AN ENHANCED COMPUTATIONAL INTEGRATED DECISION MODEL FOR PRIME DECISION-MAKING IN DRIVING

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Abstract

Recent development of technology has led to the invention of driver assistance systems that support driving and prevent accidents. These systems employ Recognition-Primed Decision (RPD) model that use driver prior experience to make prime decision during emergencies. However, the existing RPD model does not include necessary training factors. Although, there is existing integrated RPD-SA model known as Integrated Decision-making Model (IDM) that includes training factors from Situation Awareness (SA) model, the training factors were not detailed (IDM has only six training factors). Hence, the model could not provide reasoning capability. Therefore, this study enhanced the IDM by proposing Computational-Rabi's Driver Training (C-RDT) model that improves the RPD component with 18 additional training factors obtained from cognitive theories. The designed model is realized by identifying factors for prime decision-making in driving domain, designing the conceptual model of the RDT and formalizing it using differential equation. The model is verified through simulation, mathematical and automated analyses and then validated by human experiment. Verification result shows positive equilibrium conditions of the model (stability) and confirms the structural and theoretical correctness of the model. Furthermore, the validation result shows that the inclusion of the 18 training factors in the RPD training component of the IDM can improve driver's prime decision-making. This study demonstrated the ability of the enhanced C-RDT model to backtrack and provide reasoning on the undertaking decisions. Hence, the model can also serve as a guideline for software developers in developing driving assistance systems.

Keywords: Computational model, Integrated Decision-making Model, Situation Awareness model, Prime Decision-Making, Driving Assistance Systems

Abstrak

Kemajuan terkini dalam bidang teknologi telah mendorong penciptaan sistem bantuan pemanduan yang menyokong pemanduan pemandu serta mencegah berlakunya kemalangan. Sistem ini mengguna pakai model Pengecaman Keputusan Utama (RPD) yang menggunakan pengalaman terdahulu pemandu semasa membuat keputusan penting dalam keadaan kecemasan. Model RPD sedia ada, walau bagaimanapun, tidak mempunyai faktor latihan yang diperlukan. Meskipun terdapat model RPD-SA yang dikenali sebagai Model Pembuat Keputusan Berintegrasi (IDM) yang merangkumi faktor latihan dari model Kesedaran Situasi (SA), namun faktor latihan tidak diperincikan. IDM hanya mempunyai enam faktor latihan. Oleh yang demikian, model tersebut tidak dapat memberikan keupayaan penaakulan. Oleh itu, kajian ini memperkukuh model IDM dengan mencadangkan model Pengiraan-Latihan Pemandu Rabi (C-RDT) yang menambah baik komponen RPD dengan penambahan 18 faktor latihan yang diperoleh daripada teori kognitif. Model yang direkabentuk direalisasikan dengan mengenal pasti faktor pembuatan keputusan utama ketika memandu, mereka bentuk model konsep model RDT dan memformalkan model ini dengan menggunakan persamaan perbezaan. Model ini kemudiannya ditentusahkan menerusi analisis simulasi, matematik dan automatik serta disahkan menerusi eksperiman manusia. Hasil penentusahan menunjukkan keadaan keseimbangan model (kestabilan) yang positif dan mengesahkan ketepatan struktur dan teori model. Tambahan pula, keputusan pengesahan model memaparkan bahawa kemasukan 18 faktor latihan dalam komponen latihan RPD yang terdapat dalam IDM boleh meningkatkan pembuatan keputusan utama pemandu. Kajian memperlihatkan keupayaan model C-RDT yang dipertingkatkan untuk jejak ke belakang dan membuat penaakulan kepada keputusan yang dibuat. Oleh itu, model ini boleh menjadi panduan kepada pembangun perisian dalam membangunkan sistem bantuan pemanduan.

Kata kunci: Model Perkomputan, Model pembuatan keputusan bersepadu, Model kesedaran situasi, Pembuatan keputusan utama, Sistem bantuan pemanduan

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Dedication

This thesis is dedicated to my late mother Malama Hafsat Hamidu Umar and Late Brothers and Sisters. May Allah join us all in Aljannatul-Firdaus.

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List of Abbreviations

AIDA	Affective Intelligent Driving Agent
ARPDT	Automaticity Recognition Primed Decision Training
BDI	Belief Desire Intention
BI	Business Intelligence
C2	Command and Control
CDDP	Cognitive-Driven Decision Process
CDM	Classical Decision Making
CIC	Combat Information Centre
CMSA	Cognitive Model of Situation Awareness
COA	Course of Action
COGAS	COGnitive Assistant System
C-RDT	Computational-Rabi's Driver Training
C-RPD	Computational Recognition Primed Decision
CTA	Cognitive Task Analysis
DAS	Driver Assistance System
HCA	Human-Centered Automation
ICU	Intensive Care Unit
IDM	Integrated Decision Making
IVIS	In-Vehicle Information System
LLT	Long-Term Training
LTM	Long-Term Memory

MM	Multifactorial Model
MP	Model of Processes
MR	Mental Representation
NDM	Naturalistic Decision Making
PoA	Performance of Action
RDT	Rabi's Driver Training
RPD	Recognition Primed Decision model
SA	Situation Awareness model
SKR	Skill/Knowledge/Rule
SR	Situation Retrieval
STT	Short-Term Training
TCI	Task-Capability Interface model
UMD	Unified Model of driver behaviour
WM	Working Memory

CHAPTER ONE

INTRODUCTION

1.0 Background

Globally, road accident is one of the causes of death of young persons (ages from 15 to 29 years) and the 8th leading cause of death (World Health Organisation, 2017). For instance, in 2017, about 1.25 million lives were lost as a result of road accident. Ninety per cent of the accidents occurred in the middle-income countries (e.g., China, India, Mexico, Thailand and Russia) and in the low-income countries (e.g., Kenya and Bangladesh) and ten per cent in the high-income countries (e.g., U.S and Japan). Road accident has been predicted to become the seventh leading cause of death by 2030 if no appropriate measure has been taken (WHO, 2017).

However, the recent development of technology has led to the invention of driver assistance systems to facilitate drivers in preventing the number of accidents on the road. For example, it provides warnings or interferes in the process of manoeuvring the vehicle (Vaa, Assum & Elvik, 2013). Gaining an insight into the development of drivers' assistance system, driver behaviour models such as cognitive model of situation awareness (Endsley, 2000; Jeon, Walker & Gable, 2015; Stanton, Salmon, Walker, Salas & Hancock, 2017) and naturalistic decision making model such as the Recognition-Primed Decision (RPD) model (Klein, 2008, 2015; Klein, Calderwood, & Clinton-Cirocco, 2010) are reviewed. Although the review of literature showed that there is existing Recognition-Primed Decision – Situation Awareness (RPD-SA) model called integrated decision making (IDM) model for pilot decision process (Donnelly, Noyes, & Johnson 1997; Noyes, 2012). The IDM model is divided into awareness and RPD training part. The awareness part of the IDM deals with the SA while the RPD part of the IDM deals with the prime decision making process. However, in the RPD part of the IDM more training factors are needed which the current study deems to address by enhancing the RPD part of the IDM using the training factors relevant for prime decision making in driving domain gained from SA model and other literatures. This is because SA model has a learning mechanism (Endsley, 2017) to complement the underlying drawbacks. The importance of these missing training factors cannot be underemphasized as it is essential for any critical decision-making process.

The RPD model (Klein, 2008, 2015; Klein et al., 2010; Salas, Rosen, & DiazGranados, 2010) is an example of a decision model and was designed to explain how human specialists make decisions based on prior experiences. The RPD model is a conceptual model of intuitive pattern-recognition-based decision-making, which consists of three components, namely situation assessment, serial option evaluation and mental simulation of options. In situation assessment, the decision maker involves in looking for pattern and experiences; a serial option evaluation includes watching for important clues, recognising reasonable goals, providing expectancies and proposing appropriate types of reactions. The process by which actions are evaluated is called a mental simulation, and is a process to see if the chosen consequence will be workable or not before any action is taken. The RPD model has been used to study human performance in different domains such as in aviation (Winter, Fanjoy, Lu, Carney & Greenan, 2014; Donnelly et al., 1997; Noyes, 2012), business (Lu, Niu, & Zhang, 2013), training electric power systems operators (Greitzer, Robinson, Podmore & Ey, 2010), health care (Resnick, 2012) and firefighting (King, 2011; Klein et al., 2010; Resnick, 2001).
Additionally, a poor situation awareness level causes accidents more than the over speeding and inappropriate driving techniques (Jeon, Walker & Gable, 2014).

The Endsley Model of Situation Awareness is the most widely used cognitive model to explain dynamic situation such as driving (Jeon et al., 2014; Jeon et al., 2015; Kaber, Jin, Zahabi, & Pankok, 2016). It describes causal factors that make driver embarks on specific activities. Thus, the analysis also allows researchers to understand how driver's embarks on certain activities that are essential to comprehend human errors and to design a computational model which can be used in driving assistance systems to reduce the human errors (Oppenheim et al., 2010, 2012).

As stated in RPD, a situation understanding or awareness capability is the primary substance in naturalistic decision making (Endsley, 2000; 2017). It is related to situation awareness concept, which is the perception of the environmental elements within a volume of time and space, the comprehension of their meaning, and the projection of their status within limited time (Endsley, 2000; Wickens, 2008). SA consists of three main components, based on the definition, namely perception, comprehension and projection-: 1) perception is to observe the elements of the environment, 2) comprehension is to understand the observed components of the environment and 3) projection is to make a decision based on the observation and understanding of the elements in the environment. The SA model has been used in different domains, which includes education (Liu, Mao & Zhan, 2008), facility management (Gheisari & Irizarry, 2011), aviation (Helldin & Falkman, 2012), military (Ozyurt, Doring, & Flemisch, 2014; Stanton, 2014) and driving (Salmon, Lenné, Walker, Stanton & Filtness, 2014; Jeon et al., 2014), sport (Macquet & Stanton, 2014; Neville & Salmon, 2016), healthcare (Bleakley, Allard & Hobbs, 2013; Schulz, Endsley, Kochs, Gelb & Wagner, 2013) and emergency services (Seppänen, Mäkelä, Luokkala, & Virrantaus, 2013) to mention a few.

Moreover, there are three approaches to decision making models, namely: normative, prescriptive and descriptive (Smith, 2016). Each of these approaches has its own functionalities. For example, in normative (analytical) approach, time is spent on option generation and each option generated is evaluated against each other before choosing the best. The prescriptive model is a behavioural based model that is not decision-centrered. Rules are instead fixed and it does not focus on experienced and prior knowledge. Moreso, its emphasis is not on time sensitivity. Descriptive model is a decision-centered approach that describes decision-making processes in an uncertain dynamic environment. However, normative approach is suitable in circumstances when adequate time to deliberate and analyse the situation is the main criterion prior to any decision making process. For example, in the command and control applications and other real-life situations, such as when a driver is making a decision during emergency situation where time constraint is considered critical, and uncertainty is high, the naturalistic decision making (descriptive) models are more appropriate (Azuma, Daily, & Furmanski, 2006; Resnick, 2012).

Since driving combines cognitive and physical abilities that result in skilled driving, the practised ability while driving results in increased situation awareness, which in turn translates into conscious and unconscious decision making. This practice translates into the experience, and in turn, becomes skilled in picking up complex signs in making a critical decision. The critical decision making process in driving should aim to achieve the goal of combining the ability to develop the cognitive decision-making process with the physical skills required. Moreover, it is essential to improve the necessary methods through experience, and to apply methods appropriately based on the environment and current situations. These goals can be achieved by intuitions.

Intuition is the way experience is translated into action to allow easy recognition of what is going on and how to react by making decisions rapidly without conscious awareness or efforts. Intuition comes from enhanced senses that, in turn, lead to rapid decision making (Leland, 2009; Smith, 2016).

As a demonstration of rapid (prime) decision making, drivers observe information and quickly make intuitive and unconscious decisions when something suddenly happens while driving. By taking decisive actions, while driving in unexpected situations, such as swerving to a safe part of the road, or stopping quickly to avoid any hazards from occurring, a prime decision has been made. Another example of rapid (prime) decision making is sudden braking action during congested traffic. From this example, it can be concluded that prime decision is the reaction of the driver at that particular time to avoid unwanted consequences/experiences. These skills could be acquired through experience and training. The skill allows the driver to react reflexively in such an emergency situation. Similarly, the driver's situation awareness (SA) is also one of the crucial aspects of the decision-making process whereby driver must first be aware of the impending critical situation to avoid potential accident cases.

Thus, the objective for a critical decision making process is to provide the learner with experiences and instruction on cues, patterns, mental-models, and actions that efficiently establish a collection of well-learned concepts that enable the decision maker to perform mainly at the skill-based level of processing while providing enough knowledge-based foundation to perform well in new situations. Critical decision making is an important component of computational modeling (Vancouver & Weinhardt, 2012).

Computational models are computer programs that make use of simulation process to understand related phenomena. There are many studies in computational modelling, each study using different techniques. For example, a study by ChePa, Aziz, and Gratim (2017) designs a computational model for analyzing managers' performance during stress. Tabatabaei and Treur (2017) design a computational model for the role of advertisement and expectation in lifestyle changes. Abro and Treur (2017) design a computational cognitive model of self-monitoring and decision making for desire regulation. Formolo, Van Ments and Treur (2017) design a computational model to simulate development and recovery of traumatized patients. Ting, Zhou and Hu (2010) design a computational model of Situation Awareness for MOUT (Military Operation on Urban Terrain) simulations, and Ji et al. (2007) design a fuzzy logic-based computational recognition-primed decision model.

Hence, computational modelling is a useful tool in understanding systems by predicting possible behaviours through numerous dynamic variations of the variables. Also, a computational model ensure that a theory (1) is internally reliable, (2) accounts for the phenomena claimed, (3) is sufficiently specified, and (4) is exact and clear (Vancouver & Weinhardt, 2012, Adner, Polos, Ryall & Sorenson, 2009; Davis, Eisenhardt, & Bingham, 2007; Farrell & Lewandowsky, 2010; Lewandowsky & Farrell, 2011; Harrison., Lin, Carroll, & Carley, 2007). For example, computational models require theorists to reason well as the models are precise, clear, and easy to identify potential faults in them.

Hence, the drawbacks of RPD part of the IDM model can be addressed by enhacing the RPD component of the IDM using 18 training factors such as Basic practice, Practice, Basic skills, Acquired skill, Sensory ability, Driver abilities, Rehearsed experience, Attention, Priming, Habitual-direction acion, Goal-directed action. Other factors include Involuntary automaticity, Voluntary automaticity, Acquired automaticity, Experienced automaticity, Potential hazardous information, Perception about Task and Perception about Risk that are relevant for Prime Decision Making in driving domain.

1.1 Motivation

Road accident is one of the causes of death among the young people and is the 8th leading cause of death in the world (W.H.O., 2017). It is a fact that the accident rate globally is alarming and poor decision-making skills of drivers have been observed to be the major contributing factors of road accidents (Endsley & Connors, 2008; Mashadi & Majidi, 2014; Rotbring, 2010). Therefore, this study is motivated by this phenomenon and attempts to design an enhanced computational integrated decision making model called Rabi's-Driver Training model (C-RDT) for prime decision making in driving domain.

1.2 Problem Statement

Scientists in the field of computer science, psychometrics, ergonomics, military, and command and control, maintain a strong connection to the Naturalistic Decision-Making research domain (Zsambok & Klein, 2014). This research explains how people make important (prime) decisions under demanding situations with time constraint in real-world settings (Klein, 2008, 2015).

However, in the case of transportation domain, poor decision-making skills of drivers (that is due to human errors) (Salmon, Stanton, & Jenkins, 2017) have been observed as major causative factors of road accidents (Endsley & Connors, 2008; Mashadi &

Majidi, 2014; Rotbring, 2010). Driving a car involves a constant process of perception, understanding, action choice, and action execution (Inagaki, 2011; Inagaki & Itoh, 2013). An error in situational recognition may occur while driving a car, and the error can sometimes result in an 'erroneous' behaviour of the driver (Inagaki, 2011). These human errors are ranging from driver's distraction (Antonin, Kimihiko & Rencheng, 2014), lack of focus (Williams, Peters & Brazeal, 2013), over speeding due to driver's fatigue (Liu et al., 2014), driver's drowsiness (Ebrahim, Abdellaoui, Stolzmann & Yang, 2014), lane changing (Faulk, Paine, Paine, & Irwin, 2010), car following (Faulk et al., 2010), unnecessary overtaking (Vinel, Belyaev, Egiazarian & Koucheryavy, 2012) to a vehicle control (Kim, Kim & Lee, 2014).

