomes aware of the surrounding vehicles. 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.

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 reach the destination as fast as possible while maintaining speed limit. The model is given a goal to reach the destination as fast as possible while maintaining the speed limit. The lane changing ability of the model has been validated against empirical data in previous studies [155].

4.2.6 Results Study II

A one-way repeated measures ANOVA was performed using SPSS on the empirical data to determine the effect of hazard location on drivers’ BPRT. There were no outliers and the data was normally distributed, as assessed by boxplot and Shapiro-Wilk test ($p > .05$), respectively. Mauchly’s test of sphericity indicated that the assumption of sphericity had not been violated, $\chi^2(2) = 4.49$, $p = .48$. The main effect of hazard location on drivers’ BPRT was statistically significant, $F(3, 30) = 261.02$, $p < 0.005$, $\eta^2 = 0.96$.

Pairwise comparisons were conducted (with Bonferroni correction) for further analysis. The results revealed that BPRTs for the on-road condition-scenario 1 ($M = .84$, $SD = .13$ seconds) and on-road condition-scenario 2 ($M = 1.13$, $SD = .071$ seconds) was statistically significant ($M=.284$ (with 95% confidence interval, .126 to .441) seconds, $p = .001$).

However, the BPRTs for roadside condition-scenario 3 ($M=2.04$, $SD=.093$ seconds) and roadside condition-scenario 4 ($M=1.96$, $SD=.158$ seconds) did not elicit a statistically significant difference ($M=.084$ (with 95% confidence interval, -.088 to .256) seconds, $p = .838$).

Furthermore, a statistically significant difference existed between: the on-road condition-scenario 1 and road side condition-scenario 3 ($M= -1.20$ (with 95% confidence interval, -1.394 to -1.01) seconds, $p < .0005$); on-road condition-scenario 1 and road side condition-scenario 4 ($M =-1.117$ (with 95% confidence interval, -1.337 to -.896) seconds, $p < .0005$); on-road condition-scenario 2 and road side condition-scenario 3 ($M= -.917$ (with 95% confidence interval, -1.037 to -.797) seconds, $p < .0005$); and lastly , on-road condition-scenario 2 and road side condition-scenario 4 ($M = -.833$ (with 95% confidence interval, -.984 to -.682) seconds, $p < .0005$).

QN-ACT-R-SA model simulation runs were carried out eleven times in order to evaluate the model's ability to simulate drivers' BPRT for the two driving environments (on-road hazards, roadside hazards). The eleven simulation runs reached the criterion that the widths of 95% confidence interval of model BPRT in the two test conditions were all within 100 milliseconds. The overall model fitness for SA results is illustrated in Figure 4.2². The MAPE was 9.4 % and the RMSE was 0.13 seconds.

Both absolute (MAPE) and relative (RMSE) goodness-of-fit measures confirms QN-ACT-R-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 the average BPRT for the two on-road and roadside hazard condition was around 1.49 seconds (SD: 0.54). The MAPE value of less 10% also demonstrates that the model deviation from the empirical results in terms of percentage error was relatively small [43, 3]. The graphical analysis of the average model versus average human plots further indicate that the model was able to successfully map the changes in BPRT across the different experimental conditions in the study.

²The Human and Model data is reported in B.1 and B.2 respectively.

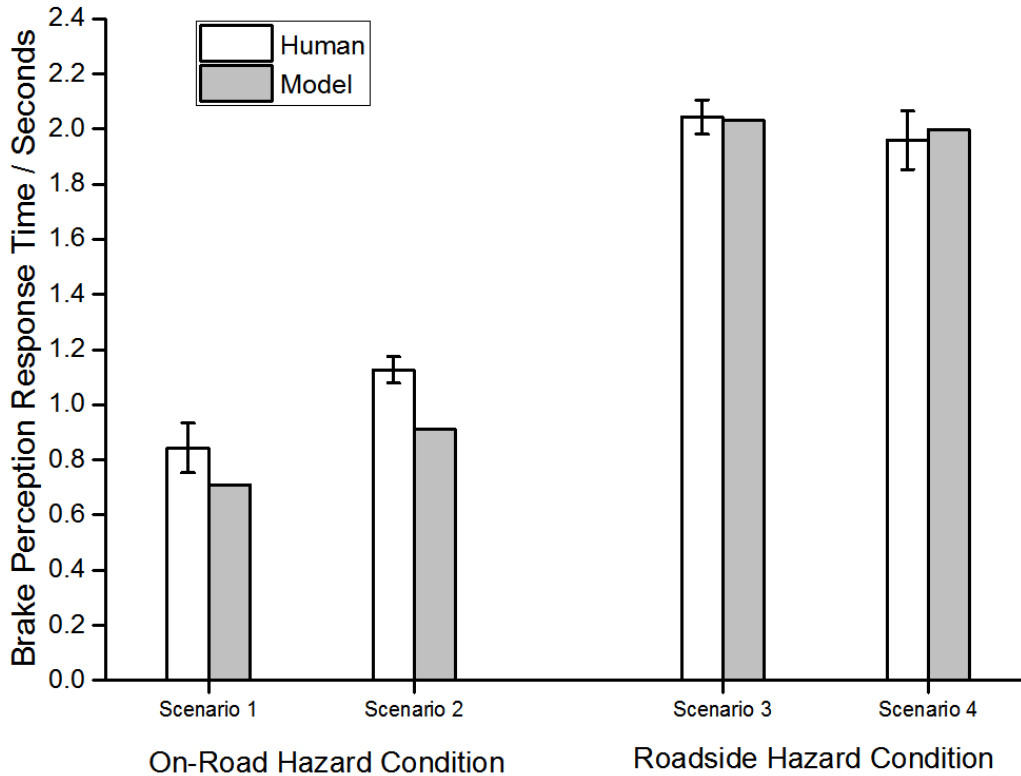


Figure 4.2: BPRT scores of model and human. Error bars represent 95% confidence intervals. The QN-ACT-R-SA focuses on modelling average results rather than variance, so the model’s variance is not shown. Source: original, UR (author).

4.3 Discussion Study II

Cognitive architecture based modelling is a valuable tool for simulating driver hazard perception skill. The present study adds a quantitative foundation to BPRT modelling by demonstrating a real-time simulation of empirical results.

4.3.1 Empirical Study

An empirical study was designed for model validation purposes. In the trials runs, the participants encountered two major types of hazards: on-road hazards in the forward view of the driver and roadside hazard which originated from the drivers’ periphery. The two contrasting conditions were mainly selected to explore the difference in drivers’ BPRT. Not surprisingly, the results demonstrated that BPRT was significantly shorter for on-road hazards as compared to roadside hazards. The significantly faster BPRT for on-road hazards can primarily be attributed to the following three reasons:

1. Firstly, for lead vehicle braking scenario the depth cues for safely judging the lead vehicle as an imminent hazard are present in the front AOI. Front AOI is most

actively scanned by the driver since it significantly effects the main driving tasks of lateral and longitudinal control. On the other hand, roadside hazards are present in the peripheral environment that is not actively scanned and as a result roadside hazards are not instantly deemed as immediate threats.

2. Secondly, as the lead vehicle slows down, the drivers instantaneously observe the brake lights in conjunction with a 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.
3. Thirdly, there is construction zone blocking one lane of the roadway in the scenario designed for this experiment and as a result most drivers expect traffic in the front to slowdown. In contrast, for roadside condition, the probability that a traffic vehicle accelerating from drivers' 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 significantly lower collision probability when compared to on-road hazard condition.

Furthermore, no significant differences existed between the two roadside hazards (merge and intersection scenario); however, the two on-road hazards resulted in significantly different BPRT. 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 the scenarios.

In the on-road condition, the deceleration of the lead vehicles were different for the two scenarios. In one of the designed scenarios, the lead vehicle braked with shorter time-headway and stronger deceleration in the right lane, whereas, in the other scenario the lead vehicle braked with longer time-headway and comparatively lighter deceleration in the left lane. The significant difference in BPRT for the two on-road conditions is probably due to difference in deceleration intensities of the two on-road scenarios tested in this study since the magnitude of the deceleration influences drivers' perceived criticality of the situation. The major cues that influence the criticality include the brake lights and perceived optical expansion of the lead vehicle. The onset of the brake lights is viewed at a faster rate for the lead vehicle that has a shorter time headway; also the perceived optical expansion is faster for the lead vehicle that undertakes a stronger braking response and consequently a faster deceleration. As a result, the BPRT is shorter for hazards with shorter time headways and faster decelerations. This explains the significant difference in BPRT for on-road conditions.

4.3.2 QN-ACT-R-SA Model

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-ACT-R-SA are dependent on the SEEV parameters. The modelling results indicate that QN-ACT-R-SA can reasonably simulate 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 against roadside hazards. The model undertakes brake response once it perceives a hazard in one of the AOIs. Since the model scans for hazards in the front view more frequently than the peripheral environment, the likelihood of identifying a potential hazard is faster for on-road hazards than for roadside hazards. The significant difference between the two on-road hazard conditions can be explained with the concept of comfort boundary, or safety zone. The comfort boundary, or safety zone, is essentially the tolerance level at which a braking lead vehicle gets categorized as an imminent hazard. The model is set up in a way that any road user violating the safety zone would trigger an automatic brake response. For on-road hazards, the safety boundary is violated much more quickly by the vehicle with the shorter time headway and subsequently faster deceleration, thereby prompting a faster BPRT.

Chapter 5

Modelling the Effects of Automation and Distraction

5.1 Introduction to Study III

Automation is becoming increasingly prevalent in road transportation as it carries the promise to improve driver safety [156]. Researchers have long highlighted the human factors challenges associated with automation in road transportation [157, 158]. Although automation is expected to improve overall driving safety, drivers are more likely to engage in non-driving tasks during automated control [159]. Performing non-driving tasks while driving requires additional cognitive resources that may result in lowered Situation Awareness (SA) and out-of-the-loop performance decrements [42].

Lack of SA is often recognized as one of the key reasons leading to motor vehicle collisions [112, 118, 115, 116]. Investigating SA is important in human-automation interaction scenarios since it can offer researchers the facility to investigate situational determinants that degrade human performance. Analyzing SA in different automated conditions can also help inform researchers with relevant human factor remedies that may aid in optimizing safety measures.

Limited research is available that has investigated the effects of automation on drivers' SA using computational modelling methods. As a way to better understand human-automation interaction within the context of road transportation, it is important to investigate the effects of automation on drivers' SA using computational and simulation models. It's equally valuable to investigate how drivers' SA changes in the presence of cognitive distractors when drivers engage in non-driving tasks. Automation in driving exists on a spectrum and ranges from fully-manual to fully-automated driving with intermediate levels that can be classified into assisted, semi-automated and highly automated driving. The role and the responsibility of the driver varies with respect to the different levels of automation since each level imposes different demands on drivers' SA [160].

In the previous sections, we employed QN-ACT-R-SA to simulate the effects of drivers' SA in easy and complex driving conditions (Chapter 3) and used QN-ACT-R-SA to model drivers' hazard perception skill to on-road versus roadside hazards (Chapter 4).

The focus of this research is specifically geared towards extending the same modelling

approach towards predicting the effects of Adaptive Cruise Control (ACC) and secondary tasks on drivers' SA using QN-ACT-R-SA. ACC falls under the category of assisted automation and is classified as Level 1 automation according to the SAE taxonomy [160]. To validate the modelling work, we compared the model's SA scores against empirical data. The empirical data was taken from a research study that had examined the effects of ACC and cellphone use on drivers' SA using SAGAT tests [42].

QN-ACT-R-SA can potentially be a useful tool to predict SA since it has a rich history of multiple model integrations that have been validated against empirical data. For instance, QN-ACT-R-SA has a validated model that can simulate human driving behavior such as lane keeping [78] and lateral control performance [161]. Furthermore, QN-ACT-R-SA has a tested visual attention allocation mechanism embedded within its architecture (3.3.1). Lastly, QN-ACT-R-SA can be directly connected to a driving simulator and be probed with SA queries similar to how SA probe tests are conducted on human participants (Chapter 3).

5.2 Methodology Study III

This section details the empirical experiment, modelling work and the comparison of QN-ACT-R-SA and empirical results.

5.2.1 Empirical Experiment

The empirical study was conducted by [Ma and Kaber \[42\]](#) and reported in the International Journal of Industrial Ergonomics. In their study, participants drove a simulated car on a four lane highway in a driving simulator. The participants were instructed to pay attention to different types of driving signs and nearby traffic. Each trial took approximately 25 minutes and the average speed was 60 mph. Participants did a total of 100 minutes of driving on the simulator.

There were two Independent Variables (IV) tested by [Ma and Kaber \[42\]](#): control mode and distraction. The control mode had two conditions: ACC and No-ACC (manual driving). The ACC maintained a lead-vehicle following distance of 2.4 seconds when activated. The other IV was the distraction task with two levels: Cellphone use and No-cellphone use. The control mode variable was manipulated within subjects whereas the distraction variable was manipulated between subjects.

The dependent variable was the SAGAT scores measured using simulation freezes at pre-determined times. The SAGAT probes covered all three SA levels and were linked to the driving environment. Drivers were asked to identify road signs, comprehend behavior of nearby traffic vehicles etc. The correct response percentage made up the final SAGAT scores for the individual trials.