Prior studies have provided some solution to reduce human errors in driving such as an affective intelligent driving agent (AIDA) (Williams et al.,2013, Yang, Jo, Kim & Kwon, 2013), a brain signal for driving assistance technologies (Kim et al., 2014), a fuzzy prediction system for the forecasting and estimation of driving fatigue (Liu et al., 2014), drowsiness warning systems (Ebrahim et al., 2014) and in-vehicle information systems (IVIS) (Antonin et al., 2014). Designing driver assistance systems (DAS) such as the aforementioned plays a vital role in implementing assistance tasks to improve and complement driver capabilities for perception and comprehension (Inagaki, 2011). Perception and comprehension are fundamental components of RPD model (Klein 1993, 2008, 2015).

However, in RPD, some essential training factors that are necessary and relevant in enhancing the effect of training on the experience of the drivers to make prime decision are inadequate (Klein 1993, 2008, 2015; Klein et al., 2010; Fadde, 2013; Javor, Pearce, Thompson, & Moran, 2014; McDevitt, 2017). Some of the training factors lacking in RPD are presented in the SA model (Endsley, 2016). Without those training factors, the decision maker will find it difficult to recognize situation, to act based on the situation assessed in a driving environment, and to acquire the experience to conduct a mental simulation of options.

Although, there exists an integrated RPD-SA model called Integrated Decision-making Model (IDM) for pilot by Donnelly et al. (1997) and Noyes (2012), the IDM offers less comprehensive training factors in it's RPD component by offerring only six (6) training factors such as experience, knowledge/rules, goals, time pressure, intention and automaticity. Therefore, there is a need to enhance the model to improve on the RPD component. This can be achieved by expanding some of the IDM factors such as experience and automaticity, being composite constructs, that need to be broken down into various interrelated factors. Other factors are obtained from SA model and other literatures, and are added to the RPD component of the ID Model. However, if the constructs are not broken down, a comprehensive conceptual model that has training factors relevant to train drivers in order to enhance their experiences to make prime decision particularly during demading situations cannot be achieved. The model has been tested in aviation domain but yet to be tested in driving domain. Moreover, it is a conceptual model and yet to be computationalised.

Hence, this study propounded an enhanced Integrated Decision-making Model for prime decision-making in driving called Rabi's Driver Training (RDT) model, which improves on the RPD component of the IDM by adding eighteen (18) training factors relevant for prime decision making.

The model is then computationalised to have an enhanced Computational Integrated Decision-making Model called Computational-Rabi's Driver Training (C-RDT) model. The computational model is important in handling reasoning ability that allows backtracking on why certain prime decision has been taken. Generally, the model is likely to enhance the experience of the driver (the automaticity level) in driving domain.

1.3 Research Questions

The research questions considered to achieve the objectives of the study are as follow:

1. What are the training factors relevant for prime decision-making in driving domain?
2. How can Integrated Decision-making Model be enhanced?
3. How to computationalize the enhanced Integrated Decision-making Model model?
4. How can the enhanced computational Integrated Decision-making Model be evaluated?

1.4 Research Objectives

The main aim of this study is to design an enhanced computational integrated decision-making model for prime decision making in driving domain.

In order to achieve the intended aim, four objectives have been formulated:

1. To identify training factors relevant for prime decision-making in driving domain.
2. To enhance the Integrated Decision-making Model by including relevant training factors to have a comprehensive conceptual model.

3. To computationalize the enhanced Integrated Decision-making Model in order to have a model with a reasoning ability to backtrack.
4. To evaluate the enhanced computational Integrated Decision-making Model by verification and validation

1.5 Research Scope

This study covers only car (road) under land transportation that is categorized under the driving domain. It includes the prime decision-making attribution of drivers within the domain mentioned and identifies relevant training factors for prime decision-making based on cognitive and naturalistic decision making theories. All these scopes enable the study to develop an enhanced computational Integrated Decision-making Model for prime decision making in the driving domain. In addition, the study was validated by a human experiment using the driving game simulator (application) and a set of questionnaires were used to test the workability of the enhanced model for prime decision-making. The designed model is not compared to the current situation/technology in the automobile industries.

1.6 The significance of the Study

The study designs an enhanced computational model (called C-RDT) model that influences prime decision-making in driving that can later be used in driving assistance systems for a better decision. Precisely, the significance of this study could be viewed from two perceptions: theoretical and practical contributions.

1.6.1 Theoretical Contribution

Theoretically, this study has four different contributions. Firstly, the identification of training factors relevant for prime decision-making in driving domain. Secondly, the study designed an enhanced Integrated Decision-making Model that is comprehensive with more training factors included such as Basic practice, Practice, Basic skills, Acquired skill, Sensory ability, Driver abilities, Rehearsed experience, Attention, Priming, Habitual-direction acion, Goal-directed action. Other factors include Involuntary automaticity, Voluntary automaticity, Acquired automaticity, Experienced automaticity, Potential hazardous information, Perception about task and Perception about risk that are relevant in achieving prime decision making. Thirdly, this study designed an instrument that is a questionnaire based on the enhanced RPD training component of the ID model, by integrating all external and temporal factors in order to validate the designed enhanced model. Lastly, the enhanced computational model designed by this study help in handling reasoning ability that allows backtracking in prime decision making process.

1.6.2 Practical Contribution

Practically, the driver assistance systems that would be designed based on the designed Computational-RDT model would be able to make better reasoning ability (Koo et al., 2015) and alert the driver on when and what prime decision to make. Hence, it serve as a guideline for software developers on the development of driving assistance systems that has better reasoning ability in handling prime decision-making processes. In relation to problem domain perspective without the designed RDT model, subsequent research on RPD would not have an advantage of a comprehensive model with more training components integrated.

1.7 Summary of the Chapter

This chapter introduced the background of the study with the main study problem and objectives. It further discussed the scope and significance of the study. The next chapter (Chapter Two) covers literature reviews within the domain of the study that provided a theoretical foundation for the study.

CHAPTER TWO

LITERATURE REVIEW

2.0 Introduction

This chapter gives an overview of models of driver behaviour, and detail review of the related literature on decision-making theories and models. In particular, section 2.0 focuses on introduction, modelling driving behaviour in section 2.1, and decision-making in section 2.2. In addition, the chapter review literature on hybridization in section 2.3 and computational modelling in section 2.4, discussion of the chapter in section 2.5. Finally, section 2.6 gives the summary of the chapter.

2.1 Modelling Driving Behaviour

The history of modelling driver behaviour started in 1938 when Gibson and Crooks provided situational driver behaviours to road infrastructure elements in the field of human factors to comprehend the nature of driving, and later to enhance safety, driver education and training (Fastenmeier & Gstalter, 2007) for the drivers. The models of driver behaviour can be classified into two major categories (based on major distinctive features), namely the descriptive and functional models as shown in Figure 2.1.

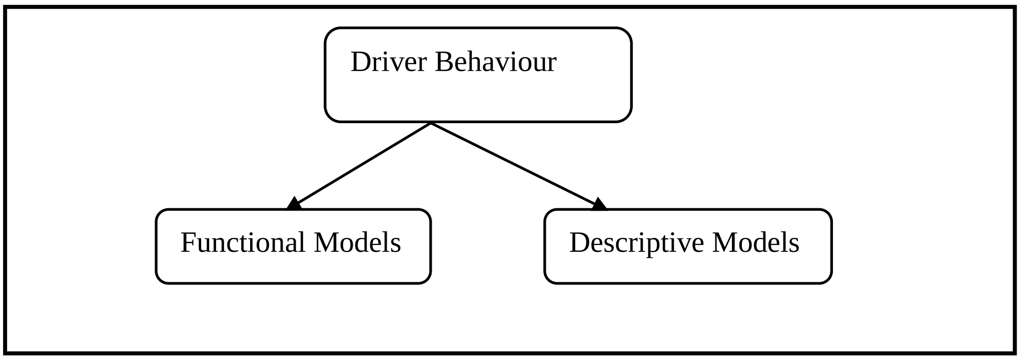


Figure 2.1. Classifications of models of driver behaviour
Adapted from (Oppenheim et al., 2012. P.35)

First, the descriptive models define the driving task in relations to what drivers do. These models try to explain the whole driving task or some elements of it, which are about what driver has to do. Significant characteristics of such models are that they are not predictive, but somewhat analytical (Carsten, 2007). The models have provided a strong motivation for driving safety research (Lee, 2008; Salvucci, 2006).

Second, the functional models describe why driver behaves the way he/she does, and how to forecast driver's performances in challenging and repetitive situations. These challenging situations are the highest performance abilities, and the repetitive situations are the regular (not necessarily the finest) behaviours (Shinar & Oppenheim, 2011). The functional models strongly focus on the driver's cognitive state and have included important behavioural modification concepts such as motivation, or risk assessment. These models have the potential for implementation either by producing a simulation of the driver behaviour, by integrating them into some already existing traffic simulation tools or driver assistive devices, such as in collision warning systems or in the formulation and development of the system (Shinar & Oppenheim, 2011; Oppenheim et al., 2012). Therefore, the cognitive theory/model of situation awareness (Endsley, 2000; 2017) and naturalistic decision-making theory (Hoffman, & Klein, 2017; Klein, 2008; Militello, Lipshitz & Schraagen, 2017) can be classified as one of the examples of a functional model.

2.2 Decision-Making

Decision-making is an essential cognitive process of human behaviour whereby an ideal alternative is chosen among options established on specific standards (Azuma et al., 2006; Wang, 2007). With respect to decision-making, decision theories and decision models are used interchangeably in the literature. Decision-making can be categorized into three theoretical approaches, namely normative, prescriptive and descriptive approaches (Wang & Ruhe, 2007; Smith, 2016). Philosophically, there are two models toward decision-making namely, i) the rationalistic (classical) model, and ii) the naturalistic model (Azuma et al., 2006; Antonik, 2007; Pfaff et al., 2014). The primed decision-making process is one of the key elements in most naturalistic decision-making models. Hence, the normative and prescriptive approaches can be classified as the rationalistic (classical) theory/model while descriptive approach can be classified as the naturalistic theory/model. The classification of the decision making theories/models are shown in Figure 2.2.

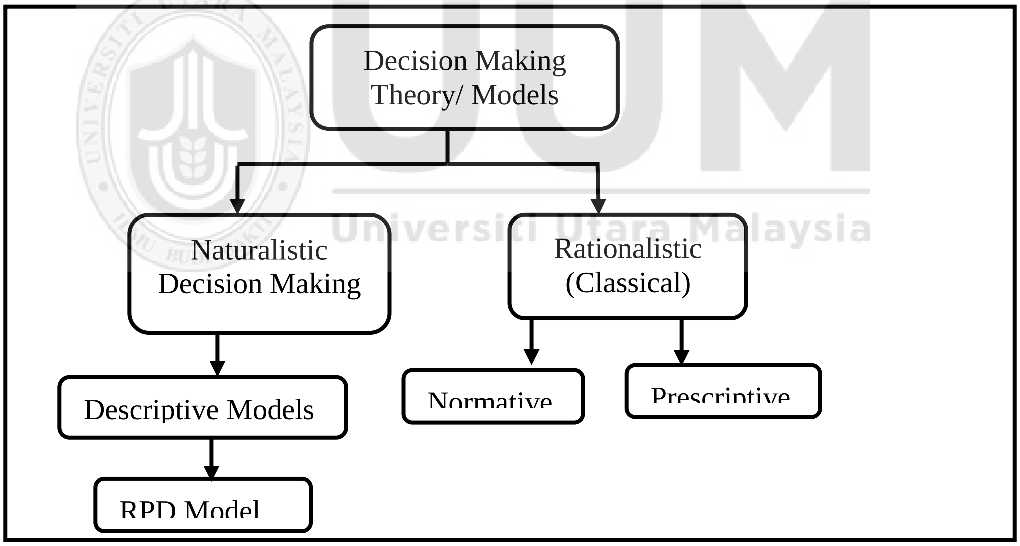


Figure 2.2. Classifications of Decision Making theories/models

2.2.1 Naturalistic Decision-Making

Naturalistic Decision Making (NDM) field emerged in 1989 to comprehend how people make decisions in applied, natural settings as opposed to laboratory settings (Klein & Hoffman, 2008; Klein, 2008, 2015). It takes research out of the laboratory into the dynamic natural environment, from the inexperienced to the experienced decision makers and from the decision events to the real processes. The Naturalistic Decision Making (NDM) reflects how experienced people make decisions. It is a method in which people use their experiences to recognize and assess their situations and make decisions in dynamic, fast-paced uncertain environments. In this method, decision makers are more concerned about sizing up the situation and refreshing their situation awareness through feedback than they are about developing multiple choices to compare. In this case, Situation Awareness (SA) is more critical than deliberating on various courses of action (Antonik, 2007). The naturalistic decision settings have some basic characteristics, which are described in Table 2.1.

Table 2.1

Characteristics of Naturalistic Decision Settings

S/No	Features	Description
1.	Undefined changing environments	The situations are not static, straightforward or unambiguous.
2.	Ill-structured problems, Shifting, ill-defined, or competing goals	The problem may be unclearly defined. The situation is rarely dominated by a single, well-understood goal or value, outside the laboratory.
3.	Action/feedback loops	A sequence of activities and decisions will alter succeeding actions and goals.
4.	Time stress	The time pressure leads to decision making involving heuristics, biases and cognitive shortcuts. E.g., travelling by Aircraft to cover many kilometres in a few minutes, so time is critical.
5.	High stakes and risk	Results of error are prominent, even to the point of life/death
6.	Multiple players and teams	Many problems of interest to NDM investigators involve not a single decision maker, but many individuals who are actively engaged in one role or other.
7.	Organizational goals and norms	Naturalistic decision making often takes place in organizational settings. The general mission statement or goals of organizations apply pressure that may conflict and bias the situation.
8.	Experienced decision makers	As most professionals are experienced or intermediates novices are rarely studied in NDM.

Source: Adapted from (Orasanu & Connolly, 1993; Deitch, 2001).

Naturalistic decision-making provides an understanding of how a decision is made in applications where time is crucial. The model of NDM is concerned with discovering an action that is “workable,” “timely,” and “cost-effective.” (Klein, 2008). Good decision-making in an emergency environment follows same traits where experience can differentiate most vital cues to achieve a prime and accurate decision (Klein, 2008).

The NDM is a pattern of change in decision-making theory from the classical, analytical and rational approach to a descriptive, intuitive and recognitional decision-making model (Klein, 2015). In the process of Classical Decision-Making (CDM) approach, human experiences are ignored. In the NDM, instead of evaluating every alternative available, situation assessment based on the operators' experience is carried out, and a single workable alternative is selected. If the solution is not working, then the next choice will be generated. A faster selection of an alternative is possible, based on similar situation in the past using experience (Klein, 2015).

Table 2.2

Comparison of Classical Decision-Making and Naturalistic Decision-Making approaches

CDM	NDM
▪ Input-output orientation- predict chosen alternative	▪ Process orientation- describe cognitive process of expert decision maker
▪ Choice – Concurrent available options	▪ Situation action matching – serial evaluation, single option
▪ Comprehensiveness – deliberate and analytic	▪ Situation assessment – recognition and automatic
▪ Context-free formal modelling- quantitative and prescriptive model	▪ Context-bound informal modelling- driven by experience and knowledge

In a nutshell, it is a descriptive approach of arriving at a decision. The idea of the comparison between classical decision-making (CDM) approach and naturalistic decision-making (NDM) was gained from Norwawi (2004) and is summarised in Table 2.2.

Gary Klein introduced naturalistic decision-making model named 'Recognition-primed decision' (RPD). The model describes the decision process in a naturalistic environment (Klein, 2008) and it has key features that are further summarized by Wong (2000) as follows:

- Situation assessment is the central part of decision-making.
- Situation assessment is based on feature matching and story building.
- The situation is based on cues presented over a period.
- A single generation of the option at a time.
- Serial option evaluation is required not concurrent.

Next is the discussion of the three different approaches.

First, the normative approach assumes the individual is logical and rational and is concerned with how to make decisions and what to do (in theory) (Smith, 2016) while the prescriptive approach attempts to improve decisions and provide answer to question of what people should and can do (Smith, 2016). Lasly the descriptive approach describes how individuals reach their decisions and are process-focused and should also respond to what people do, or have done (Smith, 2016).

By comparing these three approaches, in the conventional normative or analytical method much time will be spent on generating options and evaluating each option against each other before the best option is selected (Polic, 2009). For a well-defined-problem, the decision model is implemented in a precise and static environment under certainty.