The results revealed that both IVs, control mode and distraction, rendered a significant effect on drivers' SA, however, there was no interaction effect found in the study. The percentage of correct responses to SAGAT probes decreased in No-ACC condition (manual driving), and also when drivers were tasked to use the Cellphone during trials. Analyzing overall SA showed that for No-ACC condition, the response percentage was 68% as com-

pared to 83% for ACC condition, and for No-cellphone condition the response percentage was 81 % as compared to 71% for Cellphone use.

Our primary goal in Study III was to simulate and model the above explained empirical results. In doing so, we validate the architecture’s predictive ability and further demonstrate how SA results from QN-ACT-R-SA are comparable against empirical data acquired from different test settings. A major limitation in the QN-ACT-R-SA model is that currently it is equipped to simulate only Level 1 SA scores. This is due to the fact that the current modelling paradigms within the architecture are not nuanced enough to cater to higher levels of SA that involve comprehension of situational elements and projection of their future states. As a result, the first stage of the model validation is limited to prediction of Level 1 SA. Thus, the comparison of the results from the model and human SA scores are for Level 1 SA only. Level 1 SA results for the experiment reveal that for No-ACC condition, the response percentage was 67%; in comparison to 77% for ACC condition; and for No-cellphone condition the response percentage was 75%; in comparison to 69% for Cellphone use.

5.2.2 Modelling and Simulation

QN-ACT-R-SA perceives critical elements (pedestrians, traffic vehicles) in the driving environment and stores the information relevant to these elements as chunks in the declarative memory. These critical elements could be present in different AOIs such as on-road frontal view, mirrors, speedometer etc. A driver’s SAGAT score is essentially a measure of the correct responses to probes related to these critical elements. The likelihood of attending to a particular critical element in a specific AOI depends on the driver’s attention allocation patterns. The less visual attention towards a certain AOI, the higher will be the chances that the critical element within that AOI will not be perceived by the model.

Modelling Visual Attention Allocation Using SEEV Theory

The visual module of QN-ACT-R-SA allocates attention towards different AOIs based on the attention allocation probability computed by the SEEV model. The weight for the SEEV parameter is deduced a priori using a lowest ordinal heuristic approach. As previously described, the modeller rates all important task conditions and AOIs following a specific metric (3.3.1). This metric is driven by the modeller’s a priori deductive reasoning. This score is then weighted for all tasks and employed as a percentage for the total dwell time. Based on the total dwell time percentages for different AOIs, Monte-Carlo simulations are performed to simulate how AOIs receive visual attention in real time during simulation.

The important AOIs used in this experiment include driver’s peripheral environment and front view. The peripheral environment could further be divided into mirrors (left mirror, right mirror, and centre mirror), speedometer and roadside view. A new AOI for this experiment called cellphone screen is added to represent the driver’s attention patterns towards the secondary tasks of texting or dialing a phone number.

QN-ACT-R-SA is equipped to distribute attention amongst the following tasks: (1) lateral control (maintaining vehicle in centre lane), (2) longitudinal control (maintaining

speed limit and safe distance from a vehicle in the front or rear), (3) situational monitoring (hazard monitoring and ensuring destination lane is clear before lane changes) and (4) cellphone screen representing secondary task engagement. The attention allocation probability for a specific AOI is computed based on Equation 3.5.

The sampling frequency of an AOI depends on its bandwidth or expectancy. Expectancy values vary based on the experimental condition (No-ACC, ACC, Cellphone, No-cellphone) since different conditions require different attentional demands [94]. For instance, in No-ACC condition drivers are manually operating both the lateral and longitudinal control of the vehicle. For both the lateral and longitudinal control, the most important AOI is the forward view since drivers expect most activity relevant to the driving control tasks to occur in this AOI. Therefore on-road AOI is assigned a higher weight value as compared to peripheral AOIs. Whereas in ACC condition, the longitudinal control is managed via automation leaving drivers relatively more time to pay attention to nearby critical elements. As a result, the Expectancy values are adjusted accordingly for the ACC condition. During Cellphone condition, however, a certain degree of attention has to be dedicated towards the cellphone screen AOI; and, as a result the Expectancy values are again tuned to account for this change. Applying the lowest ordinal heuristic approach [95], the weights for Expectancy coefficient are assigned a priori based on the following values: none (0), low (0.333), moderate (0.666), and high (1.0) [94], as shown in Table 5.1 and Table 5.2.

The value is represented as the product of two sub factors: Relevance and Priority (Equation 3.5). Relevance represents how appropriate a particular AOI is for a given task. For instance, the most relevant AOI for the longitudinal control task would be the forward view; whereas, the most important AOI for the secondary task would be the cellphone screen AOI. The lowest ordinal heuristic approach was adopted for Relevance factor as well, and the AOIs were assigned one of the following values: none (0), low (0.333), moderate (0.666), and high (1.0), as shown in Table 5.1 and Table 5.2.

Priority represents the overall priority sequence for different tasks. Priority values also change based on the experimental conditions. For instance in No-ACC condition (manual driving), the lateral control is the most important task followed by longitudinal control and situational monitoring. The Priority values reflect this ordering for No-ACC condition. In ACC condition, however, the driver is not responsible for longitudinal control and therefore the priority sequence changes since situational monitoring is the second most important task for this condition. Unlike Expectancy and Relevancy factors, the Priority value is computed such that all Priority scores add up to one [94]. This is done to simplify weighted score calculations. All SEEV parameters are adjusted accordingly, when the Cellphone condition is applied in the experiment, thereby ensuring that the effects of secondary tasks on drivers' SA scores are modelled precisely. The Priority values for all tasks and conditions are represented in Table 5.1 and Table 5.2.

Table 5.1: The table represents SEEV parameters for conditions without cellphone task.

No-ACC Condition											
	T1 ^a			T2 ^b			T3 ^c				
AOI ^d	EX_1 ⁱ	R_1 ^j	P_1 ^k	EX_2	R_2	P_2	EX_3	R_3	P_3	VA_{AOI} ^l	P(AOI)% ^m
FV (RS) ^e	0.333	0.666	0.6	0.333	0.333	0.3	0.333	0.333	0.1	0.144	19.6
FV (OR) ^f	0.666	1	0.6	0.666	0.333	0.3	0.666	1	0.1	0.474	64.5
Mirror ^g	0.333	0.333	0.6	0.333	0.333	0.3	0.333	0.333	0.1	0.09	12.2
Dash ^h	0.333	0	0.6	0.333	0.333	0.3	0.333	0	0.1	0.027	3.67

ACC Condition											
	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	13.7
FV (OR)	1	1	0.6	1	0.333	0.3	1	1	0.1	0.79	75.2
Mirror	0.333	0.333	0.6	0.333	0.333	0.3	0.333	0.333	0.1	0.09	8.6
Dash	0.333	0	0.6	0.333	0.333	0.3	0.333	0	0.1	0.027	2.6

^aT1: Task 1 (Lateral Control); ^bT2: Task 2 (Longitudinal Control); ^cT3: Task 3 (Situational Monitoring);
^dAOI: Areas-of-Interests; ^eFV (RS): Forward View Roadside; ^fFV (OR): Forward View On Road; ^gMirrors: Mirrors (Left, Right, Center); ^hDash: Dashboard (Speedometer); ⁱ EX_t : Expectancy; ^j R_t : Relevance; ^k P_t : Priority; ^l VA_{AOI} : Raw Visual Attention score; ^mP(AOI)%: Percentage Normalized Score for each AOI representing probability of scanning an AOI.

Table 5.2: The table represents SEEV parameters for conditions with cellphone task.

ACC/Cellphone Condition														
	T1			T2			T3			T4				
AOI	EX_1	R_1	P_1	EX_2	R_2	P_2	EX_3	R_3	P_3	EX_4	R_4	P_4	VA_{AOI}	P(AOI)%
FV (RS)	0.3	0.6	0.8	0.3	0.3	0	0.3	0.3	0.1	0	0	0	0.153	17.5057
FV (OR)	0.6	1	0.8	0.6	0.3	0	0.6	1	0.1	0	0	0	0.54	61.7849
Mirror	0.3	0.3	0.8	0.3	0.3	0	0.3	0.3	0.1	0	0	0	0.081	9.26773
Dash	0.3	0	0.8	0.3	0.3	0	0.3	0	0.1	0	0	0	0	0
Cellphone	0	0	0	0	0	0	0	0	0	1	1	0.1	0.1	11.4416
No-ACC/Cellphone Condition														
	T1			T2			T3			T4				
AOI	EX_1	R_1	P_1	EX_2	R_2	P_2	EX_3	R_3	P_3	EX_4	R_4	P_4	VA_{AOI}	P(AOI)%
FV (RS)	0.3	0.6	0.6	0.3	0.3	0.3	0.3	0.3	0.1	0	0	0	0.144	17.2455
FV (OR)	0.6	1	0.6	0.6	0.3	0.3	0.6	1	0.1	0	0	0	0.474	56.7665
Mirror	0.3	0.3	0.6	0.3	0.3	0.3	0.3	0.3	0.1	0	0	0	0.09	10.7784
Dash	0.3	0	0.6	0.3	0.3	0.3	0.3	0	0.1	0	0	0	0.027	3.23353
Cellphone	0	0	0	0	0	0	0	0	0	1	1	0.1	0.1	11.976

Driving Environment and QN-ACT-R-SA Driving Model

The next stage of this research is to setup a similar driving environment as described in [Ma and Kaber \[42\]](#). The driving environment we implemented in terms of different road signs and traffic vehicles was the same as one of the conditions (easy condition with few vehicles and signboards) in Section 3.5. The original [Ma and Kaber \[42\]](#) article gives a general description of their driving environment used, but does not include details for exact placement of visual objects within their driving environment (e.g. exact placement of traffic signs is not provided). For Study III, the decision was made to use the same driving environment as that used for the "easy" driving condition in Study I. The benefit of using the same scenario from Section 3.5 was that the SEEV parameters for that condition had been validated by means of an empirical comparative analysis of QN-ACT-R-SA and human SAGAT scores. Therefore in Table 5.1, No ACC and No-cellphone conditions used the same SEEV parameters employed in 3.5; however the parameters for other IV conditions were marginally tailored to account for the intended differences in attention allocation patterns. Tailoring here implies that the SEEV parameters were adjusted to account for cellphone and automation conditions¹.

The driving environment was created in OpenDS driving simulator [41]. We created four tracks that catered to the different independent variables tested in [Ma and Kaber \[42\]](#). The

¹Refer to 5.2.2 for understanding the detailed changes.

four tracks included: track with ACC, without ACC (categorised as No-ACC condition), with ACC and Cellphone condition, and No-ACC but with Cellphone condition. All four tracks had similar number and types of critical elements. QN-ACT-R-SA was connected to the driving environment using User Datagram Protocol (UDP) connection. Production rules are executed within QN-ACT-R-SA in a timeframe of 150 milliseconds to simulate driving control, situational monitoring and decision making.

A previously validated driving-control model is implemented within this study to simulate lateral and longitudinal control. The vehicle’s control movements follow a steering control law adopted from [Salvucci and Gray \[40\]](#). The model tries to maintain lateral control by centring on two perceptually different targets: a near point and a far point. Additionally, the driving model maintains awareness of nearby critical elements by periodically scanning the different AOIs in the task environment. This monitoring mechanism is based on the SEEV-framework of visual attention allocation as explained earlier. Moreover, the model is equipped with basic decision-making capability such as lane changing or undertaking remedial actions in response to hazards. The model is also equipped to respond to SAGAT queries that are administered at specific times during the experiment.

During ACC condition, the model’s lateral control processes are relieved and the test vehicle’s internal ACC is switched on. Since the driving model is embedded within the cognitive architecture, it imitates human limitations on attention allocation, cognitive processing speed, and memory. As a result, reasonably realistic portrayals of Level 1 SA for the different driving conditions can be gained through SAGAT probes.

5.2.3 Results Study III

QN-ACT-R-SA model simulation runs were carried out 11 times, for each of the four tracks, in order to evaluate the model’s ability to simulate drivers’ responses to SAGAT probes. The average scores are illustrated in [Figure 5.1²](#). The ACC condition resulted in the highest SA score with an average of 84.42%. This was followed by No-ACC condition (manual driving) with an average of 76.62%. The cellphone conditions resulted in comparatively lesser SA scores; ACC condition with Cellphone task resulted in an average of 67.53%, which was better than the lowest SA performance, No-ACC with Cellphone, that results in an average score of 54.55%.

²Model data is reported in [C.1](#).

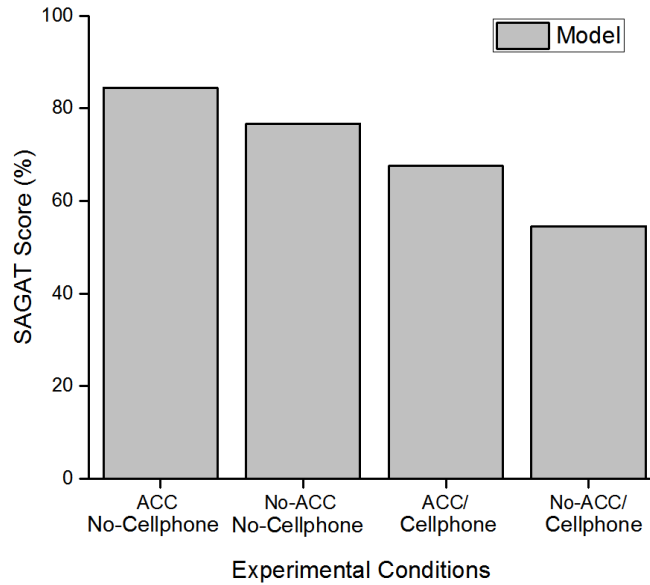


Figure 5.1: This figure represents the QN-ACT-R-SA model’s results for the four experimental tracks tested in this study. Source: original, UR (author).

Similar to [Ma and Kaber \[42\]](#) study, no significant interaction effects were found so each condition is reported separately. The QN-ACT-R-SA scores and empirical results reported by [Ma and Kaber \[42\]](#) are illustrated in Figure 5.2. The mean absolute percentage error (MAPE) was 5.6 % and the root mean square error (RMSE) was 4.9. Both absolute (MAPE) and relative (RMSE) goodness-of-fit measures show a good model fit for study III. SAGAT responses for both human and model results were converted on a scale of 0-100. The RMSE of 4.9 for SAGAT responses indicates a small error difference between the average human and modelling results since the average SAGAT scores for the different driving conditions was around 72 (4.76). The MAPE value of less 10% also demonstrates that the model deviation from the empirical results in terms of percentage error was relatively small [\[43, 3\]](#). The graphical analysis of the average model versus average human plots further indicate that the model was able to successfully map the changes in SA scores across the different experimental conditions in the study.

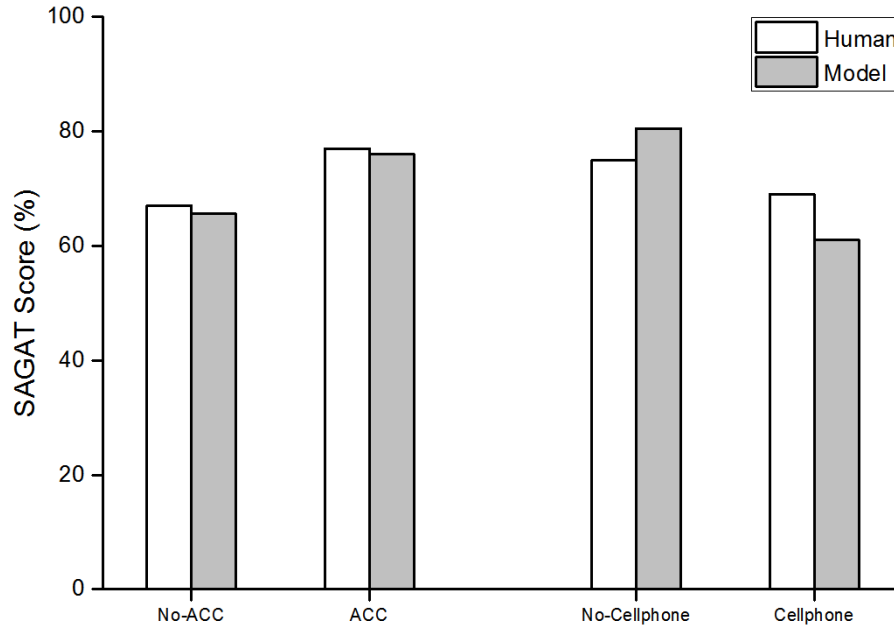


Figure 5.2: SAGAT scores for both human and model trials for different conditions tested in the experiment. As reported by [Ma and Kaber \[42\]](#), the graph was made from data sets that were combined to form aggregated results for each of the independent variables, reported separately. Here No-ACC and ACC labels each includes the combined results from with and without cellphone trials. Similarly, No-cellphone and cellphone labels each include the combined results from with and with cellphone trials. Source: original, UR (author).

5.3 Discussion Study III

Methods to measure SA are mostly empirical in nature and so, there has been a need to develop simulation tools that can equip researchers to predict SA. Capitalizing on the same QN-ACT-R-SA model and driving environments used in Study I, predictions through simulations were made for the effect of driving automation and driver distraction on Level 1 SA. Specifically, QN-ACT-R-SA was used to model the effects of ACC and cellphone use on drivers' SA. Results indicate that QN-ACT-R-SA is able to reasonably simulate the percentage of correct responses to SAGAT probes for distraction and control model conditions by [Ma and Kaber \[42\]](#). These results reinforce the applied utility of cognitive architectures for predicting human performance variables such as SA.

The empirical results in particular reveal that drivers SA improves during ACC condition. During ACC condition, drivers' are not actively engaged in longitudinal control of the vehicle and as a result can dispense extra visual resources towards monitoring the environment. When ACC is switched off, the driver's cognitive load increases due to significantly higher vehicle control demands. The increased workload during No-ACC condition leads to SA decrements since visual attention needed to monitor the driving environment is compromised. While the benefits of ACC in terms of improved SA are obvious, it is

important to highlight that study III only provides results for Level 1 SA and for drivers who knew that they were being tested in a simulator study. Study III does not address human-factors issues associated with automated driving such as out-of-the loop scenarios, loss of vigilance, boredom etc. Therefore, the benefits of ACC condition must not be generalized to naturalistic settings with actual human drivers.

QN-ACT-R-SA is able to simulate these results with the aid of the SEEV theory. When ACC is activated, the model discounts attentional demands of longitudinal control. As a result, the percentage dwell times computed for the forward view increases, and the model is able to scan the forward view of the driving environment more frequently. SAGAT probes are mostly related to identifying critical elements present in the forward view, therefore, the percentage of correct responses to SAGAT probes improves during ACC condition.

The empirical study also uncovers the deleterious effects of cell phone use on drivers' SA. Performing secondary tasks while driving affects the primary task performance since cognitive load increases due to divided attention scenarios and as a result SA deteriorates. This is primarily due to the fact that a driver's mental resources are limited and attention allocated towards secondary tasks compromises the attention needed to successfully perform primary tasks, such as maintaining vehicle control or monitoring the environment.

To simulate the effects of cellphone use on drivers' SA, an additional AOI categorised as cellphone screen is added to the SEEV modelling paradigm. For conditions involving cellphone task, dwell time percentages are computed for the AOI representing the cellphone screen. Distribution of visual resources towards cellphone screen results in reduced scanning of the forward view; and, therefore, using a cellphone while driving compromises model's ability to correctly respond to SAGAT probes.

No interaction effects between the IVs were found in the empirical study. According to [Ma and Kaber \[42\]](#) this could primarily be due to the shorter experiment time and simplicity of the experimental scenarios. The simulation results, however, indicate that using a cellphone can substantially impair drivers' SA even when ACC is activated since the benefits of ACC in terms of reduced workload are counterbalanced by the use of cellphone.

Chapter 6

Conclusion

I started this research with the goal to eventually develop a computational model that could simulate drivers' SA. Realising that SA is a cognitive construct, I explored how SA could be modelled by means of computational cognitive theories. I proposed an approach based in a cognitive architecture to develop a simulation model of SA. Cognitive architectures represent a framework for modeling human cognitive functionality by integrating multiple computational theories of human cognition in a unified manner. From a theoretical standpoint, I demonstrate the theory of modelling and predicting SA through the lens of human cognition utilizing the QN-ACTR cognitive architecture as a foundation. I integrate a dynamic visual sampling model (SEEV) to create QN-ACT-R-SA in order to allow the model to simulate realistic attention allocation patterns of human drivers at Level 1 SA (i.e perception of critical elements). A driver model is also incorporated within QN-ACT-R-SA architecture that can simulate human driving behavior by interacting with a driving simulator with the help of virtual modalities such as motor, visual and memory functions. From a practical standpoint, I evaluate the efficacy of QN-ACT-R-SA in three validation studies (Study I, II and III). These studies were conducted to determine whether Level 1 SA results produced with the QN-ACT-R-SA model correspond to empirical data collected from human drivers for the same tasks. This chapter further discusses the limitations of QN-ACT-R-SA, expands on future work and applications, and eventually concludes by offering summary of results.

6.1 Limitations of QN-ACT-R-SA

One of the major limitations of the current version of QN-ACT-R-SA is that the SA model implemented within the cognitive architecture is a simplified version of a very multi-level and well-debated theoretical concept. By its very nature, a model is a limited representation of some aspect of reality, or in the case of QN-ACT-R-SA a limited representation of how SA is accounted for in human information processing. Researchers are cautioned that model-based simulations must not be used as a substitute for participant-based SA experiments. In its current instantiation, QN-ACT-R-SA can be used to supplement early stage empirical testing. For instance, QN-ACT-R-SA can be employed to simulate SA results of multiple driving scenarios and these modelling results could later be confirmed

by means of empirical testing.

Another limitation of QN-ACT-R SA is that only Level 1 SA is taken into account whereas higher levels of SA are discounted due to limitations in understanding how to mathematically model advanced decision-making associated with SA. Higher levels of SA (i.e. Level 2 comprehension, and Level 3 projection) will require different mechanisms such as common-sense reasoning and heuristic-based decision-making. Preliminary ideas for adapting QN-ACT-R-SA are presented in Section 6.2.

Our current model does not yet differentiate drivers' SA that may be influenced by factors such as age (young vs. elderly), driving experience (novice vs. professional), or driving strategy (reactive vs. defensive). This drawback significantly limits QN-ACT-R-SA's applicability in a number of domains. It's therefore critical that researchers develop and embed human performance models within QN-ACT-R-SA that can account for additional factors that are currently not incorporated within the model. These factors will increase the operational use of QN-ACT-R-SA for modelling and simulation purposes.

In Chapter 4, QN-ACT-R-SA's modelling was restricted to simple reaction time and I did not attempt to model choice-based reaction times. This was done because QN-ACT-R-SA does not currently account for dynamic factors representing differential choices (steering and brake) in an expected utility fashion. As a result, QN-ACT-R-SA at present cannot simulate BPRT and SRPT concurrently. Future studies are needed to expand the current modelling paradigm such that it can take into account choice reaction times.

Researchers who are interested in using QN-ACT-R-SA to inform systems design have to deal with a series of programming challenges before successfully using QN-ACT-R-SA for modelling and simulation purposes. QN-ACT-R-SA is a complex program and requires a significant learning curve. Therefore, further work is needed to develop the current modelling approach into a usable tool that can be employed by practitioners and system designers so that they can benefit despite carrying limited technical expertise in the domain. One approach is to develop customized plugins that can support automated scenario setup and simulation.

6.2 Future Work

6.2.1 Expanding Current Empirical Research Using QN-ACT-R-SA

The eventual goal of this research is to allow transportation researchers to simulate SA experiments in laboratory settings using QN-ACT-R-SA. From the empirical experiments, many different avenues could further be explored using QN-ACT-R-SA's modelling and simulation capabilities. The approach can further support research towards understanding minor nuances in different driving conditions. For instance, from Study II (Chapter 4) analysing how different variables such as Time-to-Collision (TTC) influence driver's hazard perception skills. Similarly from Study I (Chapter 3) quantitatively extrapolating error percentages in post-experiment SA due to visual attention limitations and memory limitations, and due to unexpected events during the driving task.

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. While more complex problems would continue to be identified through user studies, QN-ACT-R-SA modelling can complement user testing and reduce research dependency on empirical data. For example, the results from the Study I (3.5.6) suggest driving complexity has a larger impact on SA for peripheral elements than for on-road elements sparking further scenario testing. Since predictive modelling of SA can simulate driving scenarios ruled out due to safety concerns, QN-ACT-R-SA allows for quick iterations of scenario simulations to identify the placement of objects and event-timing, as well as investigate the impact on driver awareness prior to critical safety events (e.g. collision).

Advancements in the QN-ACT-R-SA model should promote better understanding of complex traffic conditions under which drivers are most likely to be unaware of elements (i.e. Level 1 SA approaches). Such findings could be of great benefit to automotive designers designing next-generation vehicles. Leveraging early-stage predictive modelling can aid human factor engineers to discern between initial prototypes, such as deciding between two categories of in-vehicle interfaces or evaluating the impact of different roadway designs on driver SA. Predictive SA modelling with QN-ACT-R-SA can empower researchers to simulate and test important hypotheses prior to formal experimentation.

Expanding on outcomes from Chapter 4, QN-ACT-R-SA could be used to investigate the effects of different types of distractions on drivers' hazard perception ability. While driving, multiple sources of information compete for drivers' attention. With limited cognitive resources, if the driver's task demands exceed a certain threshold at any given time, it can lead to lack of SA, poor hazard perception and possible motor-vehicle collisions. QN-ACT-R-SA based modelling can mimic how different types of distractors influence drivers' SA and other performance variables.

6.2.2 Modelling Level 2 and Level 3 Situation Awareness

After modelling Level 1 SA, the next logical step would be to come up with approaches towards modelling higher levels of SA. Level 2 and 3 SA are usually formed in a linear fashion after Level 1 SA is achieved. Once a critical element is perceived, the operator tends to make sense of the present situation by analyzing the significance of that critical element with respect to the events taking place in the environment. This process is also categorized as Sensemaking [162].