Table 2.3

Features of Normative, Prescriptive and Descriptive Decision-Making Models

Approaches	Features	References
Normative	▪ Based on Classical Approach ▪ Standard decision-making method ▪ Decision problems are broken into components ▪ Decisions under certainty ▪ Alternatives are known ▪ Outcomes are known ▪ Ability to make the optimum choice ▪ Based on rational choice and behaviour ▪ Generate and compare options ▪ Provide risk assessment to guide decision-making ▪ Suitable for static environment and well-defined problem ▪ Lead to loss of time competitiveness and inaction.	Azuma et al. (2006); Wang and Ruhe (2007); Polic (2009); Towler (2010); Standing (2010); Smith (2016)
Prescriptive	▪ Behavioural Approach ▪ Heuristics(“easy and quick”) method ▪ Rules of thumbs, shortcuts, adaptive, automatic ▪ Options are generated based on skill and knowledge ▪ Inform of production rules ▪ Remembering the sequence of action as an example.	Standing (2010); Smith (2016)
Descriptive	▪ Behavioural and decision centred Approach ▪ Describes how people make a decision in “real-life.” ▪ Decisions under uncertainty and time sensitive environment ▪ Recognising bounded-rationality ▪ Intuitive and automatic processing ▪ Decision varies among experience, knowledge and complexity of the decision. ▪ It is based on pattern recognition, mental models and associative reasoning etc. ▪ Gives accurate situation assessment ▪ Influence of similarity in human perception and problem solving ▪ Recalling of similar cases ▪ Example based ▪ The use of mental imagery	Standing (2010); Smith (2016)

However, the normative approach could lead to loss of time competitiveness and inaction. Similarly, the conventional model is not fit for crucial decision-making since considerable time will be taken for evaluating all options (Polic, 2009). Therefore, in an emergency environment where rapid decisions are required, a faster decision-making model is needed. The features of the three approaches are summarised in Table 2.3.

Based on the features of the three approaches listed in Table 2.3, descriptive approach is the best to explain the decision-making processes in a dynamic and uncertain environment like driving that require timely decision. Moreover, decision makers within the normative approach lack expertise and experience and they do compare options to choose the optimum solution. As a result, they require more resources (time and mental efforts) rendering the approach impracticable, if not impossible (Kallion, 2000; Resnick, 2012; & Winter et al., 2014).

Therefore, this study is built based on descriptive approach which describes how decisions are made based on individual experiences. In addition, such an approach is based on real life situations and environment such as a naturalistic decision-making process and this is related to the RPD concepts in explaining prime decision-making during emergencies.

2.2.1.1 Recognition-Primed Decision Model

According to Kallion, (2000) “the RPD model asserts that decision makers draw on their experience to identify a situation as representative of or similar to a particular class of problem. This recognition then leads to an appropriate course of action (COA), either directly when prior cases are sufficiently similar, or by adapting previous approaches. The decision maker then evaluates the COA through a process of mental simulation”.

The RPD model was developed by Dr. Gary Klein after an interview with fire-ground commanders, to learn their strategies and account for their abilities in using experiences to handle extreme time pressure and other naturalistic decision making features. Klein’s model is concerned with how expert decision makers try to be efficient under high stress and time pressure. In addition, they compared the decision-making processes of experts and novices (Klein, 1993; Salas et al., 2010). From this perspective, the recognition-primed is defined as the fast, automatic generation of single decision option, rooted in extensive domain-specific knowledge and the recognition of patterns from prior experiences (Salas et al., 2010). Thus, the process is what Klein refers to as recognition-primed decision-making and it is made up of three main stages-: 1) situation assessment, 2) serial option evaluation, and 3) mental simulation (Klein, 2008).

For the *Situation Assessment*, the decision maker is involved in looking for pattern and experiences (Klein, 2008). Later, at the *Serial Option Evaluation*, it allows the decision maker to evaluate action alternatives one at a time until a satisfactory one is found. Actions are selected from an action queue where they are arranged according to their typicality. Thus, the first action evaluated is that rated as the most typical response to the particular situation (Klein, 2008). The process by which actions are evaluated is called a mental simulation. Next, at the *Mental simulation*, an action is assessed either it is satisfactory or not. The decision maker acts it out in his/her imagination by mentally simulating the consecutive stages to be executed (Klein, 2008).

The potential results of these stages, the obstacles that are likely to be met, and how they can be resolved are being handled at this level. As a consequence of the simulation, the decision maker implements the action as it is, modifies it, or rejects it altogether and turns to examine the next action in his or her action queue. Another outcome of mental simulation is a reassessment of the situation (Klein, 2008). Figure 2.3 shows the diagram of RPD model.

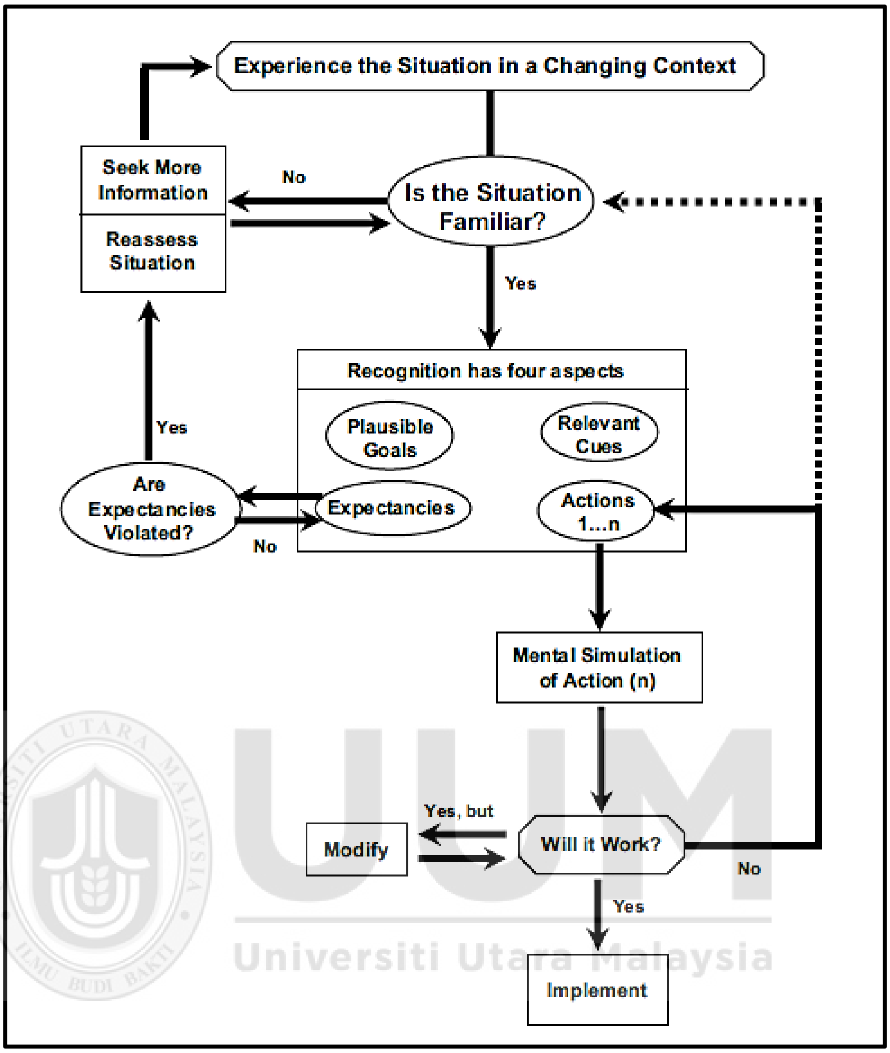


Figure 2.3. The Recognition-Primed Decision Model.
Adopted from (Klein, 2008).

Figure 2.3, focusing on relevant cues and identifying causal factors reduces the information overload and sense of confusion that hamper novice decision makers. The identification of causal factors also helps to establish accurate expectations, which together with plausible goals are essential in selecting an appropriate action. The main advantage of the second step in the model, (serial selection by typicality), is that a reasonably matching action can be implemented. The last step in the model, (mental simulation), guards against the mistakes that result from uncritical thinking (Klein, 2008).

The RPD model highlights the crucial role of domain-specific experience in expert decision-making. No stage in the model can be implemented efficiently without such knowledge. Thus, the model has challenging implications as regards the nature of expertise. Hence, the RPD model explains how individuals can make right decisions without comparing alternatives (Evans, 2008). The goal of RPD is to explain the effective decision making that does not require a concurrent evaluation of option (wrestling with different possibilities to pick the best one).

Decision making in natural settings has established that decision makers employ the RPD model in making rapid decisions. The model influences expertise and experience such that an expert must recognise the situation domain. Also, it is a decision maker centred model where the decision maker must have full control of the situation to achieve rapid response with minimum resources required (Kallion, 2000). This means that it reduces the time it takes the decision maker to go through different options to make a choice. The RPD can be considered as an intuitive model that requires little cognitive effort as the responses are coming from patterns already laid down in the mind of the decision maker; hence, it reduces the mental stress to think of the options (time and mental effort) (Kallion, 2000; Klein, 2008). The situation is perceived, the elements are recognized, and the experience for a particular response or procedure has been successful in the past to stimulate the decision "to act". Klein (1993) summarizes the features that RPD model has that differentiate it from the analytical decision models as follows:

- The first option chosen is usually reasonable and workable. It is not semi-random generation and selective retention. It demands the decision maker to generate many possibilities.
- Focuses on serial generation/evaluation of options, not simultaneous deliberation.
- Relies on satisficing not optimizing.
- Affirms that experienced decision makers evaluate option by using mental simulation, not using classical approaches to compare and contrast strengths and weaknesses of different options.
- Focuses on situation assessment, not decision events (judging one option better than others do).
- Defines how people use their experience to bear on a decision.
- Decision Maker is primed and bound to act without waiting for the whole analyses.

The key features of RPD are in contrast with the analytical approach. Table 2.4 shows the differences between the recognitional approach (RPD) and analytical approach in terms of their basic features, strengths and weaknesses.

Table 2.4

Comparison of Analytical and Recognitional Approach

	Analytical approach	**Recognitional approach**
Features	▪ Many options ▪ Current Evaluation ▪ Optimal ▪ Rational ▪ Prescriptive ▪ Quantitative	▪ Single Option ▪ Serial evaluation ▪ Satisficing ▪ Intuitive ▪ Descriptive ▪ Mental simulation ▪ Experience based ▪ Situation Assessment centred ▪ Pattern recognition
Strengths	▪ Systematic procedures ▪ In depth course of action assessment ▪ Detailed comparison of options	▪ Influences expertise and experience ▪ Decision maker centred ▪ Rapid response ▪ Minimal resource required
Weaknesses	▪ Limited effect of expertise and experience ▪ Garbage in Garbage out ▪ Dependent on accuracy of weight and scores (decision-making in a laboratory set up) ▪ Resource demanding	▪ Limited assessment of options ▪ Low evaluation of outcomes ▪ Limited amount of possibilities considered ▪ Recognitional decision making is likely more only when the decision maker is experienced, when conditions are less stable and time pressure is higher

Source: Adapted from Kallion (2000); Klein (1993, 2008)

Although the analytical approach is a systematic procedure in which the in-depth course of action assessment with detail comparison of options is the key to this approach, it is not beneficial to decision-makers in assisting in real-world settings (naturalistic settings) (Nowroozi et al. 2012). As such, it is time and resource demanding. In this case, the recognitional approach is more advantageous in facilitating rapid response with minimum resources required.

2.2.1.2 Recognition-Primed Decision Model Factors

RPD is a descriptive model that is designed in form of a flowchart to explain the processes in decision making. The processes are experiencing the situation (situation assessment), analysing the situation (serial option evaluation) and implementing the situation (mental simulation of options). The RPD model factors from Klein (2008) are classified into three; the external, the instantaneous and the temporal. Each of the classifications has one (1), five (5) and one (1) factors respectively. The total factors are seven (7) as represented in Table 2.5.

Table 2.5

External, instantaneous and the temporal factors of Recognition-Primed Decision model

External Factors	Instantaneous Factors	Temporal Factors
1. Situation	1. Goals 2. Cues 3. Expectancies 4. Mental Representation(MR) 5. Implement	1. Action

Moreover, just as SA model, the RPD model also has mental representation (MR) for effective decision making. These are: 1. Knowledge of what is happening (L1). 2. Knowledge of rules governing the situation (L2). 3. Knowledge of possible consequences or expectancies of the future (L3). However, based on the factors stated in Table 2.5, there is need for comprehensive RPD model that has detailed training factors such as Basic Practice, Practice, Basic Skills, Sensory Ability, Driver Abilities, Rehearsed Experience, Attention, Priming, Habitual-direction acion, Goal-directed action, Involuntary Automaticity, Voluntary Automaticity, Acquired Automaticity, Potential hazardous information, Perception about Task and Perception (Klein 1993, 2008, 2015; Klein et al., 2010; Fadde, 2013; Javor, Pearce, Thompson, & Moran, 2014; McDevitt, 2017) to enhance the experience of decision maker (driver) to make effective prime decision.

2.2.1.3 Applications of Recognition-Primed Decision Model

The RPD model has been used in various domains such as in aviation, business, power system, health care, and firefighting to mention a few. For example, in business domain, Resnick (2001) attempted to solve the problem related to e-commerce focused companies that went bankrupt due to poor customer service, varying fulfilment, concern for privacy, and poor business models. The author compared the outcomes of several new studies that examined decision making in the e-commerce environment to what would have been forecasted by the model. Moreover, the study argued that future studies should use approaches that focused on testing the market trend forecasts based on the RPD model so that accurate conclusions can be drawn.

Another example in business domain, Niu and Zhang (2008) proposed a solution with RPD model approach in solving that current business intelligent (BI) systems did not fully support business managers' decision-making process due to the presence of large data size, inability to handle unstructured problems, and human intuition-based decision making. They employed the basic concepts of situation awareness (SA), naturalistic decision making (NDM) /recognition-primed decision (RPD) in designing a cognition-driven decision process (CDDP) model for BI systems. The cognitive-driven decision process (CDDP) model designed is used to assist managers in making reasonable decisions as well as good performance.

In electric power domain, Greitzer et al. (2010) solved a problem of blackouts in North America due to the growing complications and interconnectivity of the power grid that were unable to be handled by the available power systems operators. They proposed an integrated NDM model by combining the concepts of situation awareness, metacognition, Skill-Rule-Knowledge (SRK), and Recognition Primed Decision-making (RPD) and evaluated the model using a Cognitive Task Analysis (CTA) approach. The proposed integrated NDM model offered a possible framework for systematic training for power system operators and teams.

In the field of fire fighting domain, King (2011) examined command decision-making models for the Sacramento Fire Department in California, U.S.A. The study was to determine and generate guiding principles for incident commanders to make incident related decisions within stated expectations. The researcher, however, discovered that the Sacramento fire department had no command principles that direct incident commanders to fruitful and foreseeable mitigation of emergency incidents. The result suggests suitable decision-making models that have to be developed specifically for fire ground commanders. It is also revealed that Sacramento fire department command officers have encouraged the use of RPD in making a fast and complex decision.

Within the healthcare domain, a study by Resnick (2012) presents two main challenges. The first one is how emotions affect the decision making of medical professionals in the healthcare domain, particularly in intensive care units (ICUs), theatre, and emergency rooms. Second, the issues of competing objectives, value-based judgement and compromises among the clinicians, patients, and insurers are attributed to the inadequate communication between patients and doctors regarding values and commitments. This reflects real differences in motivations, benefits, and incentives in the healthcare system.

Lu et al. (2013) improves on the work by Niu and Zhang (2008) by extending it to solve the growing complication of today's digital ecosystem environment as decisions within business systems are seem to be more unstructured, dynamic, and uncertain with high personal stakes and time pressure. As a result, managers are profoundly cognitively taxed. Therefore, the study emphases upon cognitive decision support in the business intelligence (BI) environment by developing a model of situation retrieval (SR). The SR model is a decision oriented process compared to the traditional problem-oriented information retrieval (IR) model. Their experimental findings demonstrated that the SR model played a significant role in assisting decision makers to design an improved SA and reuse their experience to make better decisions.

In aviation domain Winter et al. (2014) examined participants' experiences handling mid air an engine failure. The study made use of RPD model. The interest of the study was the decision-making process utilized by pilots operating an aircraft equipped with an airframe parachute system. The purpose was to complete a qualitative analysis of the decision-making process used by pilots to determine whether to deploy an airframe parachute system. Naturalistic decision-making theory was applied due to the dynamic and evolving environment related to aviation decision making. The script was examined and validated by an expert panel that determined the use of the airframe parachute importance in the study.

Table 2.6

Summary of research that applied Recognition-Primed Decision model, Recognition-Primed Decision /Situation Awareness model

Author	Domain	Problem Solved	Supporting theory/model	Result/ Model
Resnick (2001).	Business	E-commerce focused companies went bankrupt and competing goals issue.	RPD	RPD models explain e-commerce behaviour.
Niu and Zhang (2008)	Business	The business intelligence systems cannot support business managers' decision-making process, handle unstructured problems and human intuition.	RPD/SA	A cognition-driven decision process (CDDP) model for BI model was developed.
Greitzer et al. (2010)	Power system	Power Blackouts	SA, RPD, Metacognition, & SKR	An integrated NDM model was developed.
King (2011)	Fire Fighting	Lack of command principles to guide incident commanders	RPD	Appropriate decision-making models established for fire ground commanders.
Resnick (2012).	Health Care	Effect of emotions on decision making of medical personnel and issues of competing objectives, values and compromises among the clinicians, patients, and insurers.	RPD	Awareness of how emotion affects decision making, help providers and administrators develop management best practices.
Lu et al. (2013).	Business	Business intelligence systems cannot fully support executives' management processes.	SA, NDM /RPD.	A model of situation retrieval (SR) was developed.
Winter et al.(2014).	Aviation	Engine failure.	NDM/RPD	Use of the airframe parachute was determined.
Donnelly et al.(1997); Noyes(2012)	Aviation	Human error- flight crew judgement and decision-making.	RPD/SA	Integrated Decision-making Model (IDM) for Pilot.

Similarly, the studies by Donnelly et al. (1997) and Noyes (2012) argued that the degree of automation in complex systems such as those found on the civil flight deck continues to give problem by stating that ‘too much automation and the human operator is not in the loop’ when failures and faults occur. Making decisions hence becomes difficult, as the crews are not entirely aware of the situation. Table 2.6 presents the summary of the review. The study by Noyes also describes the way pilot makes decisions and errors, and highlights that the errors can be corrected by training. The study uses the SA and RPD models to develop an integrated decision making (IDM) model for the pilot decision process. Table 2.6 shows that the prior studies have a similar issue of time-criticality that triggers the use of the RPD model in their study domains. Also, it shows that there is existing model that is designed based on RPD/SA models.

However, this model negletcted some of the cognitive and naturalistic decision making factors necessary for training to make a primed decision. More so, the model cannot check if the behaviour of a system based on theories matches the real world situations; it cannot ensure reproducibility in scientific thinking; and cannot be simulated (Lewandowsky & Farrell, 2011).

2.2.1.4 Computational Recognition-Primed Decision Model

In RPD model, experience and situation recognition are the key features which translates these features into computing method, the computational model should have a mechanism to represent professional or experience knowledge and pattern recognition. Computational models are design based on several techniques, and have been used in the different domains. The use of RPD in decision support system (DSS) combat system of Aegis cruisers under the TADMUS project was said to be the first attempt to make a computational RPD model.

The studies by Warwick, Stacey, Hutton and Patty (2001), and Stanard, Hutton, Warwick, McIlwaine and McDermott (2001) stored decision maker's experience within a long-term memory structure called multiple-trace memory that was suggested by Hintzman (Nowroozi et al., 2012) and implemented in the driving domain.

Similarly, Ji et al. (2007) develop a general-purpose computational fuzzy RPD model that uses fuzzy sets, fuzzy rules, and fuzzy reasoning to represent, interpret, and compute imprecise and subjective information in every part of the model. The fuzzy RPD model was implemented in medical domain where the extent of causality between a drug and some of its adverse effects for patients has been calculated.

Mueller (2009) implemented a Bayesian RPD model called Bayesian Recognitional Decision Model (BRDM) based on episodic recognition memory models. Greitzer et al. (2010) proposed an integrated NDM Model by integrating RPD, Recognition/Meta-Recognition, and Situation Awareness in a study of power systems domain. The model was analyzed using Cognitive Task Analysis to develop a more comprehensive systematic approach to train electric power system operators.

Yin et al. (2011) classified RPD as a behaviour decision model for data mining in a survey of data mining theory and techniques in computer-generated forces (CGFs) behaviour modelling mainly applied in military training. A study by Norwawi, Ku-Mahamud, and Safaai (2005) presents a computational recognition decision-making model that adopts the temporal data mining technique in making decisions. The study also presents a case study of reservoir water level and rainfall measurement to test the developed computational recognition-primed decision (RPD) model in predicting the amount of water to be dispatched, represented by the number of spillway gates.

Nowroozi et al. (2012) presented a computational RPD model named C-RPD. Unified Modelling Language was used to represent the C-RPD model that was implemented in firefighting domain using artificial intelligence technique. Table 27 shows the summary of related works in developing computational RPD models using different techniques.

Table 2.7

Summary of studies on computational Recognition-Primed Decision models

Author(s)	**Model(s) Used**	**Model Formed**	**Domain**	**Technique**
Warwick et al. (2001)	RPD, Hintzman's multiple-trace memory model	Computational RPD	Driving	Decision-specific
Stanard et al. (2001)	RPD, Hintzman's multiple-trace memory model	Computational model of driver decision-making	Traffic control	Agent-based
Sokolowski (2002)	RPD	Computational RPD	Military	Composite agent
Norwawi et al. (2005)	RPD	Computational RPD	Reservoir Flood Control	Temporal Data Mining
Ji et al. (2007)	RPD	Fuzzy logic-based general-purpose computational fuzzy RPD	Medical	Fuzzy logic
Muller (2009)	RPD, Episodic Recognition Memory	Bayesian Recognitional Decision Model (BRDM)	Episodic and Semantic Memory	Bayesian
Greitzer et al.(2010)	SA, RPD, Recognition/Meta-Recognition	Integrated Naturalistic Decision-Making Model (INDM)	Power Systems	Cognitive Task Analysis (CTA)
Yin, Gong and Han (2011)	RPD	Computational RPD	Military	Data Mining
Nowroozi et al. (2012)	RPD	General computational RPD (C-RPD)	Fire-fighting	Artificial Intelligence Technologies

Thus, from the analysis of the computational RPD models in Table 2.6, it can be concluded that different computational models of RPD have been developed using different techniques and applied in different domains. However, the present study developed an Computational-RDT model for prime decision-making in driving using a set of first-order differential equation technique.

2.2.2 Situation Awareness Model

Cognitive modelling of human behaviour has appeared to be powerful method for exploring how users relate to complex systems and have been extensively employed to model human-computer interaction and human behaviour more generally. For example, driver behaviour modelling and cognitive tools are used for assessing driver situation awareness (Liu, Wang, Li, XU & Gui, 2009).

Situation awareness is a theory/model that focuses on operators' environment and their mental model. A mental model is generated based on the operator's experience on the current situation. The better one's expertise with a situation, the more structures exist for assimilating the data into a meaningful pattern. These structures allow for the quick understanding and prediction of status for that situation. However, an individual without expertise will have fewer structures in long-term memory and will have to rely on analytical skills and working memory for understanding and prediction. For example, novices have to use the more analytical model to discover the meaning of the data, because they do not have the patterns. The use of the mental model is important for a clear understanding of the situation, development and maintenance of SA (Salmon, Stanton & Young, 2012). Therefore, a mental model is a kind of silent information, which can be produced from people's minds using cognitive mapping. According to

Endsley (1995), “features of the environment are mapped to mental models in the operator’s mind, and the models facilitate the development of SA”. Mental models (formulated through experience and training) are utilized to enable the attainment of SA by guiding attention to crucial elements in the environment (level 1), combining the elements to aid in the understanding of their meaning (level 2) and creating probable future states and events (level 3).

A mental model offers advantages such as a device for guiding attention to relevant aspects of the situation. That is, a way of combining information perceived to form an understanding of its meaning; a tool for forecasting future states of the system based on its present state and comprehending of its dynamics (Endsley et al., 2003; Lu et al., 2013).

The requirement for performance in dynamic situations, such as piloting aircraft, driving vehicles, and operating nuclear power plants, is to examine and rapidly analyze the changing environment and make effective decisions. Information processing in these complex dynamic environments includes the perception of elements in the environment, comprehension of the perceived information in the environment, and projection of future status. The three aforementioned stages of processing are included in Endsley’s theory (1995) of situation awareness (SA). Environmental perception is the first stage where the driver should get thoroughly acquainted with the vehicle's information, the changes of environment, and traffic signal and traffic sign. Comprehensive understanding is the second *stage*. In this stage, the driver analyses the intentions of situation information according to the relevant goals, and then based on that makes projection. Projection is the third stage. At this stage, the driver makes predictions and decisions according to one's knowledge on the bases of comprehensive understanding and refinement of current situation information. This is very analogous to Klein’s Mental Representation (MR) which he outlined in his Recognition-Primed Decision (RPD) model (Klein, 2008). This MR consists of knowledge of what is happening (similar to level 1 SA), knowledge of the rules governing the situation (level 2 SA), and knowledge of possible consequences, or expectancies for the future (level 3 SA).

Situation awareness guarantees driver's finishing of the overall driving task. The driver maintains situation awareness and tries to keep/change the specific situation, perceive environment over his sense organs, and implement the interactions with the environment over manipulations. Therefore, monitoring and manipulations of the environment are essential parts of driver cognition behaviour. Figure 2.4 shows the main components of SA model and their relationships. It also shows how SA becomes an integral part of decision-making and how other factors contribute to decision-making.

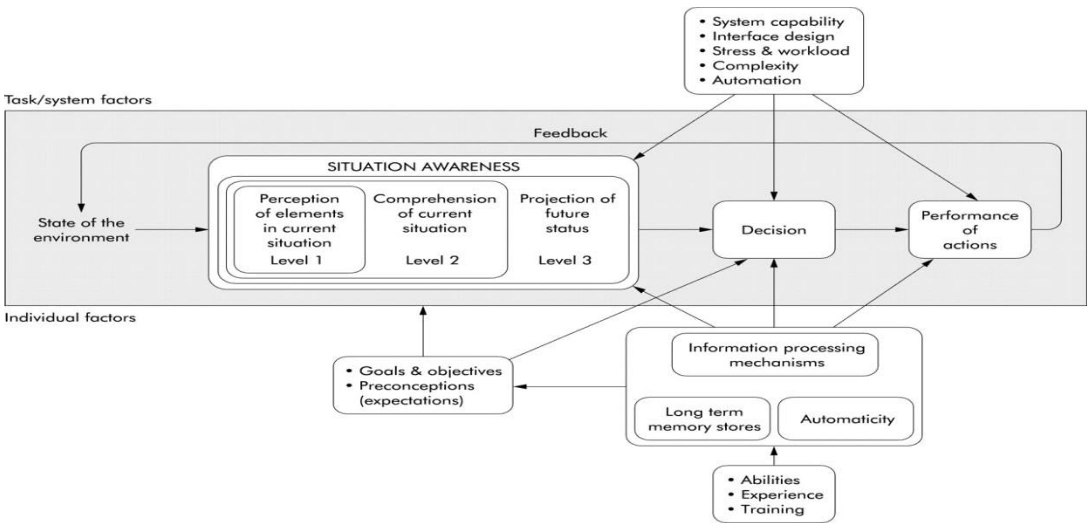


Figure 2.4. SA Model in Dynamic Decision Making.
Adapted from Endsley (2000).

2.2.1.1 Factors of Situation Awareness Model

The Endsley model of Situation Awareness is a model of cognitive theory. The model has a total of eighteen (18) factors based on the diagram in Figure 2.4., ranging from environment to decision. The factors are classified into three, namely external, instantaneous and the temporal as shown in Table 2.8.

Table 2.8

External, instantaneous and the temporal factors of Situation Awareness model

External Factors	Instantaneous Factors	Temporal Factors
1. Environment	1. Automaticity	1. Decision
2. Abilities	2. LTM	
3. Experience	3. Information Processing	
4. Training	4. MR or SA	
5. Goals	▪ Perception	
6. Expectations	▪ Comprehension	
7. System Capability	▪ Projection	
8. Interface Design	5. Performance of Action	
9. Stress		
10. Workload		
11. Complexity		
12. Automation		

The model being cognitive, it has mental representation (MR) that is always been used for the awareness level as it is believed that good SA is the key to effective decision-making in various domains such as aviation, firefighting, health care, military e.t.c.

The MR or SA as a factor is further classified into three basic components. The level 1 SA: the perception. The level 2 SA: the comprehension, and the level 3 SA: the projection. The three (3) basic components are used for awareness purpose while the remaining seventeen (17) factors can be used for other purposes like training the decision maker depending on the context of the user (Endsley, 2000, 2016). Among the eighteen (18) factors of the SA model presentented in Table 2.8, eleven (11) factors were used to enhance the IDM model while seven (7) were not used such as: System Capability, Interface Design, Stress, Workload, Automation, LTM, and Information processing because the factors are not relevant for prime decision-making. This study used only the training factors in SA model that were relevant for prime decision-making process to realise the design of the RDT Model.

Moreover, the review for cognitive model of Situation Awareness (Hoogendoorn, Van Lambalgen, & Treur, 2011; Bosse, Merk, & Treur, 2012) is necessary and they form the basis for the development of conceptual and the formal model of SA in the present study.

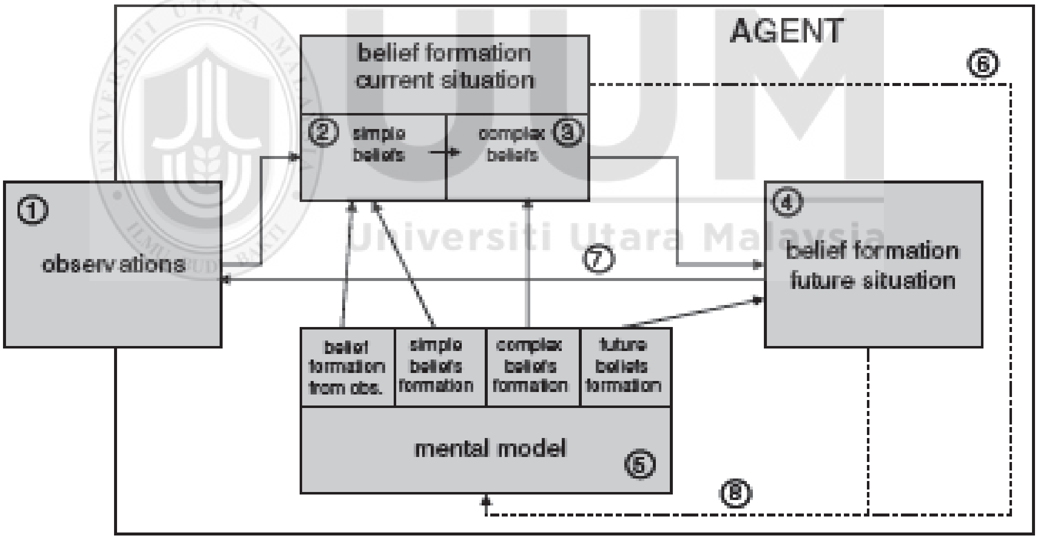


Figure 2.5. Cognitive model for situation awareness: overview
Adopted from Hoogendoorn et al. (2011).

Figure 2.5 shows the general structure of the cognitive model for situation awareness. The model presents the mental model of SA and it consists of four basic elements. Three elements were in line with the model of Endsley (2016) which includes the perception of cues (i.e. element 1), the comprehension and integration of information (the combination of 2 and 3), and the projection of information for future events (element 4). Additionally, mental model represent the 5th element.

Moreover, the cognitive model for situation awareness can be abbreviated as (CMSA), while the Endsley's model for situation awareness can also be abbreviated as (EMSA). Hence the relationship between the two models can be represented in Table 2.9.

Table 2.9

Relationship between Elements of Cognitive Model for Situation Awareness, Endsley's Model for Situation Awareness and their levels

Elements of CMSA		**Elements of EMSA**	**Levels**
Observation.	Determined certainty of observations made and used it to obtain the activation values of the beliefs directly associated with the observation.	Perception of cues	L1
Belief formation for current situation (Simple and complex beliefs).	The updated activation values of beliefs on the present and past are achieved.	Comprehension and Integration of information.	L2
Belief formation for future situation.	The updated activation values of beliefs for the future are attained.	Projection of information for future events.	L3

2.2.2.1 Application of Situation Awareness Model

An effective SA is critical for many driving behaviours, including monitoring and updating the positions of other vehicles, navigating busy roadway, monitoring road conditions, and maintaining proper speed (Heenan, Herdman, Brown & Robert, 2014). Much of the research on SA originated from the aviation domain, but SA as a construct is widely studied, and it exists as a basis of performance across many different domains. The domain includes driving a vehicle, command and control operations, piloting an aircraft where information needs to be processed very quickly and where one of its consequences can be of poor decision-making (Jones, Connors & Endsley, 2011). SA in these domains (health care, education, military, business, and driving) will be analysed.