To represent it computationally in QN-ACT-R-SA, consider the Sensemaking process as forming a "belief" based on perception of a critical element. The process of forming a belief can be represented by implementation of production rules. A production rule is implemented only when the set of conditions match and corresponding rules fire triggering the model to produce a certain action. Once declarative knowledge is effectively retrieved from the buffer, the buffer passes the value of critical element to the procedural memory module so that it could implement the corresponding rules (Figure 3.2). Multiple production rules can potentially be implemented at a given time, but only the rule with the greatest utility U_i is selected (Equation 3.1). Once the "if" part of the procedural memory, which contains production (if-then) rules, matches the content of the buffer, the pattern matching process selects the corresponding rule to be implemented. If the optimal production rule with the

highest utility U_i is chosen, the critical element would be categorized as fully understood either in the form of its present meaning (Level 2) or a projected one (Level 3). This could result in the model undertaking some sort of action. In most circumstances, Level 1 SA is necessary for Level 2 and 3 SA to come into effect.

To give a very simple example, a driver perceives an oncoming car. The oncoming car is a critical element and represented as a chunk in QN-ACT-R-SA. During perception, multiple production rules can be fired such as: “If a critical element (oncoming vehicle) is perceived, then determine its criticality based on time to collision (or safety distance from drive vehicle, heading etc.). If time to collision is less than or equal to 3 seconds, then critical element is unsafe (Level 2 SA - comprehension process achieved). If critical element is unsafe then undertake hazard mitigation response (Level 3 SA – Projection)”.

Also QN-ACT-R-SA integrates ACT-R’s process of spreading chunk activation to similar chunks. This facilitates the comprehension and projection process as procedural rules can also be implemented on chunks that have received activation due to source spreading. For example, the model perceives a pedestrian and as a result another chunk representing a street sign of a pedestrian crossing receives activation due to source spreading. On increase in activation level, the QN-ACT-R-SA model can now implement a relevant production rule that may cause the model to undertake actions such as reducing the vehicle’s speed.

Evaluating Level 2 and 3 SA using a SA probe technique is problematic because probe techniques cannot truly capture the process of comprehension and projection since the probe itself would give clues to the human participants which would influence SA results. Moreover, querying the model on optimal procedural rules would be tricky since all possible rules would have to be delineated which would complicate the modelling process. It is recommended that Level 2 and 3 SA be assessed using empirical driver performance data which can be compared to model outcomes.

While QN-ACT-R-SA in its current form may be able to model Level 2 and 3 SA, it is important to understand that the modelling mechanisms are not ideal for modelling higher levels of SA. Within the QN-ACT-R-SA framework, chunks are the only component that represents factual information rather than declarative knowledge (i.e. rules and procedures necessary for sensemaking). There is a need to introduce another cognitive construct in the QN-ACT-R-SA framework that could represent a collection of chunks. This would allow the model to develop a macrocognitive perspective of the present situation. These combination of chunks could be categorized as frames (mental models or schema). Frames in QN-ACT-R-SA could also have a sub-symbolic parameter which could be represented by the combined activation levels of chunks present in the frame. Based on the strength of this sub-symbolic parameter, frames could be retrieved from the declarative memory when required. Frames would essentially serve as explanatory structures that would assist the model in making sense of on-going events. The model would have the option to alter, adapt or compare frames by adding, removing or matching chunks present in the frames through commands given by procedural memory. This is just a theoretical recommendation to improve the functionality of QN-ACT-R-SA architecture to better facilitate modelling of higher levels of SA.

6.2.3 Application of Model in Other Areas

The current modelling research could be extended to address challenges in several other research areas, as discussed below.

The utility of computational models in predicting human performance in real life situations is considerable; and, models like QN-ACT-R-SA could be further developed to address such needs [146]. For instance, it would be of value to the driving research community if QN-ACT-R-SA can predict driver SA in real life scenarios especially in instances when SA diminishes beyond reasonable safety levels. Such predictions can be used to enhance human performance by reducing human error of drivers under real life conditions. Data driven models alone are not enough to achieve the next-moment prediction challenge since they lack top-down theoretical reasoning thereby resulting in situations that often lead to “missing the forest” issues [146]. This challenge of predicting “what would happen next” can be achieved if cognitive architecture-based human performance models are integrated with bottom-up data driven techniques. Data driven models rely on quality and quantity of data to generate meaningful insights, whereas, theory driven models such as QN-ACT-R-SA depend on well formulated procedural rules. QN-ACT-R-SA can be extremely useful and complimentary to data-driven models that are relying on scarce data sets. For instance, QN-ACT-R-SA could be integrated with driving assistance programs to generate alerts when drivers’ SA deteriorates beyond a reasonable level. Data-driven models can function to acquire and optimize vehicle sensor data, whereas, QN-ACT-R-SA could use this information to understand human drivers’ SA fluctuations. This complimentary workflow could allow us to track human behavior in naturalistic conditions and generate real-time alerts with the goal to optimize human safety and experience.

QN-ACT-R-SA can be further developed to incorporate mechanistic and computational models from social science and social psychology [163]. For instance, driver on-road behaviours can be affected by physical condition (e.g. tired), psychological state (e.g. anxious), and motivation (e.g. driving to an important meeting)[164], especially in complex and uncertain conditions. Embedding computational theories that explain such constructs within QN-ACT-R-SA would be a great stride towards improving the current human performance modelling paradigms.

Validating human performance models has always been a cause of concern for researchers. In the current era, data from physiological devices (e.g. eye tracking, skin conductance, heart rate etc.) is being routinely used for human factors analysis [165]. Likewise, the application of physiological data for validating human performance models cannot be overlooked. Future studies may focus on comparing physiological correlates of human performance against predictions from QN-ACT-R-SA for a more extensive and robust validation of the model and simulations.

QN-ACT-R-SA could be integrated with additional modeling capabilities that could include modeling haptic perception, cross-modal links, attention fatigue, and skill acquisition. Together, these models can be used to analyse cognitive bottlenecks and human performance issues in a comprehensive fashion.

Future versions of QN-ACT-R-SA could also be employed for exploring a potential connection that bridges the macro-level simulation research of social-technological systems, and the micro-level modeling of brain cell functions. For example, QN-ACT-R-SA could be

embedded in control systems of high reliability organizations such as nuclear power plants for tracking operator SA and launching alerts when SA decreases to risky levels. Such an application of QN-ACT-R-SA could potentially improve overall human performance and have an impact on the social-technological structure of the organization. However, the procedural rules within QN-ACT-R-SA would be applied at the brain cell level to improve attention allocation, memory retrieval etc. Investigating this potential connection between macro-level simulation research of social technological systems, and the micro-level modeling of brain cell functions would be a practical and valuable application of cognitive architectures.

QN-ACT-R-SA could also be developed to represent mechanisms present in multi-agent systems for the purposes of simulating collaborative behaviors. For instance, currently QN-ACT-R-SA is implemented as a single agent model designed to simulate actions of a single human driver. It would be noteworthy to explore a multi-agent system implementation of QN-ACT-R-SA. For example, a cohort of vehicles in a driving scenario could theoretically be operated by multiple versions of QN-ACT-R-SA that are running concurrently. This would be a unique area to explore since most agent-based models lack cognitive and perceptual underpinnings.

Another planned direction is to explore the role of cognitive architectures for automating testing of digital interfaces. Cognitive-architecture-based engineering tools can be used by designers and engineers for interface design and evaluation, bridging the gap between theoretical modeling research and industrial applications. For instance, QN-ACT-R-SA could be used as a surrogate user to undergo usability tests on mobile interfaces. Rather than eye tracking studies on actual participants, the visual attention allocation processes of QN-ACT-R-SA can be simulated to generate heat maps and human saccade patterns. Such tools can significantly improve the quality of design and reduce the cost of human tests by facilitating rapid analysis of interfaces using computerized simulations.

Lastly, QN-ACT-R-SA can be used for the creation of synthetic data for training machine learning algorithms. Insufficient training data is a perennial problem plaguing the use of machine learning in different application areas [166]. For example, driving companies are extensively looking to gather human driving data to improve the accuracy of their respective machine learning algorithms. Driving data is a rare commodity and might not be available for all edge cases and different atypical driving environments. Cognitive architectures such as QN-ACT-R-SA could be used to generate vehicle lateral and longitudinal control data by recreating edge cases and atypical driving environments in simulated settings such as driving simulators. This data could potentially be employed to train machine learning algorithms. Furthermore, synthetic training data generated by cognitive architectures can also improve machine learning algorithms by pre-training neural networks prior to training with real world data. Cognitive architectures therefore offer a cost effective and time efficient alternative to traditional human data collection processes. Furthermore, such datasets are free from privacy concerns. Therefore, this approach has the potential to be an invaluable part of the modern data scientist's toolkit.

6.3 Thesis Contribution Highlights

I have presented and evaluated QN-ACT-R-SA as a computational model capable of simulating drivers' SA. Modelling the limitations of both visual attention allocation and memory decay, the QN-ACT-R-SA model demonstrates the benefits of an integrated modelling approach. QN-ACT-R-SA can be used by researchers to study the implications of SA in a variety of real-world and simulator-based scenarios. Three research studies were conducted to validate the model by comparing empirical results with QN-ACT-R-SA simulation results for the same tasks. Goodness-of-fit measures that include RMSE and MAPE were employed for model validation. Based on an exhaustive literature review, I was unable to find studies that demonstrate development and validation of a computational model capable of simulating drivers' SA in different driving contexts. As a result, I was unable to benchmark the goodness-of-fit scores against existing modelling work. Nevertheless, other researchers working towards developing computational models of SA can use the current results to evaluate efficacy of their respective models.

While there is no absolute criterion for a value of RMSE or MAPE that may be considered acceptable for model results, the goodness-of-fit measures indicated that the relative error between the average human and model results was minimal. The MAPE values of less than 10% were obtained from the modelling results, across the three studies, indicating that the empirical results were comparable to the model's simulated values, thereby, resulting in a good model fit [43, 3]. The RMSE value further showed that the standard deviation of the residuals (simulation errors) from the average modelling results was not far away from the regression line data points of average empirical results. This proved that the spread of the residuals was concentrated around the line of best fit and the error difference between average empirical results and modelling results was small. The graphical analysis of the model versus human plots further showed that the model was able to map the changes in SA scores across different experimental conditions in the three studies.

In Section 3.5, QN-ACT-R-SA and human participants are probed for SA using SAGAT and post-experiment questions. The modelling outcomes are similar to the human Level 1 SA results collected under the same driving conditions. A quantitative comparative assessment demonstrates that QN-ACT-R-SA can reasonably simulate aggregate drivers' responses to Level 1 SA probes for easy and complex driving conditions. The RMSE of 3.47 for SAGAT responses indicates a small error difference between the average human and modelling results given the average SAGAT scores (measured on a scale of 0-100) for the easy and complex driving condition was around 71.9 (SD: 21.1). The RMSE of 6.13 for post-experiment SA questionnaire also indicates a small error difference between the average human and modelling results given the average post-experiment SA questionnaire scores (on a scale of 0-100) for the two driving condition was around 73.8 (SD: 16.2). The modelling results and empirical findings are also in line with this research [167, 168, 169].

In Chapter 4, BPRT was used as a hazard perception measure to further evaluate model's ability to simulate drivers' SA. The model and human participants encounter two major types of hazards: on-road hazards in the forward view of the drivers; and, roadside hazard which originate from the drivers' periphery. Both model and human results demonstrate that BPRT is shorter for on-road hazards as compared to roadside hazards. The RMSE of 0.13 seconds indicates a small error difference between the average

human and modelling results given the average BPRT for the two on-road and roadside hazard condition in was around 1.49 seconds (SD: 0.54).

Although it seems intuitive that drivers may take a shorter BPRT for on-road hazards than for road-side hazards, I am not aware of any study that provided an empirical account of this premise. Most research either examined the factors that influence BPRT or investigated BPRT to different types of hazards. Moreover, the modelling and simulation work in this area was limited and came with its own set of confines. For instance, SEEV attention model lacks memory related functionalities [31]. Therefore, Study II (Chapter 4) carries applied value for practitioners exploring tools that can simulate BPRT, and theoretical value for researchers investigating how drivers' perception changes when encountering different types of roadway hazards.

In Chapter 5, I investigated the ability of QN-ACT-R-SA to predict the effects of automation and cellphone use on Level 1 SA. QN-ACT-R-SA was successful in quantitatively mapping the finding of an empirical experiment that was conducted in a different test setting. The RMSE of 4.9 for SAGAT responses indicates a small error difference between the average human and modelling results since the average SAGAT scores for the different driving conditions was around 72 (4.76). The modelling approach detailed in Chapter 5 offers researchers a unique perspective towards predicting SA results across a range of conditions and exploring the underlying cognitive mechanisms using computational and simulation tools.

In Section 6.1, I discuss the limitations of the model, specifically focussing on the model's inability to simulate higher levels of SA; the model's inability to account for factors such as age, driving experience, or driving strategy; the model's incapacity to simulate choice-based reaction times; and lastly discussing the programming challenges associated with the setting up scenarios in the model. In Section 6.2, I discuss the future applications of the model. Section 6.2 is divided into different subsections where I explore how the current empirical work could be expanded using QN-ACT-R-SA; how the model could be improved to simulate Level 2 and Level 3 SA; and finally exploring the application of the model in areas other than driving.