In education domain, Liu, Mao and Zhan (2008) designed an e-Learning system based on SA model. The result of the study revealed that learner's learning ability had been improved dramatically by adapting the model.

Gheisari and Irizarry (2011) study Facility Managers (FM) decision-making process and performance in complex and dynamic environments. The rationale for the study is to provide a conceptual model of SA method that can be applied to the facility management domain. The decision-making process and performance of the facility manager can be improved by enhancing the ambient awareness of the facility manager. Enhancing the ambient awareness of system-users who work in complex and dynamic environments can be achieved through the concept of Situation Awareness.

Helldin and Falkman (2012) attempt to solve the problem of fighter pilot workloads and their situation awareness. Human-Centered Automation (HCA) has been introduced to aid the pilots to perform their tasks and to make decisions fast in an often rapidly changing environment with the aim of easing the pilots' workloads and improving their situation awareness. HCA is an approach to create an environment in which humans and machines collaborate to reach stated objectives. Conclusions drawn from the study are that HCA concept was used to design automated support systems to reduce Pilots' workloads and improve their SA.

Meanwhile, in the military domain, Ozyurt, Doring, and Flemisch (2014) study the Combat Information Centre (CIC) of German Navy ships equipped with highly advanced Command and Control (C2) systems. The Command and Control (C2) processes are characterized by high complexity due to different tasks that affect the operator's workload, and as a result, the workflow encounters error rate. In addition, a COGnitive Assistant System (COGAS) was developed in a simulation study using situation awareness model to support air target identification on German Navy Ships. The COGAS was able to reduce the high complexity that affects the operator's workload by reducing the workflow error rate.

However, in the driving domain, the study by Walker and Gable (2014) documents that emotional (anger) state results in driving performance using situation awareness. An experiment was carried out using 30 undergraduates that drove in a simulator after generating either anger or neutral effect. The study compared variables, including driving performance, situation awareness, subjective judgment, and perceived workload in the generated angry state with those in the neutral state. The result showed that generated anger could worsen driving performance and driver situation awareness when compared to a neutral state. However, the angry state did not have a consequence on the participants' subjective judgment or perceived workload, which implied that the consequences of anger happened below their level of conscious awareness. Table 2.10 shows the summary of a literature review on the application of situation awareness model in different domains, the problem solved and results obtained in those studies.

Table 2.10

Application of Situation Awareness model in different domains

Author	Domain	Problem Solved	Result
Liu, Mao and Zhan (2008).	Education	Learning efficiency	E-Learning system designed based on situation awareness model, and it has improved the learning ability of learners greatly.
Gheisari and Irizarry (2011).	Facility Management	Decision-making process and its consequent performance.	Improved by enhancing ambient awareness of the facility manager.
Helldin and Falkman (2012).	Aviation	Pilots' workloads and their situation awareness.	HCA concept to design automated support systems to reduce Pilots' workloads and improve their situation awareness.
Ozyurt, Doring, and Flemisch (2014).	Military	High complexity	A COGnitive Assistant System (COGAS) was developed to reduce the high complexity.
Walker and Gable (2014)	Driving	Anger effects on driving performance.	Compared to a neutral state, induced anger can worsen driving performance and driver's situation awareness.

From the review of the literature, it can be concluded that the situation awareness model is fundamental and is used in almost all domains ranging from education to driving. Particularly, SA is used in those domains that deal with the complex and dynamic environment such as fighter aircraft, military, aviation and driving where situation recognition is paramount.

2.2.2.2 Computational Models of Situation Awareness

There are other studies on the computational model of situation awareness in dynamic environments. For example, Belief Desire Intention (BDI) models by Rao and Georgeff (1995) generally can be seen as models of situation awareness that were applied to air-traffic management domain. The study explores BDI agent, a type of rational agent. It aimed at incorporating the theoretical foundations of the BDI agent from both quantitative decision-theoretic aspect and a symbolic reasoning aspect.

So and Sonenberg (2004) designed a computational model of situation awareness to define pro-activeness of behaviour. It is an agent-based model implemented using rule-based knowledge and forward reasoning. Using Endsley model as their basis, the study integrated beliefs with certainty factors and applied the model in a meta-level control strategy that directs the agent's attention to its situated environment during runtime. However, Hoogendoorn, Van Lambalgen, and Treur, (2011) criticise their model that it does not take care of beliefs activations as perceived in human reasoning.

Hoogendoorn et al. (2011) designed a general computational model for situation awareness, which uses the mental model as input to generate a scenario of the current situation. The model has been applied in the domain of F-16 fighter pilot training. Bosse, Merk and Treur (2012) also present a computational model of situation awareness as an extension of Hoogendoorn et al.'s (2011) model. This model integrated qualitative time references, which offer the option to use temporal relations (Allen, 1981), and an explicit representation of situation awareness model (Endsley, 2000). The model has been tested by simulating its behaviour in a simulation environment for F-16 fighter pilots, and it has been verified formally. The study by Aydoğan, Sharpanskykh and Lo (2014) presents a computational, agent-based situation awareness model integrating trust to allow the building of more human-like decision-making tools. The model is based on the theoretical model of SA by Endsley and computational model of SA by Hoogendoorn et al. (2011).

A simulation case study has been conducted in the airline operation control domain to show the example of the proposed model. The results of this study indicate that the trustworthiness of information sources had a significant effect on airline operation controller's situation awareness. Table 2.11 shows the summary of research on computational models of situation awareness.

Table 2.11

Summary of Studies on computational models of Situation Awareness

Author	Models used	Model Formed	Techniques	Domain
Rao and Georgeff (1995)	__	Computational model	BDI agent (rational)	Air-traffic management
So and Sonenberg (2004)	SA	Computational model	Agent-based	A meta-level control strategy
Hoogendoorn et al. (2011)	Cognitive model, SA	Computational, general model for situation awareness	Agent-based	F-16 fighter pilot training
Bosse et al. (2012)	Cognitive model, SA.	Computational model of SA	Agent-based	F-16 fighter pilot training
Aydoğan et al. (2014)	SA	Computational, Trust-Based Situation Awareness	Agent-based	Airline operation control

Therefore, based on the review of the related literature, the present study discovers that the previous studies designed computational, agent-based situation awareness models applied in various domains.

2.3 Hybridization

The term "hybrid" in computer science is a combination of two or more different techniques, methods, or models, which are separated from each other naturally. The reason is to generate something new, which can take advantage of different combination of techniques and methods or models (Alobaedy, 2015).

According to Alobaedy (2015), these techniques, methods or models are applied in three ways, namely sequential, parallel and mixed approach. In the sequential approach, the output of any model is passed to the input of the next model and so on. In the parallel method, two or more models are combined at the same time, and their outputs are combined in a single output. The mixed method is the combination of both sequential and parallel methods

Hybridization can be defined as a method of combining two or more complementary, single-stranded models to form a single, double-stranded model through base pairing. From the reviewed concept of models of hybrid soft computing architectures by Abraham (2003), hybrid intelligent architectures are classified into four categories: (1) Stand-alone (2) Transformational (3) Hierarchical hybrid and (4) Integrated.

2.3.1 Types of Hybridization Methods

Stand-alone Model

The main concept of stand-alone models consists of independent software that does not interact in any way. Stand-alone models are designed to achieve several objectives depending on the purpose of the developer. Figure 2.6 shows the stand-alone models where a neural network and a fuzzy system are used separately. Stand-alone models have the benefits of ease and simplicity regarding its development.

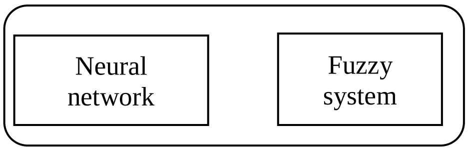


Figure 2.6. Stand-alone models

Transformational Hybrid Intelligent Models

In the transformational hybrid model, the system starts as one type and finishes up as the other. Determining which method is used for development and which is used for delivery is depended on the desirable characteristics that the technique offers. Figure 2.7 shows the interaction between a neural network and an expert system in a transformational hybrid model. In this case, either the expert system is incapable of sufficiently solving the problem, or the speed, adaptability or robustness of neural network is required.

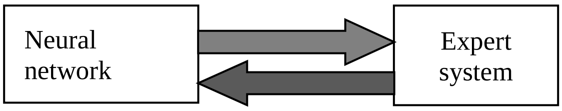


Figure 2.7. Transformational hybrid model

Hierarchical Hybrid Intelligent Models

This model is built hierarchically, with each layer having different functionality. The general function of the model depends on the correct functioning of all the layers. Figure 2.8 shows a hierarchical hybrid architecture involving a neural network, an evolutionary algorithm and a fuzzy system. The neural network uses an evolutionary algorithm to optimize its performance, and the network outputs act as a pre-processor to a fuzzy system, which then produces the final output.

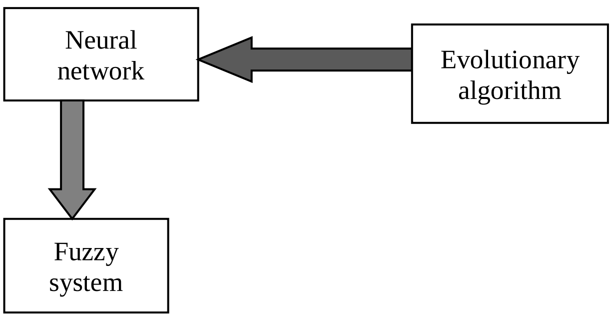


Figure 2.8. Hierarchical hybrid model

Integrated Model (Fused)

Fused architectures are the first real form of integrated intelligent models. They include systems, which combine different methods into one single computational model. They share data and knowledge representations. Hybrid method otherwise known as the integrated method is said to achieve excellent performance in many fields compared with stand-alone methods (Kolodziej, 2012). Moreover, the four categories of the hybridization methods, their properties and advantages, based on (Abraham, 2003) are shown in Table 2.12.

Table 2.12

Hybridization methods, properties and advantages

Hybridization Method	Properties	Advantages
Stand-alone	▪ Provides direct means of comparing problem-solving capabilities of different techniques. ▪ Often used to develop a quick initial prototype, while a more time-consuming application is developed. ▪ The method is not transferable nor can it support the weakness of the other method.	▪ Simple ▪ Easy to develop
Transformational	▪ The system begins as one type and ends up as the other. Determining which technique used for development and delivery.	▪ Can be developed quickly. ▪ Require maintenance on only one system ▪ Offer operational benefits.
Hierarchical	▪ Architecture is built hierarchically, with each layer having different functionality ▪ The overall function of the model depends on the correct functioning of all the layers. ▪ Poor performance in one of the layers directly affects the final output	▪ Its structure is more flexible. ▪ A better option for some complex systems that cannot be easily represented.

Table 2.12 Continued

Hybridization Method	**Properties**	**Advantages**
Integrated	▪ A first real form of integrated intelligent systems. ▪ They include systems that combine different techniques into one single computational model. ▪ They share data and knowledge representations.	▪ Robustness ▪ Improved performance ▪ Increased problem-solving capabilities. ▪ Fully integrated models can provide a full range of capabilities such as adaptation, generalization, noise tolerance and justification.

From Table 2.12, the integrated method of hybridization has more advantages over the three counter parts methods.

2.3.2 Integrated Decision-making Model

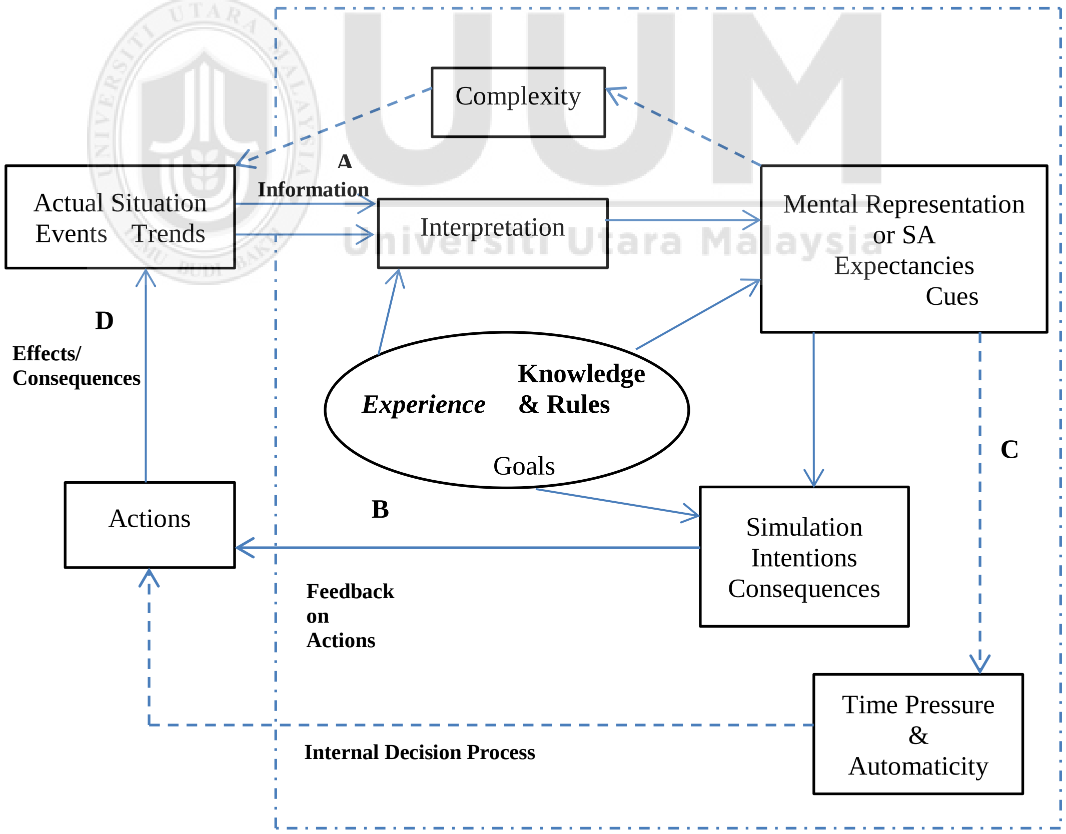


Figure 2.9. Integrated Decision-making Model of Pilot Decision Process
Adapted from Donnelly et al. (1997); Noyes (2012).

Figure 2.9 shows the existing RPD-SA model called Integrated Decision-making Model (IDM) of Pilot Decision Process by Donnelly et al. (1997) and Noyes (2012). However, the difference in the two studies is that, Donnelly et al. (1997) propounded the conceptual model without validation. Hence, Noyes (2012) validated the conceptual IDM model using experimental study. An experiment was conducted using 29 participants (18 males and 11 females). The participants were divided into two groups, namely experimental (15 participants) and control (14 participants). This is to assess the action of decision makers under time pressure and automaticity. It was hypothesised in their study that "people making decisions do not consider the full consequences of their action when under time pressure and acting automatically and therefore will make more errors under these conditions". The participants were put under time pressure in order to control the time given to respond to the event. Fixed time was given to the decision maker in order to respond to an event in a simulated time pressure. The participants in the control condition had five (5) seconds to respond, while the participants in the experimental condition had two (2) seconds only. Also, the type of event and frequency were controlled in order to have automatic response. By using two events that are similar, and have changing frequency of occurrence, the automaticity can also be simulated. As the event becomes routine, its response turns out to be automatic, whereas as the event is less frequent it comes to be non-routine. Therefore the ratio of the occurrence of the two events is a measure of automaticity.

A questionnaire was administered and completed by the participants to give information on these conditions (time pressure and automaticity) and to provide information on their performance and motivation. The results showed that decisions of the participants under time pressure are faster. Though there was no variance in time taken to answer when the number of activities was higher. This is because in the event handling used for the experiment, simple automaticy (yes/no decisions) criterion was used and decision chosen in the IDM to represent automaticity path was itself automatic. Therefore, consideration of consequences is not needed under any conditions. However, under time pressure and distraction conditions, simple automaticy can lead to slips or mistakes. This is contrary to when complex automaticity (decision require knowledge processing level in order to make correct decision) was used for the experiment.

The Integrated Decision-making Model in Noyes (2012) described pilot behaviour and was applied in supporting their decisions process. It also showed areas in the decision process where flaws can be made and may be detected. It suggested the use of decision support as an intervention points to prevent the errors and assist to mend the errors. Aviation decision-making differs from decision-making in other fields. In aviation decision-making, the pilot starts with high SA which decreases over time as compared to others fields (such as fire fighters, military, driving e.t.c.). In this case, when the SA degrades, a potential for error occurs (i.e. when the pilot's MR is different from the actual situation), contrary to when a situation is wrongly assessed. When assessing a situation, time factor is also involved which may not be important when the situation is familiar. The model utilized three theories that are important for decision making processes in the development of their model. These theories are Endsley theory of SA (Endsley, 1995, 2016), the Naturalistic Decision Making theory (Klein, 2015) and the Rasmussen's theory of information processing (Rasmussen, 1993).

The pilot SA is very essential for effective decision-making. Endsley (1995, 2016) described SA as comprising of three components known as levels of SA. Level 1 SA is perception of cues; level 2 SA is comprehension of the cues and level 3 SA is the Projection of future developments. The Naturalistic Decision Making theory (Klein, 2008, 2015) is equally important for decision-making process in order to maintain MR and to identify which procedure is appropriate. Experience is important in matching the information and cues to a known situation and this is where Klein's model is most relevant. The Rasmussen's Skill-Rule-Knowledge theory (Rasmussen, 1993) also serves as important theory in the pilot decision making process. The theory states that "different tasks require different levels of mental processing depending on the nature of the task".

Moreover, the IDM model shows the pilot's MR and the difference between the pilot's MR and the real situation plays a vital role in the decision process.The use of MR (Klein, 1993, 2008, 2015) is important for successful decision-making. Analogous to SA, the RPD MR consists of three components: 1. Knowledge of what is happening (Perception of cues, level 1 SA). 2. Knowledge of rules governing situation (Comprehension of cues, level 2 SA). 3. Knowledge of possible consequences, or expectancies for the future (Projection of future developments level 3 SA). The levels in SA/ RPD models also relates to Rasmussen's theory of information processing which he called Skill-Rule-Knowledge theory (Ramaussen, 1993). Pilot has hierarchy of goals and sub-goals that are related to the process tasks in the IDM model which relates to Rasmussen's levels of information processing that are presented in Table 2.13.

Table 2.13

Rasmussen's levels as related to Inegrated Decision-making Model Goals/Tasks

Rasmussen's Level	Goals/Sub-goals	Tasks	Examples
Skill	Lower	Automaticity	Immediate flying tasks
Rule	Intermediate	Actions following known procedures	To know which procedure is relevant and when to switch levels
Knowledge	Higher	Paths forming intention and considering consequences	Maintaining safe flight

The development of the IDM was as result of the reviewed of the decision-making theories mentioned. Based on Figure 2.9, there are three ways that the pilot may take in making a decision that are stated as follows:

1. If there is not sufficient information, or the situation is complex, the individual may seek additional information to clarify their representation of the situation.
2. If the pilot is satisfied with the representation, the pilot may form intentions to act.
3. There will be effects and consequences of the pilot's actions, or failure to act.

Points in the decision-making process where errors are likely to occur were identified in the model. The suggested intervention points are shown in Figure 2.9 as A, B, C and D.

A – The pilot's mental representation/SA and the difference between this and the actual situation play a vital role in the decision process.

Situation awareness reduces due to poor information or misinterpretation. This might lead to error in the situation assessment phase of the model. Intervention includes presenting information to the pilot in a better manner, or inferring what has been missed and re-presenting it in a different format. This is an error-prevention approach, which cannot guarantee the pilot to maintain or recover situation awareness.

B – The crew may not realise the consequences of a course of action, due to inexperience or misrepresentation.

Intervention involves informing the pilot of the consequences of their actions, either when the actions are risky, or by inferring intentions. This is an error-tolerant approach. The system needs to wait for actions and then assess if they are risky or unintentional. This does include an important feedback element, which may allow the crew to restore situation awareness.

C – The pilot may not put into consideration the consequences of a course of action, as a result of time pressure and/or automaticity. They might wrongly assume that a particular situation has been encountered before, and will therefore not seek to clearly consider the consequences of his/her actions. This direction might also be taken when there is no enough time to mentally simulate events.

Intervention is the same as in B. Though the two are fundamentally different errors, the result is similar.

D – Erroneous actions might go undetected due to distraction or lack of feedback.

If the pilot fails to gain enough feedback following an action then their mental representations might not be protected, and further essential action may not be taken.

Intervention includes providing feedback on actions as with B and C. Feedback may be given when actions are unsafe, or by inferring pilot intentions, when actions are unintentional. If the crew are distracted, they may not notice feedback information and so an effective "attention-getter" would be needed. This approach also accepts error, and situation awareness may be reinstated if information is presented in the correct manner.

In the IDM model under time pressure, a short cut can be taken that bypasses the process of forming intentions and considering consequences. In that case, when the situation is repetitive, the pilot might act or react automatically called automaticity and it is an important component for human decision-making and problem solving.

Also, based on Figure 2.9, the IDM model has twelve (12) factors for the pilot decision process including four (4) external factors, seven (7) instantaneous factors and one (1) temporal factor as shown in Table 2.14.

Table 2.14

Integrated Decision-making Model Factors

External Factors	Instantaneous Factors	Temporal Factors
1. Actual Situation ▪ Events ▪ Trends	1. Mental Representation (MR) or SA	1. Action
2. Knowledge/Rules	2. Expectancies	
3. Experience		
4. Goals	3. Cues	
	4. Complexity	
	5. Intention	
	6. Time Pressure	
	7. Automaticity	

From Figure 2.9 and Table 2.14, the four (4) external factors of the IDM are as follows. *Actual situation* represented by *Events* or *Trends*, *Experience*, *Knowledge/Rules* and *Goal* while the seven (7) *instantaneous* factors are: *Mental Representation (MR) (or SA)* which, by SA theory (Endsley, 2017) is represented as *Perception*, *Comprehension* and *Projection*. There are also other factors such as *Cues, Complexitiy, Intention, Time pressure* and *Automaticity*. The only *temporal* factor in the IDM is *Action*.

The IDM model is divided into two components namely, the SA and the RPD. Among the twelve factors presented in the IDM, five (5) factors such as *Mental Representation (MR) or SA*, *Experience*, *Complexity*, *Time pressure* and *Automaticity* are representing the SA component of the model. Then, seven (7) factors such as *Actual situation*;

Events or *Trends*, *Goals*, *Expectancies*, *Cues*, *Knowledge/Rules*, *Intention (simulation intention)* and *Actions* are representing the RPD component of the model. However, among the 12 factors mentioned, only six (6) factors such as *experience, knowledge/rules, goals, complexity, intention* and *automaticity* presented the training factors in the IDM. Therefore, the IDM has features that are highlighted in Table 2.15.

Table 2.15

Features of the existing Integrated Decision-making Model

Models	**IDM of Pilot Decision Process**
Features	▪ Three paths of decisions; if not enough information or the situation is complicated, or when a situation is routine or if there is time pressure. ▪ It is a general model. ▪ It describes the way pilots make decisions and make errors. ▪ It shows the continuity of the decision-making process. ▪ Highlights that training is essential for the flight deck systems. ▪ six (6) training factors presented
Application Domain	▪ Aviation
Weaknesses	▪ The flight deck needs improvement using vital training factors. ▪ Conceptual model.

2.3.3 Enhanced Integrated Decision-making Model Factors

In enhancing the IDM, training factors that are relevant for prime decision- making were identified based on literatures on cognitive theories such as cognitive theory of SA (1995, 2012; Hoogendoorn et al., 2011), Task Capability Interface (TCI) (Fuller, 2005), Unified Model of Driver Behaviour (UMD) (Hjälmdahl et al., 2011; Shinar & Oppenheim, 2011; Oppenheim et al., 2012), Model of Process underlying driving behavior (Deey, 1999), Multifactorial Model (MM) for driving safety (Anstey, Wood, Lord, & Walker, 2005) and Naturalistic Decision Making (NDM) theory (Kein, 2008, 2015). Hence, the details on how the factors were identified and the causal relationship based on literatures are as follows.

Environment is refered to as state of the environment in Endsley model (1995, 2016) where he stated that “an automobile driver needs to know where *other vehicles* and *obstacles* are, *their dynamics*, and the *status* and *dynamics of one’s own vehicle*.” Other models such as TCI model by Fuller (2005) and UMD behaviour of the ITERATE (IT for Error Remediation And Trapping Emergencies) project by Hjälmdahl et al. (2011), Shinar and Oppenheim (2011), Oppenheim et al. (2012), identified some environmental factors known as the environmental parameters (Traffic, Road, Visibility) that the driver needs to take care of. However, based on these studies, the present study comes up with six elements (Road, Traffic, Obstacles, Car condition and Visibility) a driver needs to perceive (observe) from the driving environment.

Observation: SA model (Endsley, 2000, 2016) refes to it as perception of elements or cues in the current situation. The RPD model by Klein (2008) refers to it as knowledge of what is happening, while in Cognitive Model of Situation Awareness (CMSA) (Hoogendoorn et al., 2011) it is referred to as observation. Endsley (1995, 2016), Fuller (2005), Hjälmdahl et al. (2011) stated some elements to be observed in driving environment such as road, Traffic, Obstacles, Car condition, Visibility e.t.c. *Belief Formation* is referred to as the comprehension and integration of information in SA model (Endsley, 2000, 2016), knowledge of rules governing the situation in RPD model (Klein, 2008) and belief formation for current situation (simple and complex belief) as in CMSA (Hoogendoorn et al., 2011; Bosse, Merk, & Treur, 2012). *Belief Activation* is referred to as the projection of information for future events in SA model (Endsley, 2000, 2016), knowledge of possible consequences or expectancies for the future in RPD model (Klein, 2008) and belief formation for future situation in CMSA (Hoogendoorn et al., 2011; Bosse et al., 2012).

Expectations in Endsley model (2000, 2016) is known as expectations or preconceptions while in RPD model (Klein, 2008, 2015) and IDM l for Pilot by Noyes, et al. (2012) is known as Expectancies. According to (Endsley, 2000, 2016), expectation "is built based on mental models of perception, comprehension and observation, and also based on previous experiences". It directs how attention is disseminated and how individual absorbs the information perceived. It serves as a shortcut in mental processing in information perceived and this gives advantage to working memory. That is, there is no information processing overflow.

Moreover, the causal relationships among the factors are based on literature. Therefore these studies (Endsley, 2000; Endsley, 2016; Hoogendoorn et al., 2011) noted that there is a relationship between *environment* and *observation* (perception). The *environment* and *attention* also influenced the observation. Hence, the present study observes the six environmental elements mentioned in order to form the beliefs about them. Same studies indicated that there is a relationship between *observation* and *belief formation*. Based on that, the present study forms beliefs on those items observed by the driver from the environment in order to form belief activation about them. These studies (Hoogendoorn, et al., 2011; Bosse, et al., 2012) showed that there is also a relationship between *beliefs formation* and *beliefs activation* in the sense that when the driver as an agent forms beliefs about certain observations he then forms certainty of that observations made. That is translated into activation values in form of weight and it triggers the belief activation of the driver. If the driver is stressed, he will not have full certainty on the observation he made (Aydoğan, Sharpanskykh & Lo, 2014). Endsley (2016) shows that *expectation* is related to *observation* by stating that, people normally have notions of what they expect to see, hear, or taste in a given situation. Meaning that, all their expectations in a given situation are to be observed (or perceived).

Basic practice in Endsley model (1995, 2016) and TCI model (Fuller, 2005) is known as basic training. *Basic Skill* is denoted as competence in TCI (Fuller, 2005) and is said to be acquired through training and experience. It also refers to training ability in Endsley model, Endsley (1995, 2016). *Sensory Ability* denotes ability to have cognitive, physical and visual functions based on Multifactorial Model in the study by Anstey et al. (2005). *Driver's goal* means the goals of the driver as in prior studies (Endsley 1995, 2016; Klein, 2008; Fuller, 2005; Noyes, 2012). *Potential hazardous information* denotes potential hazard in these previous empirical studies (Borowsky, Shinar and Oron-Gilad, 2010; Horswill, 2016; Huestegge & Böckler, 2016; Takahashi, Ukishima, Kawamoto, and Hirota, 2007; Konishi, Kokubun, Higuchi, Kurahashi & Umemura, 2004). *Exposure on Task Complexity* known as complexity in SA model by Endsley (1995, 2011) and in IDM model by Noyes (2012) while in TCI model by Fuller (2005) it is referred to as task difficulty. *Intention* is one the features of automaticity (Endsley, 2000, 2016; Moskowitz, 2013; Panek, Bayer, Dal-Cin, & Campbell, 2015) and named as simulation intention IDM Model for Pilot (Noyes, 2012). It was defined by Moskowitz (2013) as mental state that translates goals into reality.

Practice as in Endsley, (2000, 2016), Endsley and Garland (2000) refers to training while in Fuller (2005) is refers to training education. It is used interchangeably with training in the literature. *Acquired skills* in TCI model (Fuller, 2005) denotes competence, which is acquired through training and experience. *Driver ability* in SA model Endsley (1995, 2016) and TCI model (Fuller, 2005) refers to ability and capability, respectively.

Rehearsed experience: The idea of this factor is gain from the study by Gazzaniga, Heatherton, Halpern and Heine (2006). Rehearsal means repeated action in the aforementioned study. Therefore, *rehearsed experience* based on their study is a repeated or a re-occurrence experience. *Driver's experience* is denoted as experience (Hjälmdahl, Shinar, Carsten & Peters, 2011; Shinar & Oppenheim 2011; Oppenheim et al., 2010, 2012) and experience was defined as the accumulation of the reoccurrence of knowledge or skills acquired that result from direct participation in the driving activity. It was also referred to as experience in SA model (Endsley, 2000, 2016), TCI model (Fuller, 2005), and IDM model by Noyes (2012).

Perception about hazard (Hp) is otherwise called hazard perception (Borowsky, Shinar & Oron-Gilad, 2010; Crundall et al., 2012; Horswill, 2016). Borowsky et al. (2010) described "Hp" as the ability to identify hazardous situations while driving, which enables the driver to overcome complex cognitive demands that the traffic environment dictates. According to Horswill (2016) "Hp in driving refers to a driver's ability to anticipate potentially dangerous situations on the road ahead" while Crundall et al. (2012) refers to it as a "process of detecting, evaluating and responding to dangerous events on the road that have a high likelihood of leading to a collision". The concept "Hp" was in line with the model of processes underlying driving behavior in response to potential hazards (Deery, 1999). In this model "Hp" described as the ability to detect hazard and considered it dangerous potential. *Perception about task (Tp)* is otherwise known as task perception in other studies. According to Fuller (2005), drivers perceive task as either relatively easy or very difficult. If very difficult, the driver fails at that tasks and loss of control occurs, and this leads to collision or the vehicle running off the roadway. *Perception about risk (Rp)* is a subjective experience of risk in potential traffic hazards (Rosenbloom, Shahar, Elharar & Danino, 2008; Brown & Groeger, 1999; Deery, 1999).

Attention is one of the features of automaticity (Endsley, 2000, 2016; Moskowitz, 2013; Panek et al., 2015). Azuma et al. (2006) define attention as how brain consciously selects information for cognitive processing and Gazzaniga et al. (2006) define attention as a process of getting information from sensory memory to short term memory otherwise known as working memory. According to the author, "each time attention is paid to something, its activation is enhanced and by stop paying attention to it, it activation level decays and it becomes difficult to recall". *Priming* is a concept used in automaticity and is defined by Wheatley and Wegner (2001) as a technique that triggers both unconscious and conscious processes. This definition is supported by the empirical literatures (Wasserman & Wasserman, 2016; Moskowitz, 2013; Noyes, 2012; Endsley, 2000, 2016). *Habitual-directed action* is a form of automaticity and studies (Wasserman & Wasserman, 2016; Moskowitz, 2013) use the concept. According to Wasserman and Wasserman (2016), when action is repeated and is sufficiently practiced it becomes habitual. *Goal-directed action* is a form of automaticity that refers to goal-dependent automaticity and goal-directed in Moskowitz (2013) and Wasserman and Wasserman (2016) respectively. *Involuntary* is a form of automaticity and it is defined as unconscious and automatic behaviours experienced (Wheatley & Wegner, 2001) while

Voluntary is also a form of automaticity and it is defined as consciously willed and non-automatic (consciously controlled) behaviours experienced (Wheatley & Wegner, 2001).

One of the theoretical concepts used in this study is automaticity. It is a process of overlearning of information or operations to the point they can be used or recalled with small mental effort. According to Panek et al. (2015), automaticity is a process that requires limited conscious attention, awareness, and control of one's actions, intentions, or psychological processes.While Moskowitz (2013) describes it as a process that occurs without awareness or intent. Automaticity needs a learned or conditioned response to stimuli, while learning and conditioning, in turn, require rehearsal (Gardner, 2014). It is developed due to experience and high level of learning (training). At that point, automatic processing tends to be fast, autonomous, effortless and unavailable to conscious awareness in that it can occur with no attention. Based on that, this study break down the construct into eight component factors such as *attention, priming, habitual-directed action, goal-directed action, voluntary, involuntary, acquired automaticity* and *experienced automaticity* in order to have comprehensive model.