In conclusion, this research explores the design and evaluation of a computational cognitive architecture capable of simulating drivers' Level 1 SA. The results from the cognitive architecture were validated against empirical results construed from established SA measures. The dissertation, and the body of research that it represents confirms the fundamental premise that QN-ACT-R-SA can reasonably simulate human drivers' Level 1 SA scores across different experimental conditions and scenarios. Additional efforts are required before computational models can simulate different levels of SA and a range of other human factors constructs. I hope that other researchers can use QN-ACT-R-SA as impetus and inspiration for more comprehensive computational modelling of human SA in a variety of domains.

References

- [1] U. Rehman, S. Cao, and C. MacGregor, “Using an Integrated Cognitive Architecture to Model the Effect of Environmental Complexity on Drivers Situation Awareness,” *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 63, no. 1, pp. 812–816, Nov. 2019. [Online]. Available: <https://doi.org/10.1177/1071181319631313>
- [2] D. E. Knuth, “Computer Programming as an Art,” *Communications of the ACM*, vol. 17, no. 12, pp. 667–673, 1974.
- [3] S. Cao and Y. Liu, “Queueing network-adaptive control of thought rational (QN-ACTR): An integrated cognitive architecture for modelling complex cognitive and multi-task performance,” *International Journal of Human Factors Modelling and Simulation* 55, vol. 4, no. 1, pp. 63–86, 2013.
- [4] P. M. Salmon, N. A. Stanton, G. H. Walker, C. Baber, D. P. Jenkins, R. McMaster, and M. S. Young, “What really is going on? Review of situation awareness models for individuals and teams,” *Theoretical Issues in Ergonomics Science*, vol. 9, no. 4, pp. 297–323, Jul. 2008. [Online]. Available: <http://www.tandfonline.com/doi/abs/10.1080/14639220701561775>
- [5] M. R. Endsley, “Toward a theory of situation awareness in dynamic systems,” *Human Factors: The Journal of the Human Factors and Ergonomics Society*, vol. 37, no. 1, pp. 32–64, 1995. [Online]. Available: <http://hfs.sagepub.com/content/37/1/32.short>
- [6] M. R. Endsley and C. A. Bolstad, “Individual differences in pilot situation awareness,” *The International Journal of Aviation Psychology*, vol. 4, no. 3, pp. 241–264, 1994. [Online]. Available: http://www.tandfonline.com/doi/abs/10.1207/s15327108ijap0403_3
- [7] M. R. Endsley and M. D. Rodgers, “Situation awareness information requirements analysis for en route air traffic control,” in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 38. SAGE Publications, 1994, pp. 71–75. [Online]. Available: <http://pro.sagepub.com/content/38/1/71.short>
- [8] D. Golightly, J. R. Wilson, E. Lowe, and S. Sharples, “The role of situation awareness for understanding signalling and control in rail operations,” *Theoretical Issues in Ergonomics Science*, vol. 11, no. 1-2, pp. 84–98, 2010.

- [9] C. M. Burns, G. Skraaning Jr, G. A. Jamieson, N. Lau, J. Kwok, R. Welch, and G. Andresen, "Evaluation of ecological interface design for nuclear process control: situation awareness effects," *Human factors*, vol. 50, no. 4, pp. 663–679, 2008.
- [10] M. C. Wright and M. R. Endsley, "Building shared situation awareness in healthcare settings," in *Improving healthcare team communication*. CRC Press, 2017, pp. 97–114.
- [11] G. H. Walker, N. A. Stanton, T. A. Kazi, P. M. Salmon, and D. P. Jenkins, "Does advanced driver training improve situational awareness?" *Applied Ergonomics*, vol. 40, no. 4, pp. 678–687, Jul. 2009. [Online]. Available: <http://linkinghub.elsevier.com/retrieve/pii/S0003687008001130>
- [12] J. C. de Winter, R. Happee, M. H. Martens, and N. A. Stanton, "Effects of adaptive cruise control and highly automated driving on workload and situation awareness: A review of the empirical evidence," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 27, pp. 196–217, Nov. 2014. [Online]. Available: <http://linkinghub.elsevier.com/retrieve/pii/S1369847814000904>
- [13] D. Kaber, Y. Zhang, S. Jin, P. Mosaly, and M. Garner, "Effects of hazard exposure and roadway complexity on young and older driver situation awareness and performance," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 15, no. 5, pp. 600–611, Sep. 2012. [Online]. Available: <http://linkinghub.elsevier.com/retrieve/pii/S1369847812000575>
- [14] S. J. Kass, K. S. Cole, and C. J. Stanny, "Effects of distraction and experience on situation awareness and simulated driving," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 10, no. 4, pp. 321–329, Jul. 2007. [Online]. Available: <http://linkinghub.elsevier.com/retrieve/pii/S1369847806001082>
- [15] F. Wulf, M. Rimini-Doring, M. Arnon, and F. Gauterin, "Recommendations Supporting Situation Awareness in Partially Automated Driver Assistance Systems," *IEEE Transactions on Intelligent Transportation Systems*, vol. 16, no. 4, pp. 2290–2296, Aug. 2015. [Online]. Available: <http://ieeexplore.ieee.org/document/7000589/>
- [16] M. D. Byrne and R. W. Pew, "A History and Primer of Human Performance Modeling," *Reviews of Human Factors and Ergonomics*, vol. 5, no. 1, pp. 225–263, Jun. 2009. [Online]. Available: <http://journals.sagepub.com/doi/10.1518/155723409X448071>
- [17] I. S. MacKenzie, "Fitts' law as a research and design tool in human-computer interaction," *Human-computer interaction*, vol. 7, no. 1, pp. 91–139, 1992.
- [18] R. Hyman, "Stimulus information as a determinant of reaction time." *Journal of experimental psychology*, vol. 45, no. 3, p. 188, 1953.
- [19] S. Kornblum, T. Hasbroucq, and A. Osman, "Dimensional overlap: cognitive basis for stimulus-response compatibility: a model and taxonomy." *Psychological review*, vol. 97, no. 2, p. 253, 1990.

- [20] K. R. Laughery, “Microsaint: a tool for modeling human performance in systems,” in *Applications of human performance models to system design*. Springer, 1989, pp. 219–230.
- [21] C. Samms, “Improved performance research integration tool (IMPRINT): human performance modeling for improved system design,” in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 54. SAGE Publications Sage CA: Los Angeles, CA, 2010, pp. 624–625.
- [22] J. E. Laird, A. Newell, and P. S. Rosenbloom, “Soar: An architecture for general intelligence,” *Artificial intelligence*, vol. 33, no. 1, pp. 1–64, 1987.
- [23] S. K. Card, “The model human processor: A model for making engineering calculations of human performance,” in *Proceedings of the Human Factors Society Annual Meeting*, vol. 25. SAGE Publications Sage CA: Los Angeles, CA, 1981, pp. 301–305.
- [24] D. E. Kieras and D. E. Meyer, “An overview of the EPIC architecture for cognition and performance with application to human-computer interaction,” *Human Computer Interaction*, vol. 12, no. 4, pp. 391–438, 1997.
- [25] D. A. Winter, *Biomechanics and motor control of human movement*. John Wiley & Sons, 2009.
- [26] P. Langley, J. E. Laird, and S. Rogers, “Cognitive architectures: Research issues and challenges,” *Cognitive Systems Research*, vol. 10, no. 2, pp. 141–160, 2009.
- [27] F. E. Ritter and R. M. Young, “Embodied models as simulated users: introduction to this special issue on using cognitive models to improve interface design,” *International Journal of Human-Computer Studies*, vol. 55, no. 1, pp. 1–14, Jul. 2001. [Online]. Available: <http://linkinghub.elsevier.com/retrieve/pii/S1071581901904719>
- [28] R. E. T. Jones, E. S. Connors, M. E. Mossey, J. R. Hyatt, N. J. Hansen, and M. R. Endsley, “Using fuzzy cognitive mapping techniques to model situation awareness for army infantry platoon leaders,” *Computational and Mathematical Organization Theory*, vol. 17, no. 3, pp. 272–295, Sep. 2011. [Online]. Available: <http://link.springer.com/10.1007/s10588-011-9094-6>
- [29] R. Koopmanschap, M. Hoogendoorn, and J. J. Roessingh, “Tailoring a cognitive model for situation awareness using machine learning,” *Applied Intelligence*, vol. 42, no. 1, pp. 36–48, Jan. 2015. [Online]. Available: <http://link.springer.com/10.1007/s10489-014-0584-3>
- [30] G. D’Aniello, A. Gaeta, V. Loia, and F. Orciuoli, “A granular computing framework for approximate reasoning in situation awareness,” *Granular Computing*, vol. 2, no. 3, pp. 141–158, 2017.
- [31] C. D. Wickens, J. McCarley, L. Thomas, M. I. D. Foyle, A. Goodman, and B. L. Hooley, “Attention-situation awareness (A-SA) model,” in *NASA Aviation Safety*

Program Conference on Human Performance Modeling of Approach and Landing with Augmented Displays, 2003, p. 189.

- [32] V. B. Mountcastle, *Perceptual neuroscience: The cerebral cortex*. Harvard University Press, 1998.
- [33] J. S. Bruner and L. Postman, “Perception, cognition, and behavior,” *Journal of personality*, vol. 18, no. 1, pp. 14–31, 1949.
- [34] W. Fish, *Philosophy of perception: A contemporary introduction*. Routledge, 2010.
- [35] P. M. Salmon, N. A. Stanton, G. H. Walker, C. Baber, D. P. Jenkins, R. McMaster, and M. S. Young, “What really is going on? Review of situation awareness models for individuals and teams,” *Theoretical Issues in Ergonomics Science*, vol. 9, no. 4, pp. 297–323, Jul. 2008. [Online]. Available: <http://www.tandfonline.com/doi/abs/10.1080/14639220701561775>
- [36] M. R. Endsley, “Theoretical underpinnings of situation awareness: A critical review,” *Situation awareness analysis and measurement*, pp. 3–32, 2000.
- [37] M. Endsley, “Direct measurement of situation awareness: Validity and use of sagat,” in *Situational Awareness*. Routledge, 2017, pp. 129–156.
- [38] T. Nguyen, C. P. Lim, N. D. Nguyen, L. Gordon-Brown, and S. Nahavandi, “A review of situation awareness assessment approaches in aviation environments,” *IEEE Systems Journal*, vol. 13, no. 3, pp. 3590–3603, 2019.
- [39] C. Montemayor and H. H. Haladjian, “Perception and cognition are largely independent, but still affect each other in systematic ways: arguments from evolution and the consciousness-attention dissociation,” *Frontiers in psychology*, vol. 8, p. 40, 2017.
- [40] D. D. Salvucci and R. Gray, “A Two-Point Visual Control Model of Steering,” *Perception*, vol. 33, no. 10, pp. 1233–1248, Oct. 2004. [Online]. Available: <http://journals.sagepub.com/doi/10.1068/p5343>
- [41] R. Math, A. Mahr, M. M. Moniri, and C. Muller, “OpenDS: A new open-source driving simulator for research,” in *Proceedings of the International Conference on Automotive User Interfaces and Interactive Vehicular Applications, Adjunct Proceedings*, 2012, pp. 7–8.
- [42] R. Ma and D. B. Kaber, “Situation awareness and workload in driving while using adaptive cruise control and a cell phone,” *International Journal of Industrial Ergonomics*, vol. 35, no. 10, pp. 939–953, 2005. [Online]. Available: <http://www.sciencedirect.com/science/article/pii/S0169814105000776>
- [43] C. D. Lewis, *Industrial and business forecasting methods: A practical guide to exponential smoothing and curve fitting*. Butterworth-Heinemann, 1982.

- [44] G. Bedny and D. Meister, "Theory of activity and situation awareness," *International Journal of cognitive ergonomics*, vol. 3, no. 1, pp. 63–72, 1999. [Online]. Available: http://www.tandfonline.com/doi/abs/10.1207/s15327566ijce0301_5
- [45] K. Smith and P. A. Hancock, "Situation awareness is adaptive, externally directed consciousness," *Human Factors: The Journal of the Human Factors and Ergonomics Society*, vol. 37, no. 1, pp. 137–148, 1995. [Online]. Available: <http://hfs.sagepub.com/content/37/1/137.short>
- [46] U. Neisser, *Cognition and reality: Principles and implications of cognitive psychology*. WH Freeman/Times Books/Henry Holt & Co, 1976. [Online]. Available: <http://doi.apa.org/psycinfo/2003-00066-000>
- [47] N. B. Sarter and D. D. Woods, "Situation awareness: A critical but ill-defined phenomenon," *The International Journal of Aviation Psychology*, vol. 1, no. 1, pp. 45–57, 1991. [Online]. Available: http://www.tandfonline.com/doi/abs/10.1207/s15327108ijap0101_4
- [48] R. M. Taylor, "Situational awareness rating technique (SART): The development of a tool for aircrew systems design," in *Situational Awareness*. Routledge, 2017, pp. 111–128.
- [49] M. J. Adams, Y. J. Tenney, and R. W. Pew, "Situation awareness and the cognitive management of complex systems," *Human Factors: The Journal of the Human Factors and Ergonomics Society*, vol. 37, no. 1, pp. 85–104, 1995. [Online]. Available: <http://hfs.sagepub.com/content/37/1/85.short>
- [50] G. J. Alexander and H. Lunenfeld, "A users' guide to positive guidance in highway control," in *Proceedings of the Human Factors Society Annual Meeting*, vol. 23, no. 1. SAGE Publications Sage CA: Los Angeles, CA, 1979, pp. 452–455.
- [51] M. Matthews, D. Bryant, R. Webb, and J. Harbluk, "Model for Situation Awareness and Driving: Application to Analysis and Research for Intelligent Transportation Systems," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 1779, pp. 26–32, Jan. 2001. [Online]. Available: <http://trrjournalonline.trb.org/doi/10.3141/1779-04>
- [52] J. A. Michon, "A critical view of driver behavior models: what do we know, what should we do?" in *Human behavior and traffic safety*. Springer, 1985, pp. 485–524.
- [53] N. J. Ward, "Automation of task processes: An example of intelligent transportation systems," *Human Factors and Ergonomics in Manufacturing & Service Industries*, vol. 10, no. 4, pp. 395–408, 2000.
- [54] R. Ma and D. B. Kaber, "Situation awareness and driving performance in a simulated navigation task," *Ergonomics*, vol. 50, no. 8, pp. 1351–1364, Aug. 2007. [Online]. Available: <http://www.tandfonline.com/doi/abs/10.1080/00140130701318913>

- [55] L. Gugerty and others, "Situation awareness in driving," *Handbook for driving simulation in engineering, medicine and psychology*, vol. 1, 2011. [Online]. Available: <http://gugerty.people.clemson.edu/Gugerty2011SAdriving.pdf>
- [56] N. A. Stanton, A. Dunoyer, and A. Leatherland, "Detection of new in-path targets by drivers using Stop & Go Adaptive Cruise Control," *Applied ergonomics*, vol. 42, no. 4, pp. 592–601, 2011.
- [57] H. W. Leibowitz and D. A. Owens, "Nighttime driving accidents and selective visual degradation," *Science*, vol. 197, no. 4302, pp. 422–423, 1977.
- [58] G. E. Schneider, "Two visual systems," *Science*, vol. 163, no. 3870, pp. 895–902, 1969. [Online]. Available: <https://science.sciencemag.org/content/163/3870/895>
- [59] J. L. Harbluk, Y. I. Noy, P. L. Trbovich, and M. Eizenman, "An on-road assessment of cognitive distraction: Impacts on drivers visual behavior and braking performance," *Accident Analysis & Prevention*, vol. 39, no. 2, pp. 372–379, 2007.
- [60] R. H. Logie and C. Marchetti, "Visuo-spatial working memory: Visual, spatial or central executive," *Mental images in human cognition*, vol. 80, 1991.
- [61] L. Gugerty, M. Rakauskas, and J. Brooks, "Effects of remote and in-person verbal interactions on verbalization rates and attention to dynamic spatial scenes," *Accident Analysis & Prevention*, vol. 36, no. 6, pp. 1029–1043, 2004.
- [62] T. A. Dingus, S. G. Klauer, V. L. Neale, A. Petersen, S. E. Lee, J. Sudweeks, M. A. Perez, J. Hankey, D. Ramsey, S. Gupta *et al.*, "The 100-car naturalistic driving study, phase ii-results of the 100-car field experiment," Department of Transportation, National Highway Traffic Safety, United States, Tech. Rep. DOT-HS-810-593, 2006.
- [63] B. Graab, E. Donner, U. Chiellino, and M. Hoppe, "Analyse von verkehrsunfällen hinsichtlich unterschiedlicher fahrerpopulationen und daraus ableitbarer ergebnisse für die entwicklung adaptiver fahrerassistenzsysteme," in *Tagung Aktive Sicherheit durch Fahrerassistenz*, 2008.
- [64] W. J. Horrey, C. D. Wickens, and K. P. Consalus, "Modeling drivers' visual attention allocation while interacting with in-vehicle technologies." *Journal of Experimental Psychology: Applied*, vol. 12, no. 2, pp. 67–78, 2006. [Online]. Available: <http://doi.apa.org/getdoi.cfm?doi=10.1037/1076-898X.12.2.67>
- [65] M. R. Endsley, "Design and evaluation for situation awareness enhancement," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 32. SAGE Publications, 1988, pp. 97–101. [Online]. Available: <http://pro.sagepub.com/content/32/2/97.short>
- [66] R. E. Nisbett and T. D. Wilson, "Telling more than we can know: Verbal reports on mental processes." *Psychological review*, vol. 84, no. 3, p. 231, 1977.

- [67] S. Cao, Y. Qin, X. Jin, L. Zhao, and M. Shen, “Effect of driving experience on collision avoidance braking: an experimental investigation and computational modelling,” *Behaviour & Information Technology*, vol. 33, no. 9, pp. 929–940, 2014.
- [68] C. Deng, C. Wu, S. Cao, and N. Lyu, “Modeling the effect of limited sight distance through fog on car-following performance using QN-ACTR cognitive architecture,” *Transportation Research Part F: Traffic Psychology and Behaviour*, 2018.
- [69] D. D. Salvucci, “Modeling Driver Behavior in a Cognitive Architecture,” *Human Factors: The Journal of the Human Factors and Ergonomics Society*, vol. 48, no. 2, pp. 362–380, Jun. 2006. [Online]. Available: <http://journals.sagepub.com/doi/10.1518/001872006777724417>
- [70] C. Wu and Y. Liu, “Queuing network modeling of driver workload and performance,” *IEEE Transactions on Intelligent Transportation Systems*, vol. 8, no. 3, pp. 528–537, 2007.
- [71] J. R. Anderson, “ACT: A simple theory of complex cognition.” *American Psychologist*, vol. 51, no. 4, p. 355, 1996.
- [72] S. Miller and A. Kirlik, “Modeling the Task Environment: Act-R and the Lens Model,” *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 50, no. 11, pp. 1127–1131, Oct. 2006. [Online]. Available: <http://journals.sagepub.com/doi/10.1177/154193120605001103>
- [73] B. Wortelen and A. Ludtke, “Dynamic simulation and prediction of drivers attention distribution,” *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 21, pp. 278–294, Nov. 2013. [Online]. Available: <https://linkinghub.elsevier.com/retrieve/pii/S1369847813000946>
- [74] F. A. Shaw, A. T. Greenwood, J. Bae, G. M. Corso, M. O. Rodgers, and M. P. Hunter, “Effects of roadway factors and demographic characteristics on drivers perceived complexity of simulated roadway videos,” *Transportation Letters*, pp. 1–10, Jul. 2018. [Online]. Available: <https://www.tandfonline.com/doi/full/10.1080/19427867.2018.1492220>
- [75] A. Heenan, C. M. Herdman, M. S. Brown, and N. Robert, “Effects of Conversation on Situation Awareness and Working Memory in Simulated Driving,” *Human Factors*, vol. 56, no. 6, pp. 1077–1092, Sep. 2014. [Online]. Available: <http://dx.doi.org/10.1177/0018720813519265>
- [76] Y. Liu, “Queuing network modeling of human performance of concurrent spatial and verbal tasks,” *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans*, vol. 27, no. 2, pp. 195–207, 1997.
- [77] C. Deng, S. Cao, C. Wu, and N. Lyu, “Modeling Driver Take-Over Reaction Time and Emergency Response Time using an Integrated Cognitive Architecture,” *Transportation Research Record*, p. 0361198119842114, 2019.

- [78] S. Cao and Y. Liu, “Concurrent processing of vehicle lane keeping and speech comprehension tasks,” *Accident Analysis & Prevention*, vol. 59, pp. 46–54, 2013.
- [79] L. A. Baxter, *Probability, statistics, and queueing theory with computer sciences applications*. Taylor & Francis, 1992.
- [80] C. Wu, O. Tsimhoni, and Y. Liu, “Development of an adaptive workload management system using the queueing network-model human processor (QN-MHP),” *IEEE Transactions on Intelligent Transportation Systems*, vol. 9, no. 3, pp. 463–475, 2008.
- [81] Y. Liu, R. Feyen, and O. Tsimhoni, “Queueing Network-Model Human Processor (QN-MHP): A computational architecture for multitask performance in human-machine systems,” *ACM Transactions on Computer-Human Interaction (TOCHI)*, vol. 13, no. 1, pp. 37–70, 2006.
- [82] M. Holt and R. Jahn, “Synaptic vesicles in the fast lane,” *Science*, vol. 303, no. 5666, pp. 1986–1987, 2004.
- [83] S. Cao, “Queueing network modeling of human performance in complex cognitive multi-task scenarios.” Ph.D. dissertation, 2013.
- [84] C. Lebiere and J. R. Anderson, “A connectionist implementation of the ACT-R production system,” in *Proceedings of the fifteenth annual conference of the Cognitive Science Society*, 1993, pp. 635–640.
- [85] N. A. Taatgen, C. Lebiere, and J. R. Anderson, “Modeling paradigms in ACT-R,” *Cognition and multi-agent interaction: From cognitive modeling to social simulation*, pp. 29–52, 2006.
- [86] J. P. Borst and J. R. Anderson, “Using the ACT-R Cognitive Architecture in combination with fMRI data,” in *An introduction to model-based cognitive neuroscience*. Springer, 2015, pp. 339–352.
- [87] Y. Qin, D. Bothell, and J. R. Anderson, “ACT-R Meets fMRI,” in *International Workshop on Web Intelligence Meets Brain Informatics*. Springer, 2006, pp. 205–222.
- [88] M.-H. Sohn, S. Ursu, J. R. Anderson, V. A. Stenger, and C. S. Carter, “The role of prefrontal cortex and posterior parietal cortex in task switching,” *Proceedings of the National Academy of Sciences*, vol. 97, no. 24, pp. 13 448–13 453, 2000.
- [89] C. Deng, S. Cao, C. Wu, and N. Lyu, “Predicting drivers’ direction sign reading reaction time using an integrated cognitive architecture,” *IET Intelligent Transport Systems*, 2018.
- [90] J. R. Anderson, D. Bothell, M. D. Byrne, S. Douglass, C. Lebiere, and Y. Qin, “An Integrated Theory of the Mind.” *Psychological Review*, vol. 111, no. 4, pp. 1036–1060, 2004. [Online]. Available: <http://doi.apa.org/getdoi.cfm?doi=10.1037/0033-295X.111.4.1036>

- [91] D. Bothell, “Act-r 6.0 reference manual,” *Working Draft*, 2004.
- [92] D. D. Salvucci, “An integrated model of eye movements and visual encoding,” *Cognitive Systems Research*, vol. 1, no. 4, pp. 201–220, 2001.
- [93] C. D. Wickens, J. Helleberg, J. Goh, X. Xu, and W. J. Horrey, “Pilot task management: Testing an attentional expected value model of visual scanning,” *Savoy, IL, UIUC Institute of Aviation Technical Report*, 2001.
- [94] B. F. Gore, B. L. Hooey, C. D. Wickens, and S. Scott-Nash, “A computational implementation of a human attention guiding mechanism in MIDAS v5,” in *International Conference on Digital Human Modeling*. Springer, 2009, pp. 237–246.
- [95] J. S. McCarley, C. D. Wickens, J. Goh, and W. J. Horrey, “A Computational Model of Attention/Situation Awareness,” *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 46, no. 17, pp. 1669–1673, Sep. 2002. [Online]. Available: <http://journals.sagepub.com/doi/10.1177/154193120204601730>
- [96] W. J. Horrey, C. D. Wickens, and K. P. Consalus, “Modeling drivers’ visual attention allocation while interacting with in-vehicle technologies.” *Journal of Experimental Psychology: Applied*, vol. 12, no. 2, p. 67, 2006.
- [97] C. D. Wickens, A. Sebok, T. Bagnall, and J. Kamienski, “Modeling of situation awareness supported by advanced flight deck displays,” in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 51. Sage Publications Sage CA: Los Angeles, CA, 2007, pp. 794–798.
- [98] D. D. Salvucci and R. Gray, “A two-point visual control model of steering,” *Perception*, vol. 33, no. 10, pp. 1233–1248, 2004.
- [99] D. D. Salvucci, “Modeling Driver Behavior in a Cognitive Architecture,” *Human Factors: The Journal of the Human Factors and Ergonomics Society*, vol. 48, no. 2, pp. 362–380, Jun. 2006. [Online]. Available: <http://journals.sagepub.com/doi/10.1518/00187200677724417>
- [100] M. F. Land and D. N. Lee, “Where we look when we steer,” *Nature*, vol. 369, no. 6483, p. 742, 1994.
- [101] D. D. Salvucci and J. R. Anderson, “Automated Eye-Movement Protocol Analysis,” *Human Computer Interaction*, vol. 16, no. 1, pp. 39–86, Mar. 2001. [Online]. Available: https://www.tandfonline.com/doi/full/10.1207/S15327051HCI1601_2
- [102] D. D. Salvucci and A. Liu, “The time course of a lane change: Driver control and eye-movement behavior,” *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 5, no. 2, pp. 123–132, Jun. 2002. [Online]. Available: <http://linkinghub.elsevier.com/retrieve/pii/S1369847802000116>