Therefore, *acquired automaticity* and *experienced automaticity* were used in this study to denote short-term and long-term automaticity. *Driving Knowledge* is found in IDM model (Noyes, 2012) as knowledge/rules. It is defined as skills acquired by the driver through experiences and training (Fuller, 2005; Stanton, Walker, Young, Kazi & Salmon, 2007). Decision making according to Azadeh, Zarrin and Hamid (2016) "is the selection of a procedure to weigh alternatives and find a solution for a problem".

Smith (2016) also described it as the internal processes by which a course of action or inaction is selected from a set of alternatives. Studies (Klein, 2008; Noyes, 2012) refer to it as action. Experienced (rehearsed) and perception about risk influenced *attention*. *Performance of action* in SA model (Endsley, 2016) and RPD model (Klein, 2015) is known as *performance of action* and *implement*, respectively.

More so, the causal relationships among the factors based on literature are explained as follows. *Decision* based on SA model (Endsley, 2000, 2016) is triggered by the SA of the environment that is either safe or risky and the automaticity. Based on same model, decision triggered the performance of action. *Driver's practice* and ability influenced rehearsed experience (Gazzaniga et al., 2006). That is, "with continuous practice, any knowledge or skill is retained in short term memory and later transfer to long term memory otherwise it will decay". Sexton, Baughan, Elliott & Maycock (2004) that "learning how to drive initially requires continuous practice to master the skills. Once the skill has been mastered, experience has been accumulated, and one can drive successfully". Based on those views, *practice* and *driver's ability* is said to influence the rehearsed experience of a driver. The *driver's experience* is influenced by rehearsed experience and driver's knowledge (Endsley, 2000, 2016). *Driver's ability* is influenced by the skills acquired and experiences of the driver in training (Fuller, 2005; Johnston & Cyr, 2012). Acquired skills are influenced by the basic skills and ability (Endsley, 2000, 2016, Fuller, 2005). In accordance with the model of process (Deery, 1999) perception about hazard is influenced by potential hazard information together with the goals to be achieved (Crundall et al., 2012; Horswill, 2016). Also, the perception about risk is influenced by information on hazards perceived in traffic environment and ability of driver.

In a nutshell, there are thirty one (31) factors in the proposed Rabi's Driver Training model. These thirty one (31) factors identified were categorized into three different groups, namely external, instantaneous and temporal factors. The external factors serves as inputs and independent factors to the model, while the instantaneous and the temporal factors are the dependents factors. The two are time bounded factors but for the instantaneous factors the process is instant contrary to the temporal factors were the process involved much delay. The causal relationships among the categories of the factors are represented symbolically in form of nodes and flow arrows to form a conceptual model. The conceptual model is divided in terms of awareness and training. The conceptual model is further formalized in form of equations to obtain computational models (Ajoge, Aziz, & Yusof, 2017a; Ajoge, Aziz, & Yusof, 2017b; Aziz, Ahmad, Yusof, Ahmad, & Yusof, 2016). Therefore, Chapter Four gives the details of the three classifications of factors and the computational models generated. Table 2.16 shows the comparison of IDM and the proposed enhanced IDM factors.

Table 2.16

Comparison of Factors in Integrated Decision-Making and the Proposed Enhanced Integrated Decision-Making

IDM Model (Noyes, 2012)	**Proposed Enhanced IDM Model**
Actual Situation ▪ Events ▪ Trends	Environment
Mental Representation (MR) or SA	Observation Belief formation for current situation Belief formation for future situation
Goals	Driver Goals
Expectancies	Expectations
Action	Decision
	Performance of Action

Table 2.16 Continued

	Basic Practice Practice
	Basic Skills Acquired Skills Sensory Abilities Potential Hazardous Information Driver Abilities
Experience	Driver's Experience Rehearsed Experience
Complexity	Exposure on Task Complexity
Automaticity Cues	Experienced Automaticity Attention Priming Habitual-directed Action Goal-directed Action Involuntary Automaticity Voluntary Automaticity Acquired Automaticity
Simulation intention	Intention
	Perception about Risk Perception about Task Perception about Hazard
Time Pressure	
Knowledge/Rules	Driver's Knowledge

Table 2.16 shows the comparison between the IDM (Noyes, 2012) and the proposed enhanced IDM. The IDM offers less comprehensive training factors in it RPD component. It is a conceptual base model and hence need to be computational. Based on these drawbacks of the IDM for pilot decision making process, the present study proposed an enhanced IDM (RDT) model by improving on the RPD model component of the IDM. This is to be achieved by expanding some of the IDM training factors and adding some training factors obtained from SA model and other literatures. Although, two factors in the IDM cues and time pressure will not be utilised in the proposed enhanced IDM. Based on that, eighteen (18) training factors such as *Basic practice, Practice, Basic skills, Acquired skills, Sensory ability, Driver abilities, Rehearsed experience, Attention, Priming, Habitual-direction acion, Goal-directed action, Involuntary automaticity, Voluntary automaticity, and Acquired automaticity.*

Others include *experienced automaticity*, *Potential hazardous information*, *Perception about task* and *Perception about risk* are realised in order to have a comprehensive conceptual model that has 24 relevant training factors to train the decision makers (drivers) to enhance their experiences to make prime decision particularly during demanding situations.

More so, computational model is generated in this study based on the designed enhanced conceptual IDM and it is important to have a computational model because the model is precise and unambiguous, and errors can be detected more easily (Vancouver & Weinhardt, 2012). The model can also help in checking if the behaviour of a system based on theories really matches the real world situations that can ensure reproducibility in scientific thinking, and they can be simulated (Farrell & Lewandowsky, 2010; Lewandowsky & Farrell, 2011).

Training the drivers to be more skilful and knowledgeable is the first priority for increasing safety. To take more risk, high levels of skill and knowledge are often used. The objective of training for critical decision-making is to provide the learner with experiences, and instruction on cues, patterns, mental models, and actions that could efficiently establish a collection of well-learned concepts. This enables the drivers to perform mainly at the skill-based level of processing, while providing adequate knowledge-based foundation to perform well in new situations (Greitzer et al., 2010).

Therefore, studies indicate that it's most significant for the learner to get sufficient practice in a variety of conditions once the basic skills has been mastered (Liu, Wang, Li, Xu, & Gui, 2009). Thus, in this study, training is needed for recognizing situations, in communicating situation assessment, and in acquiring the experience to conduct mental simulation of options through the act of human cognitive unconscious/subconscious (or automatic) decision-making, (Klein et al.,1993; Klein, 2008). Having analysed this ability, it will provide a good perspective towards driving assisting systems.

2.4 Computational Modelling

Computational modelling is a method of developing, comprehending and communicating theories. The main goal of computational modelling is to check what is stated in theories can be obtainable in real life environment. In revealing the "real" behaviour of a system, the formal model can discover insights that informal reasoning process may not identify (Farrell & Lewandowsky, 2010; Lewandowsky & Farrell, 2011). It also maximizes communication among the actual behaviour of a postulated system, and its behaviour acquired through reasoning and raises the reliability of communicating the theories to others (Farrell & Lewandowsky, 2010). Formal models are more advantageous over non-formal due to their preciseness, transparent, and they have a consistent internal approach to theories (Adner et al., 2009). The reasoning is one of the advantages of computational models, and it can be described as the process of thinking about something logical to form a conclusion or judgement. One of the methods is analogical reasoning (deducing new solutions through similarity to known solutions/methods). From the computational point of view, reasoning is vital in finding errors more easily and also eases decision making in the model (Vancouver & Weinhardt, 2012).

There are many techniques used in modelling such as Differential Equations (DE), First Order Logic (FOL), Case Base Reasoning, Fuzzy Logic and Agent-based system. This present study makes use of differential equation for its modelling. DE involves one or more derivatives of some unknown function or functions. Systems of DEs have been applied in many fields such as physics, electronic engineering and population dynamics. It is a powerful tool for analyzing the relationship between various dynamic systems. DE contains functions of one independent variable and its derivatives with a general form:

$$F(x\,(t)) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..... (1)$$

Assume variable x is a position of a car on the road and the position of the car changes as the time changes. Then, x is dependent on time (t). That is $x = f(t)$. Differentiation gives a function $\frac{dx}{dt}$, which represents the car's speed. It is the rate of change of its position with respect to time as presented in equation (1).

Table 2.17 shows computational models in different studies that applied different techniques such as agent-based, case-based reasoning, fuzzy logic, and differential equation. This study also used the differential equation technique in modelling the decision-making of drivers. The use of this technique is essential based on this reason: it is most suitable and widely used for describing dynamic systems where time criticality is of essence (Süli, 2014; Treur, 2016a, 2016b, 2016c; Aziz, Ahmad, Yusof, Ahmad & Yusof, 2016; Abro and Treur, 2017; ChePa et al., 2017; Tabatabaei and Treur, 2017). It enables reasoning in which faults can easily be detected. The executable numerical representation can be used for simulation to compare the behaviour of a system simulated with the real-life settings. The numerical representations can be analysed mathematically to check the stability (equilibrium) of the system (Aziz, Klein, & Treur, 2009; Treur, 2016c).

Table 2.17

Summary of Computational models and Techniques

References	Techniques	Scenario
ChePa et al. (2017)	DE	Performance during stress
Tabatabaei and Treur, (2017)	DE	Lifestyle Changes.
Abro and Treur (2017)	DE	Desire Regulation
Formolo et al. (2017)	DE	Traumatized patients
Aziz, Ahmad, Yusof, Ahmad and Yusof, (2016)	DE	Virtual patients
Treur (2014)	DE	Social Response Patterns
Bouhoute, Oucheikh, Berrada and Omari (2014)	FOL	Driving
Thilakarathne and Treur (2013)	DE	Intentional inhibition of actions
Faghihi, McCall and Franklin (2012)	DE	Attentional Learning in a Cognitive Agent
Ting, Zhou and Hu (2010)	CBR	Situation Awareness for MOUT (Military Operation on Urban Terrain) Simulations
Hanratty et al. (2009)	Agent	Knowledge Visualization
Ji et al. (2007)	Fl	Recognition based on experience
Salvucci (2006)	KB cognitive architecture	Driving

NOTE: DE: Differential Equation; FOL: First Order Logic; CBR: Case-Based Reasoning; FL: Fuzzy logic; KB: Knowledge-based

However, computational RPD models and computational SA models are presented in subsections 2.2.1.3 and 2.2.2.2 of this chapter, respectively. So far in the literature, computational integrated RPD-SA model for prime decision making in driving domain has not been presented. Hence, the present study enhanced the IDM using training factors relevant for prime decision making in driving domain and then computationalized the model.

2.5 Discussion

This chapter discusses in detailed modelling driving behaviour where functional and descriptive models were discussed. The concept of decision-making as a basis for this study is highlighted. Decision-making approaches such as normative, descriptive, and prescriptive is also described in this chapter. Additionaly, Naturalistic Decision Making theory and model by Gary Klein described Recognition-Primed Decision model as a model for prime decision in natural settings. Cognitive models such as Endsley model of Situation Awareness, Cognitive Model of Situation Awareness by Hoogendoorn et al. (2011) were also discussed in this chapter and they serve as a basis for this study.

More so, Integrated Decision-making Model (IDM) and its factors were highlighted comprehensively. Based on the discussion on the IDM, The IDM is divided into two components namely, the SA and the RPD as discussed in section 2.3.2. The model is presented with twelve factors, among which, five (5) factors such as, Mental Representation or SA, Experience, Complexity, Time pressure and Automaticity are representing the SA component of the model. Then, seven (7) factors such as Actual situation; Events or Trends, Goals, Expectancies, Cues, Knowledge/Rules, Intention (simulation intention) and Actions represents the RPD component of the model. However, among the 12 factors mentioned, only six (6) factors such as experience, knowledge/rules, goals, complexity, intention and automaticity presented the training in the IDM model.

Some drawbacks of IDM were identified such as, the model offers less comprehensive training factors in it RPD component. It is also a conceptual base model and hence need to be computationalised. Therefore, this study deems to address these drawbacks by improving on the RPD component. This is achieved by expanding some of the IDM training factors and inluding some training factors obtained from SA model and other literatures. The present study therefore enhanced the IDM by using eighteen (18) training factors to enhanced the IDM model by Noyes (2012). The enhanced model presented by the present study is known as Rabi's Driver Ttraining (RDT) model for prime decision making in driving domain which is a conceptual base and it has been computationalised to have an enhanced computational IDM known as Computational Rabi's Driver Training model (C-RDT).

2.6 Summary of the Chapter

This chapter explains in detail the underlying decision theories used to describe the concept of decision-making models in which the use of recognition-primed decision (RPD) model are extremely explored. Also, major concepts within the cognitive model of situation awareness have also been explained. The ideas of computational modelling and its applications are also examined. Therefore, this chapter provides a theoretical underpinning and understanding of the basic concepts of this study. The next chapter of this study explains in detail the methodology used to answer the research questions of the study.

CHAPTER THREE
METHODOLOGY

3.0 Introduction

This chapter describes the study methodology that is employed in achieving the proposed objectives as stated in Chapter one. Section 3.1 presented the study framework as a reference for this study, while Section 3.2, 3.3, 3.4, 3.5 and 3.6 described the overall processes to achieve the intended objectives. Section 3.7 discussed pre-testing and pilot study. Lastly, section 3.8 concluded the chapter.

3.1 Research Framework

In this section, a framework underlying design structure of the study and its conclusion is given. The framework implemented is based on the framework of Drogoul, Vanbergue, & Meurisse (2003). It is an agent-based simulation methodology framework as shown in Figure 3.1.

As a result of complex and dynamic nature of driver behaviour, this decentralized methodology is applicable for formal specification and representation. The research methodology framework serves as a guide to develop and evaluate the computational model that is grouped into five stages, namely domain, design, operational, simulation and evaluation stages. In developing a computational model, the first three stages (domain, design and operational) were used as a basis for the model construction whereas the remaining two stages involved simulation and the model evaluation.

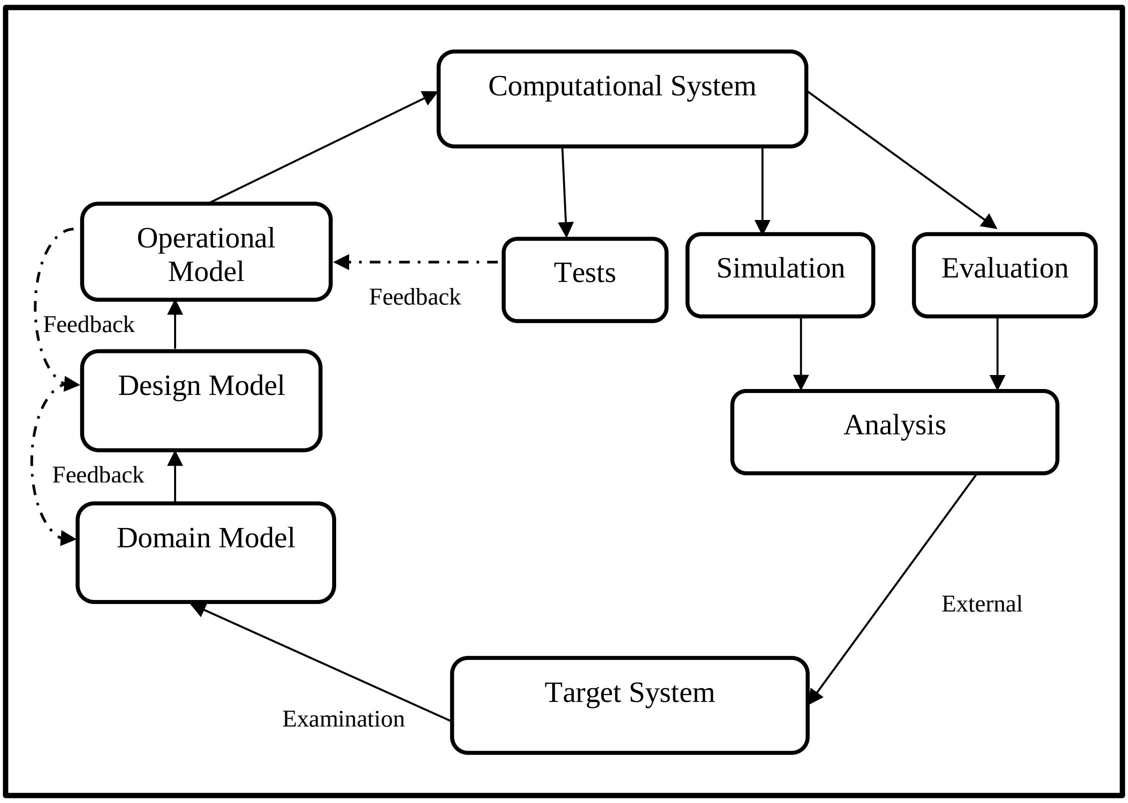


Figure 3.1. Agent Modelling Methodology Framework
Adapted from Drogoul et al. (2003)

Target system in this study methodology refers to the software (City Car Driving simulator) utilized to test the model validity whereas the agents are known as the virtual drivers that operate the simulator. The computational system refers to the simulation environment where the computational model developed is being tested. The implementation and expected outcomes of these stages were illustrated in Figure 3.2.