- [103] J. R. Anderson, M. Matessa, and C. Lebiere, "ACT-R: A theory of higher level cognition and its relation to visual attention," *Human-Computer Interaction*, vol. 12, no. 4, pp. 439–462, 1997.
- [104] F. Faul, E. Erdfelder, A.-G. Lang, and A. Buchner, "G* power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences," *Behavior research methods*, vol. 39, no. 2, pp. 175–191, 2007.
- [105] J. T. Richardson, "Eta squared and partial eta squared as measures of effect size in educational research," *Educational Research Review*, vol. 6, no. 2, pp. 135–147, 2011.
- [106] M. E. Rice and G. T. Harris, "Comparing effect sizes in follow-up studies: Roc area, cohen's d, and r," *Law and human behavior*, vol. 29, no. 5, pp. 615–620, 2005.
- [107] M. Jeon, B. N. Walker, and T. M. Gable, "Anger effects on driver situation awareness and driving performance," *Presence: Teleoperators and Virtual Environments*, vol. 23, no. 1, pp. 71–89, 2014.
- [108] Z. Lu, X. Coster, and J. de Winter, "How much time do drivers need to obtain situation awareness? a laboratory-based study of automated driving," *Applied ergonomics*, vol. 60, pp. 293–304, 2017.
- [109] D. Kaber, S. Jin, M. Zahabi, and C. Pankok Jr, "The effect of driver cognitive abilities and distractions on situation awareness and performance under hazard conditions," *Transportation research part F: traffic psychology and behaviour*, vol. 42, pp. 177–194, 2016.
- [110] R. A. Schmidt, T. D. Lee, C. Winstein, G. Wulf, and H. N. Zelaznik, *Motor control and learning: A behavioral emphasis*. Human kinetics, 2018.
- [111] W. Consiglio, P. Driscoll, M. Witte, and W. P. Berg, "Effect of cellular telephone conversations and other potential interference on reaction time in a braking response," *Accident Analysis & Prevention*, vol. 35, no. 4, pp. 495–500, 2003.
- [112] L. J. Gugerty, "Situation awareness during driving: Explicit and implicit knowledge in dynamic spatial memory." *Journal of Experimental Psychology: Applied*, vol. 3, no. 1, p. 42, 1997. [Online]. Available: <http://psycnet.apa.org/journals/xap/3/1/42/>
- [113] S. G. Klauer, T. A. Dingus, V. L. Neale, J. D. Sudweeks, D. J. Ramsey *et al.*, "The impact of driver inattention on near-crash/crash risk: An analysis using the 100-car naturalistic driving study data," Department of Transportation, National Highway Traffic Safety, United States, Tech. Rep. DOT-HS-810-594, 2006.
- [114] J. Treat, N. Tumbas, S. McDonald, D. Shinar, R. Hume, R. Mayer, R. Stansifer, and N. Castellan, "Tri-level study of the causes of traffic accidents: Executive summary," National Technical Information Services, Bloomington: University of Indiana, Tech. Rep. DOT-HS-805 099, 1979.

- [115] A. Katrahmani, N. Ahmadi, and M. Romoser, "Using Situation Awareness as a Measure of Driver Hazard Perception Ability," in *Proceedings of the 9th International Driving Symposium on Human Factors in Driver Assessment, Training, and Vehicle Design: driving assessment 2017*. Manchester Village, Vermont, USA: University of Iowa, 2017, pp. 256–262. [Online]. Available: <http://ir.uiowa.edu/drivingassessment/2017/papers/39>
- [116] C. Moran, J. M. Bennett, and P. Prabhakaran, "Road user hazard perception tests: A systematic review of current methodologies," *Accident Analysis & Prevention*, vol. 129, pp. 309–333, Aug. 2019. [Online]. Available: <http://www.sciencedirect.com/science/article/pii/S0001457519302131>
- [117] F. P. McKenna and J. L. Crick, "Hazard Perception in Drivers: A Methodology for Testing and Training," *TRL Contractor Report*, no. 313, 1994. [Online]. Available: <https://trid.trb.org/view/457386>
- [118] M. S. Horswill and F. P. McKenna, "Drivers hazard perception ability: Situation awareness on the road," *A cognitive approach to situation awareness: Theory and application*, pp. 155–175, 2004.
- [119] P. M. Salmon, N. A. Stanton, and K. L. Young, "Situation awareness on the road: review, theoretical and methodological issues, and future directions," *Theoretical Issues in Ergonomics Science*, vol. 13, no. 4, pp. 472–492, Jul. 2012. [Online]. Available: <http://www.tandfonline.com/doi/abs/10.1080/1463922X.2010.539289>
- [120] M. R. Endsley, "Designing for situation awareness in complex systems," in *Proceedings of the Second International Workshop on symbiosis of humans, artifacts and environment*, 2001. [Online]. Available: http://www.c4ads.seas.gwu.edu/classes/CSci297_Fall_2004/5/endsley_03.pdf
- [121] P. L. Olson, *Forensic aspects of driver perception and response*. Lawyers & Judges Publishing Co., Tuscon, AZ (1996), 1996.
- [122] A. Borowsky and T. Oron-Gilad, "Exploring the effects of driving experience on hazard awareness and risk perception via real-time hazard identification, hazard classification, and rating tasks," *Accident Analysis & Prevention*, vol. 59, pp. 548–565, 2013. [Online]. Available: <http://www.sciencedirect.com/science/article/pii/S0001457513002765>
- [123] P. L. Olson, "Driver perception response time," SAE Technical Paper, Tech. Rep., 1989.
- [124] M. Green, "' How long does it take to stop?' Methodological analysis of driver perception-brake times," *Transportation human factors*, vol. 2, no. 3, pp. 195–216, 2000.
- [125] M. Blommer, R. Curry, R. Swaminathan, L. Tijerina, W. Talamonti, and D. Kochhar, "Driver brake vs. steer response to sudden forward collision scenario

- in manual and automated driving modes,” *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 45, pp. 93–101, Feb. 2017. [Online]. Available: <https://linkinghub.elsevier.com/retrieve/pii/S1369847816305587>
- [126] J. M. Hankey, “Unalerted emergency avoidance at an intersection and possible implications for ABS implementation.” Ph.D. dissertation, 1997.
- [127] H. Summala, M. Leino, and J. Vierimaa, “Drivers’ steering behavior when meeting another car: the case of perceptual tropism revisited,” *Human factors*, vol. 23, no. 2, pp. 185–189, 1981.
- [128] J. W. Muttart, “Evaluation of the influence of several variables upon driver perception response times,” in *York, England: Proceedings of the 5th International Conference of the Institute of Traffic Accident Investigators*, 2001, pp. 116–129.
- [129] H. Summala, “Brake reaction times and driver behavior analysis,” *Transportation Human Factors*, vol. 2, no. 3, pp. 217–226, 2000.
- [130] F. Sagberg and T. Bjornskau, “Hazard perception and driving experience among novice drivers,” *Accident Analysis & Prevention*, vol. 38, no. 2, pp. 407–414, Mar. 2006. [Online]. Available: <http://www.sciencedirect.com/science/article/pii/S0001457505001855>
- [131] P. Addario and B. Donmez, “The effect of cognitive distraction on perception-response time to unexpected abrupt and gradually onset roadway hazards,” *Accident Analysis & Prevention*, vol. 127, pp. 177–185, 2019.
- [132] P. L. Olson and M. Sivak, “Perception-response time to unexpected roadway hazards,” *Human factors*, vol. 28, no. 1, pp. 91–96, 1986.
- [133] R. Burge and A. Chaparro, “The effects of texting and driving on hazard perception,” in *Proceedings of the human factors and ergonomics society annual meeting*, vol. 56. SAGE Publications Sage CA: Los Angeles, CA, 2012, pp. 715–719.
- [134] A. Pradhan, B. Simons-Morton, S. Lee, and S. Klauer, “Hazard perception and distraction in novice drivers: Effects of 12 months driving experience,” in *Proceedings of the Sixth International Driving Symposium on Human Factors in Driver Assessment, Training and Vehicle Design*. IA: Public Policy Center, University of Iowa, 2011, pp. 614–620.
- [135] S. W. Savage, D. D. Potter, and B. W. Tatler, “Does preoccupation impair hazard perception? A simultaneous EEG and eye tracking study,” *Transportation research part F: traffic psychology and behaviour*, vol. 17, pp. 52–62, 2013.
- [136] S. Samuel, A. Borowsky, S. Zilberstein, and D. L. Fisher, “Minimum Time to Situation Awareness in Scenarios Involving Transfer of Control from an Automated Driving Suite,” *Transportation Research Record: Journal of the Transportation Research Board*, vol. 2602, pp. 115–120, Jan. 2016. [Online]. Available: <http://trrjournalonline.trb.org/doi/10.3141/2602-14>

- [137] P. L. Olson, "Parameters affecting stopping sight distance," The University of Michigan, Transportation Research Institute, Tech. Rep. UMTRI-84-15, 1984.
- [138] R. H. Wortman and J. S. Matthias, *An evaluation of driver behavior at signalized intersections*. Arizona Department of Transportation Phoenix, Arizona, 1983.
- [139] D. V. McGehee, E. N. Mazzae, G. H. S. Baldwin, P. Grant, C. J. Simmons, J. Hankey, and G. Forkenbrock, "NHTSA light vehicle antilock brake systems research program task 5, Part 1: Examination of drivers' collision avoidance behavior using conventional and antilock brake systems on the Iowa Driving Simulator," 2000.
- [140] G. Johansson and K. Rumar, "Drivers' brake reaction times," *Human factors*, vol. 13, no. 1, pp. 23–27, 1971.
- [141] G. V. Barrett, "Feasibility of studying driver reaction to sudden pedestrian emergencies in an automobile simulator," *Human Factors*, vol. 10, no. 1, pp. 19–26, 1968.
- [142] N. L. Broen and D. P. Chiang, "Braking response times for 100 drivers in the avoidance of an unexpected obstacle as measured in a driving simulator," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 40. SAGE Publications Sage CA: Los Angeles, CA, 1996, pp. 900–904.
- [143] D. Lechner and G. Malaterre, "Emergency maneuver experimentation using a driving simulator," SAE Technical Paper, Tech. Rep., 1991.
- [144] D. V. McGehee, E. N. Mazzae, and G. S. Baldwin, "Driver Reaction Time in Crash Avoidance Research: Validation of a Driving Simulator Study on a Test Track," *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 44, no. 20, pp. 3–320–3–323, Jul. 2000. [Online]. Available: <http://journals.sagepub.com/doi/10.1177/154193120004402026>
- [145] G. Underwood, D. Crundall, and P. Chapman, "Driving simulator validation with hazard perception," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 14, no. 6, pp. 435–446, Nov. 2011. [Online]. Available: <http://linkinghub.elsevier.com/retrieve/pii/S1369847811000477>
- [146] C. Wu, "The five key questions of human performance modeling," *International Journal of Industrial Ergonomics*, vol. 63, pp. 3–6, Jan. 2018. [Online]. Available: <https://linkinghub.elsevier.com/retrieve/pii/S0169814116300427>
- [147] J. Setti, H. Rakha, and I. El-Shawarby, "Analysis of Brake Perception-Reaction Times on High-Speed Signalized Intersection Approaches," in *2006 IEEE Intelligent Transportation Systems Conference*. Toronto, ON, Canada: IEEE, 2006, pp. 689–694. [Online]. Available: <http://ieeexplore.ieee.org/document/1706822/>
- [148] G. T. Taoka, "Brake reaction times of unalerted drivers," *ITE journal*, vol. 59, no. 3, pp. 19–21, 1989.

- [149] A. Rakhshan, H. Pishro-Nik, and E. Ray, “Real-time estimation of the distribution of brake response times for an individual driver using Vehicular Ad Hoc Network,” in *2014 IEEE Intelligent Vehicles Symposium Proceedings*. MI, USA: IEEE, Jun. 2014, pp. 1181–1186. [Online]. Available: <http://ieeexplore.ieee.org/document/6856416/>
- [150] J. W. Muttart, “Development and evaluation of driver response time predictors based upon meta analysis,” *SAE transactions*, pp. 876–896, 2003.
- [151] J. Wood and S. Zhang, “Evaluating Relationships Between Perception-Reaction Times, Emergency Deceleration Rates, and Crash Outcomes Using Naturalistic Driving Data,” Mountain-Plains Consortium, North Dakota State University, Fargo, ND, Tech. Rep., 2017.
- [152] A. Mehmood and S. M. Easa, “Modeling Reaction Time in Car-Following Behaviour Based on Human Factors,” *International Journal of Civil and Environmental Engineering*, vol. 3, no. 9, p. 9, 2009.
- [153] I. Kotseruba and J. K. Tsotsos, “40 years of cognitive architectures: core cognitive abilities and practical applications,” *Artificial Intelligence Review*, pp. 1–78, 2018.
- [154] C. D. Wickens, J. G. Hollands, S. Banbury, and R. Parasuraman, *Engineering psychology & human performance*. Psychology Press, 2015.
- [155] D. D. Salvucci, E. R. Boer, and A. Liu, “Toward an integrated model of driver behavior in cognitive architecture,” *Transportation Research Record*, vol. 1779, no. 1, pp. 9–16, 2001.
- [156] N. Merat, A. H. Jamson, F. C. Lai, and O. Carsten, “Highly automated driving, secondary task performance, and driver state,” *Human factors*, vol. 54, no. 5, pp. 762–771, 2012.
- [157] M. Kyriakidis, J. C. de Winter, N. Stanton, T. Bellet, B. van Arem, K. Brookhuis, M. H. Martens, K. Bengler, J. Andersson, and N. Merat, “A human factors perspective on automated driving,” *Theoretical Issues in Ergonomics Science*, vol. 20, no. 3, pp. 223–249, 2019.
- [158] R. E. Llaneras, J. Salinger, and C. A. Green, “Human factors issues associated with limited ability autonomous driving systems: Drivers allocation of visual attention to the forward roadway,” in *Proceedings of the Seventh International Driving Symposium on Human Factors in Driver Assessment, Training and Vehicle Design*. Public Policy Center, University of Iowa, 2013.
- [159] A. H. Jamson, N. Merat, O. M. Carsten, and F. C. Lai, “Behavioural changes in drivers experiencing highly-automated vehicle control in varying traffic conditions,” *Transportation research part C: emerging technologies*, vol. 30, pp. 116–125, 2013.
- [160] T. M. Gasser, A. T. Frey, A. Seeck, and R. Auerswald, “Comprehensive definitions for automated driving and ADAS,” in *25th International Technical Conference on the*

Enhanced Safety of Vehicles (ESV) National Highway Traffic Safety Administration, 2017.

- [161] S. Cao, Y. Qin, L. Zhao, and M. Shen, “Modeling the development of vehicle lateral control skills in a cognitive architecture,” *Transportation research part F: traffic psychology and behaviour*, vol. 32, pp. 1–10, 2015.
- [162] M. R. Endsley, “Situation awareness misconceptions and misunderstandings,” *Journal of Cognitive Engineering and Decision Making*, vol. 9, no. 1, pp. 4–32, 2015. [Online]. Available: <http://edm.sagepub.com/content/9/1/4.short>
- [163] J. M. Epstein, “Agent-based computational models and generative social science,” *Complexity*, vol. 4, no. 5, pp. 41–60, 1999.
- [164] S. Plous, *The psychology of judgment and decision making*. McGraw-Hill Book Company, 1993.
- [165] N. Stanton, P. M. Salmon, and L. A. Rafferty, *Human factors methods: a practical guide for engineering and design*. Ashgate Publishing, Ltd., 2013.
- [166] V. Bolón-Canedo, N. Sánchez-Marroño, and A. Alonso-Betanzos, “A review of feature selection methods on synthetic data,” *Knowledge and information systems*, vol. 34, no. 3, pp. 483–519, 2013.
- [167] G. Jahn, A. Oehme, J. F. Krems, and C. Gelau, “Peripheral detection as a workload measure in driving: Effects of traffic complexity and route guidance system use in a driving study,” *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 8, no. 3, pp. 255–275, May 2005. [Online]. Available: <http://www.sciencedirect.com/science/article/pii/S1369847805000264>
- [168] A. Jamson and N. Merat, “Surrogate in-vehicle information systems and driver behaviour: Effects of visual and cognitive load in simulated rural driving,” *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 8, no. 2 SPEC. ISS., pp. 79–96, 2005.
- [169] M. S. Young, J. M. Mahfoud, N. A. Stanton, P. M. Salmon, D. P. Jenkins, and G. H. Walker, “Conflicts of interest: The implications of roadside advertising for driver attention,” *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 12, no. 5, pp. 381–388, Sep. 2009. [Online]. Available: <http://www.sciencedirect.com/science/article/pii/S136984780900028X>

APPENDICES

Appendix A

Data from Study I

A.1 Empirical Results SAGAT

Table A.1: Study I raw data and averages for complex condition representing participants responses to SAGAT probes.

Participants	Empirical Results in Complex Condition								
	Peripheral AOI					On Road AOI			
1	1	1	0	1	1	1	1	1	1
2	0	0	0	0	1	1	1	1	1
3	1	1	0	0	0	1	1	1	1
4	0	0	0	1	1	1	1	1	1
5	1	1	1	0	1	1	1	1	0
6	1	0	0	1	0	1	1	1	1
7	0	0	1	0	0	1	1	1	1
8	1	1	0	0	1	1	0	1	1
9	0	1	1	0	0	1	1	1	1
10	1	1	0	1	1	1	1	1	1
11	1	0	0	0	0	1	0	1	1
12	0	1	1	0	1	1	1	1	1
13	1	0	0	1	0	1	1	1	1
14	1	0	0	1	1	1	1	1	0
Total	64.3	50	28.6	42.9	57.1	100	85.7	85.7	
Average			48.6				90.5		

Table A.2: Study I raw data and averages for easy condition representing participants responses to SAGAT probes.

Participants	Empirical Results in Easy Condition							
	Peripheral AOI				On Road AOI			
1	1	1	1	0	1	1	1	1
2	1	1	1	0	1	1	1	1
3	1	1	1	1	1	1	1	0
4	1	0	0	1	1	1	1	1
5	1	1	1	0	0	1	1	1
6	1	0	0	1	1	1	1	1
7	0	0	1	0	1	1	1	1
8	1	1	0	1	1	1	1	1
9	0	1	0	1	1	1	0	1
10	0	1	1	1	1	1	1	1
11	1	1	1	1	0	1	1	1
12	1	1	0	0	1	1	1	1
13	1	0	1	1	1	1	1	1
14	1	1	1	0	0	1	1	1
Total	78.6	71.4	64.3	57.1	78.6	100	92.9	92.9
Average	70.0			95.3				

A.2 QN-ACT-R-SA Simulation Results SAGAT

Table A.3: Study I raw data and averages for complex condition representing QN-ACT-R-SA responses to SAGAT probes.

Simulation Runs	Model Results in Complex Condition								
	Peripheral AOI					On-Road AOI			
1	1	1	0	1	1	1	1	1	1
2	0	0	0	0	1	1	1	1	1
3	1	1	0	1	0	1	1	1	1
4	1	0	0	0	1	1	1	1	1
5	0	1	1	0	0	1	1	1	1
6	1	0	0	1	1	1	1	1	0
7	0	1	1	0	0	1	0	1	1
8	1	0	0	0	0	1	1	1	1
9	0	1	0	0	1	1	1	1	1
10	0	1	1	1	1	1	1	1	1
11	1	1	1	1	1	1	1	1	1
12	1	0	0	0	1	1	1	1	0
13	1	0	0	1	0	1	1	1	1
14	1	1	1	1	0	1	1	1	1
Total	64.3	57.1	35.7	50	57.1	100	92.9	85.7	
Average	52.9					92.9			

Table A.4: Study I raw data and averages for easy condition representing QN-ACT-R-SA responses to SAGAT probes.

Simulation Runs	Model Results in Easy Condition							
	Peripheral AOI				On-Road AOI			
1	1	1	1	0	1	1	1	1
2	1	0	1	1	1	1	1	1
3	1	1	0	1	1	1	1	1
4	1	0	1	1	1	1	1	1
5	1	1	0	0	0	1	1	1
6	0	0	0	1	1	1	1	1
7	1	1	0	0	1	1	1	1
8	0	1	1	0	1	1	1	1
9	0	1	1	0	1	1	1	0
10	1	1	0	1	1	1	0	1
11	0	1	1	1	1	1	1	1
12	0	1	1	0	1	1	1	1
13	1	0	1	0	0	1	1	0
14	1	1	0	1	1	1	1	1
Total	64.3	71.4	57.1	50	85.7	100	92.9	85.7
Average	65.7				92.9			

A.3 Empirical Result Post Experiment SA Questionnaire

Table A.5: Study I raw data and averages by condition representing participants responses to Post Experiment SA Questionnaire.

Participants	Critical Elements in Easy Condition						Critical Elements in Complex Condition					
1	1	1	1	1	1	1	1	1	1	1	0	1
2	1	1	1	1	1	1	1	1	0	1	1	1
3	1	1	1	0	1	1	0	0	0	1	0	1
4	1	1	1	0	1	0	1	1	1	0	1	1
5	1	1	1	1	1	1	0	0	0	1	1	0
6	1	1	1	1	1	1	0	1	0	0	1	1
7	0	1	0	1	1	0	0	0	1	1	0	1
8	1	1	1	1	1	1	1	0	1	1	1	0
9	1	0	1	1	1	1	1	0	1	1	0	0
10	1	1	1	1	1	1	1	1	1	0	1	0
11	1	1	1	1	1	1	1	0	0	0	1	1
12	0	1	1	1	1	1	1	1	0	0	1	1
13	1	1	1	1	1	1	1	0	0	1	0	0
14	1	1	0	1	0	1	1	1	1	1	1	0
Total	85.7	92.9	85.7	85.7	92.9	85.7	71.4	50	50	64.3	64.3	57.1
Average	88.1						59.5					

A.4 Model Result Post Experiment SA Questionnaire

Table A.6: Study I raw data and averages by condition representing QN-ACT-R-SA responses to Post Experiment SA Questionnaire.

Simulation Runs	Critical Elements in Easy Condition						Critical Elements in Complex Condition					
1	1	1	1	1	1	1	0	0	0	1	1	1
2	1	1	1	1	1	1	0	1	1	0	1	1
3	1	1	1	1	1	1	0	1	1	1	1	1
4	1	1	1	1	1	1	0	1	0	1	1	1
5	1	1	1	1	1	1	0	0	0	1	1	1
6	1	1	1	1	1	1	0	0	0	1	1	1
7	1	1	1	1	1	1	0	1	1	1	1	1
8	0	1	1	1	1	1	0	1	1	0	0	1
9	0	1	1	1	1	1	1	1	0	1	1	1
10	1	1	1	1	1	1	0	0	0	0	1	1
11	1	1	1	1	1	1	0	0	0	0	1	0
12	0	1	1	1	1	1	0	0	1	1	1	1
13	1	1	1	1	1	1	0	1	0	0	1	1
14	1	1	1	1	1	1	0	1	1	0	0	1
Total	78.6	100	100	100	100	100	7.14	57.1	42.9	57.1	85.7	92.9
Average	96.4						57.1					

Appendix B

Data from Study II

B.1 Empirical Results Brake Perception Response Time

Table B.1: Study II raw data and averages by condition (S1-S4) representing BPRT of eleven participants.

Participants	S1	S2	S3	S4
1	0.8	1.113	2.182	1.999
2	0.7	1.103	1.966	1.809
3	0.915	1.25	1.946	2.184
4	0.848	1.012	2.058	1.891
5	0.775	1.138	2.022	1.718
6	0.777	1.199	2.12	1.897
7	1.061	1.057	1.938	1.958
8	0.671	1.203	2.095	2.175
9	1.098	1.156	1.971	1.783
10	0.804	1.083	1.983	2.124
11	0.818	1.075	2.196	2.014
Average	0.84	1.13	2.04	2.00

B.2 QN-ACT-R-SA Results Brake Perception Response Time

Table B.2: Study II raw data and averages by condition (S1-S4) representing BPRT of eleven model simulation runs.

Simulation Runs	S1	S2	S3	S4
1	0.704	0.754	2.074	2.172
2	0.692	0.938	1.977	1.792
3	0.695	0.947	2.125	2.06
4	0.718	0.959	1.976	1.709
5	0.734	0.845	1.831	2.105
6	0.78	0.906	2.137	1.791
7	0.695	0.703	2.16	1.956
8	0.707	1.13	1.983	1.934
9	0.691	0.844	2.194	2.193
10	0.692	0.854	1.95	2.058
11	0.701	1.12	1.918	2.195
Average	0.71	0.91	2.03	2.00

Appendix C

Data from Study III

C.1 QN-ACT-R-SA Responses to SAGAT Probes

Table [C.1](#) on page [91](#) characterises QN-ACT-R-SA responses to SAGAT probes from Study III. The four tracks include the following four conditions: No-ACC and No Cellphone, ACC and Cellphone, No Cellphone and ACC, No-ACC and Cellphone. The probes were concerning seven critical elements that mostly represented nearby traffic vehicles and road signs. The results in table are a percentage score of one simulation run for seven critical elements. Each subcondition (e.g ACC) was tested twice and therefore we report twenty-two responses for eleven simulation runs that were carried out for the four main conditions.

Table C.1: Study III raw data by condition representing QN-ACT-R-SA responses to SAGAT probes.

Cellphone	No Cellphone	ACC	No-ACC
42.85714286	57.14285714	71.42857143	42.85714286
57.14285714	85.71428571	71.42857143	57.14285714
71.42857143	71.42857143	71.42857143	71.42857143
42.85714286	71.42857143	57.14285714	42.85714286
57.14285714	85.71428571	71.42857143	57.14285714
57.14285714	71.42857143	71.42857143	57.14285714
57.14285714	71.42857143	85.71428571	57.14285714
57.14285714	85.71428571	71.42857143	57.14285714
57.14285714	71.42857143	57.14285714	57.14285714
57.14285714	85.71428571	57.14285714	57.14285714
42.85714286	85.71428571	57.14285714	42.85714286
71.42857143	71.42857143	71.42857143	57.14285714
71.42857143	85.71428571	85.71428571	85.71428571
71.42857143	85.71428571	85.71428571	71.42857143
57.14285714	100	100	71.42857143
71.42857143	71.42857143	71.42857143	85.71428571
71.42857143	100	100	71.42857143
85.71428571	85.71428571	85.71428571	71.42857143
71.42857143	100	100	85.71428571
57.14285714	71.42857143	71.42857143	71.42857143
57.14285714	85.71428571	85.71428571	85.71428571
57.14285714	71.42857143	71.42857143	85.71428571
61.0	80.5	76.0	65.6