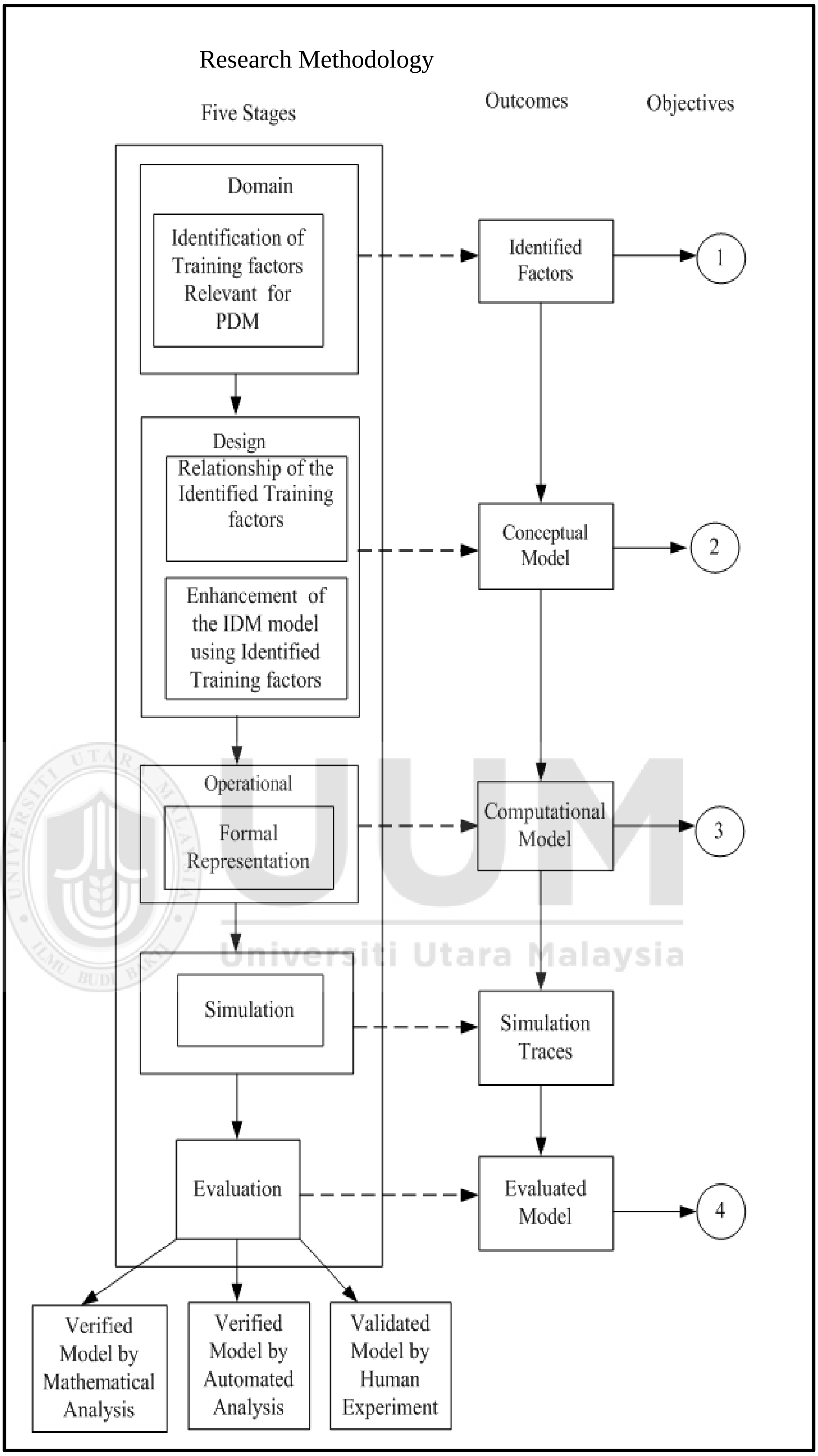


Figure 3.2. Methodology Framework
Adapted from Drogoul et al. (2003)

This methodology has been used in agent-based modelling research for various domains such as in economics (Luna & Stefansson, 2012), social behaviour (Conte & Paolucci, 2014), environment (Serrano, Moncada, Garijo & Iglesias, 2014), medicine (Wang, Butner, Kerketta, Cristini & Deisboeck 2015) and energy consumption (Rai & Robinson, 2015).

3.2 Domain Model Stage

In this stage, the factors in Situation Awareness and Recognition-Primed Decision models that are relevant for prime decision making during emergencies are identified. For the identification of those factors, this study has utilized internet and library resources to review relevant literatures from experts in the respective domains, such as experts in the domains of cognitive and computational sciences.

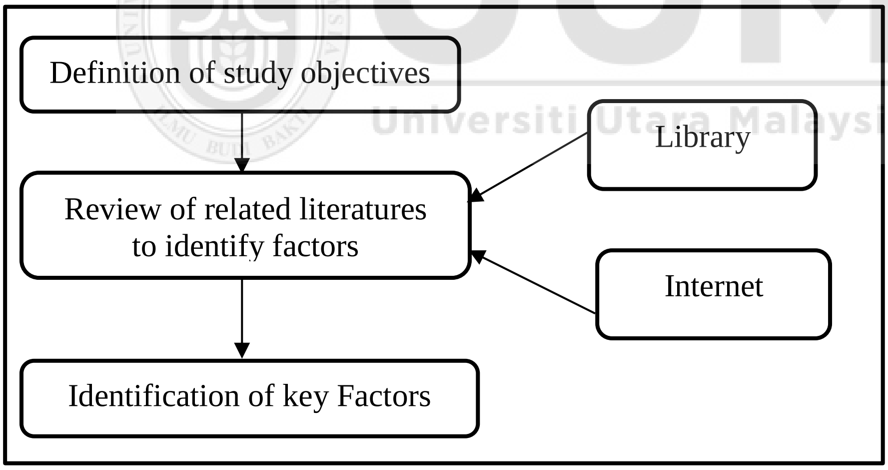


Figure 3.3. Domain Model Stage Activities

The outcome of this stage is the identified factors for the RDT model that were discussed and presented in Chapter Four Section 4.1. Figure 3.3 shows the steps taken to obtain the domain model stage. The result of this stage fulfills the first research objective.

3.3 Design Model Stage

In this stage, the eighteen (18) training factors including Basic Practice, Practice, Basic Skills, Acquired skills, Sensory Ability, Driver Abilities, Rehearsed Experience, Attention, Priming, Habitual-direction acion, Goal-directed action, Involuntary automaticity, Voluntary automaticity, Acquired automaticity, Experienced automaticity, Potential hazardous information, Perception about task and Perception about Risk obtained by expanding some of the IDM factors and identifying other factors from SA model and other related literatures are combined to enhance the RPD component of the IDM model. A node is use to represent each of the factors and the causal relationship between the factors in the model was represented using a set of flow arrows. For each factor, the direct and indirect relationships were considered based on underpinning theories of each concept. This is done to obtain an enhanced conceptual IDM model. The factors in the model were categorized into external, instantaneous and temporal factors. The external factors were set of input factors to the model while the instantaneous factors were those factors whose processes occur instantly. The temporal factors were time-bounded factors whose processes occur with many delays in time. The result of this research stage fulfills the second research objective. The results from this stage were presented in Chapter Four Section 4.2. The activities in the design model are shown in Figure 3.4 and it followed the process used by Bosse, Hoogendoorn, Klein, Treur and van der Wal (2011).

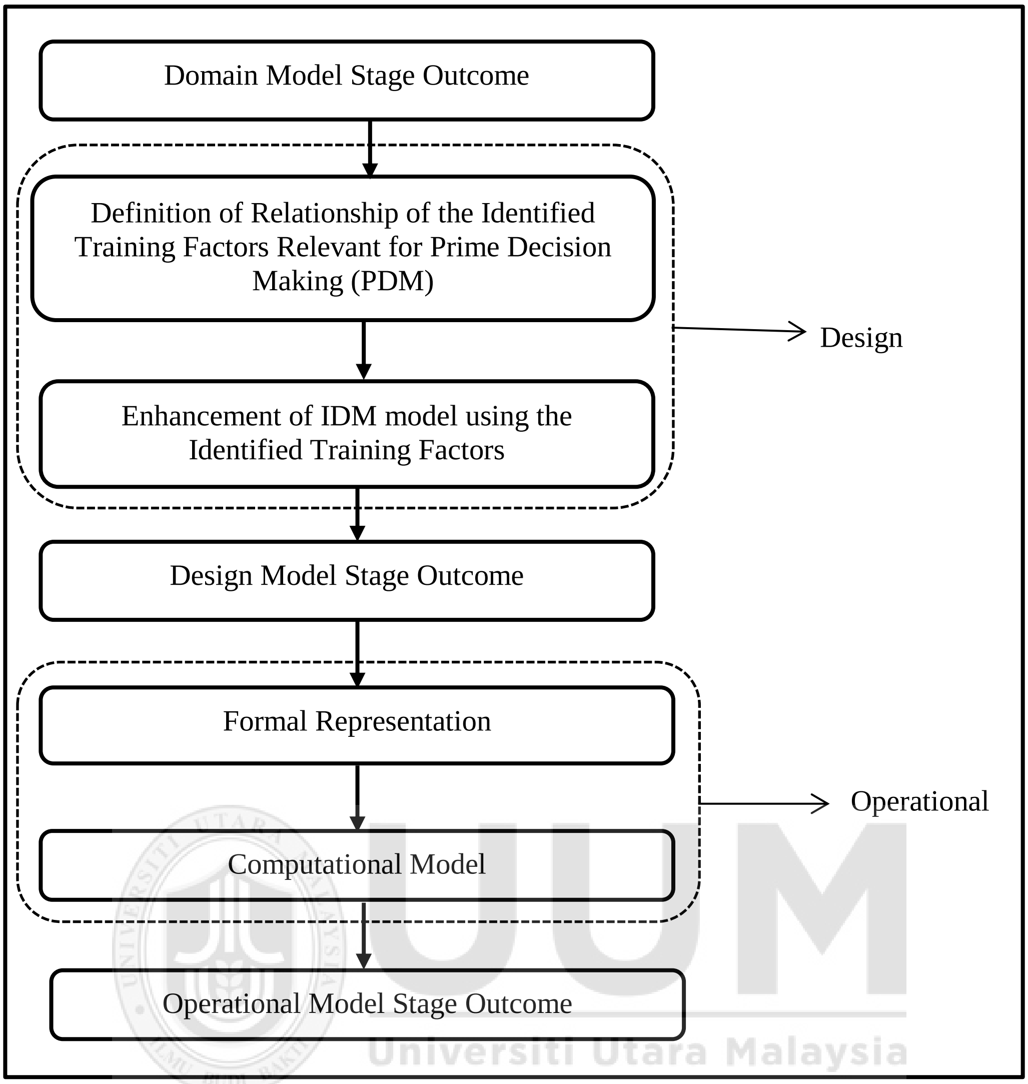


Figure 3.4. Design and Operational Model Stage Activities
Adapted from Klein, Treur and van der Wal (2011).

As an example of the design model, a toy problem was given for instance to demonstrate the stage, if *P*, *Q*, *R*, *X* and *Z* are factors identified from the domain model stage, then, the design model can be presented in Figure 3.5. This shows that the design model represents the relationship between these five factors (*P*, *Q*, *R*, *X* and *Z*) using a set of flow arrows. The relationship was obtained based on theories where the factors were identified.

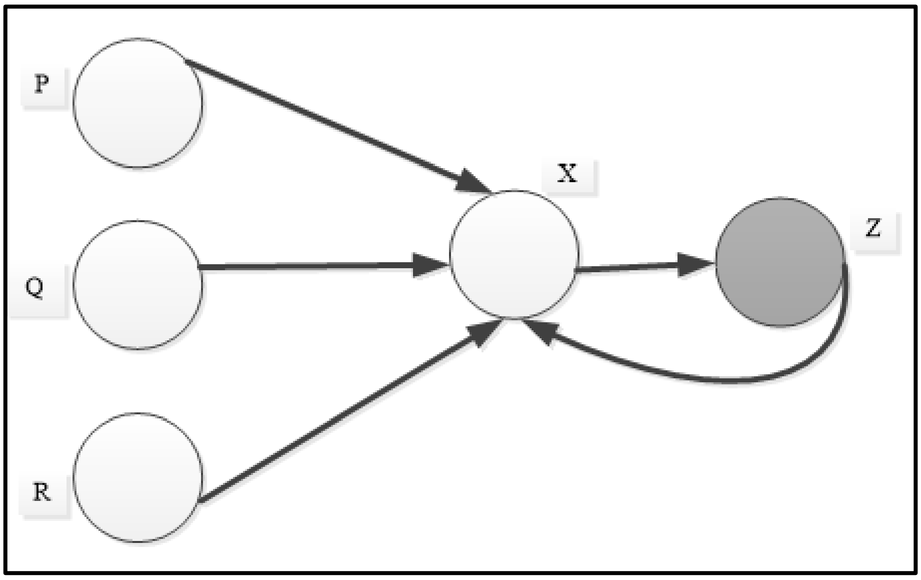


Figure 3.5. Example of Design Model.

From Figure 3.5, the relationship among the factors shows that *P*, *Q*, *R* are input factors, *X* is an instantaneous factor while *Z* is the temporal factor determined by the combination of the input and instantaneous factors.

3.4 Operational Model Stage

At this stage, the conceptual model obtained from the design model is formalized. The result of this research stage fulfils the third research objective. For example, from Figure 3.5 (section 3.3) the mutual interactions of the four identified factors (*P*, *Q*, *R* and *X*) determine *Z*. Assumptions can be made that the causal interactions of these factors are based on cognitive and naturalistic theories such as Endsley and Naturalistic Decision Making. For this purpose, it can be assumed that if equations 3.1 and 3.2 are non-zero or not equal to one, then the concepts conditions stated in Table 3.1, can be formalized to gain equations 3.3 and 3.4. Assuming *Z* is the combination of factors as can be seen in Figure 3.5, hence,

Table 3.1

Example of Different Condition of X

Conditions	Values of Factors	Value of Z	Description
Condition 1	*P* = High *Q* = High *R* = High *X* = High	*Z* = High	*Z* will be high if *P*, *Q*, *R* and *X* are high or any of the three are high and vice versa.
Condition 2	*P* = Low *Q* = High *R* = Low *X* = High	*Z* = Moderate	
Condition 3	*P* = Low *Q* = Low *R* = Low *X* =Low	*Z* = Low	

$$Z = f\,[P, Q, R, X] \tag{3.1}$$

Where $0 \leq P \leq 1$, $0 \leq Q \leq 1$, $0 \leq R \leq 1$, $0 \leq X \leq 1$ and $0 \leq Z \leq 1$ (3.2)

$$X(t) = \omega_{x1}.P(t) + \omega_{x2}.Q(t) + \omega_{x3}.R(t) + \omega_{x4}.Z(t) \tag{3.3}$$

$$\sum_{i=1}^{4} \omega_{xj} = 1$$

where ω_{x1}, ω_{x2}, ω_{x3} and ω_{x4} are weight parameters of the equation.

$$Z(t + \Delta t) = Z(t) + \gamma_z.\big(X(t) - Z(t)\big).Z(t).\big(1 - Z(t)\big).\Delta t \tag{3.4}$$

From equation 3.4, it can be depicted that *Z* will be high if at least three variables from this equation are high and Table 3.1 describes the implemented concepts in a simulation environment. The procedure for the simulation is explained in Section 3.5.

3.5 Simulation Stage

The simulation is implemented in a numerical simulation environment and then verified by selected testing procedures. Figure 3.6 shows the activities to be taken to achieve the simulation traces as a simulation result.

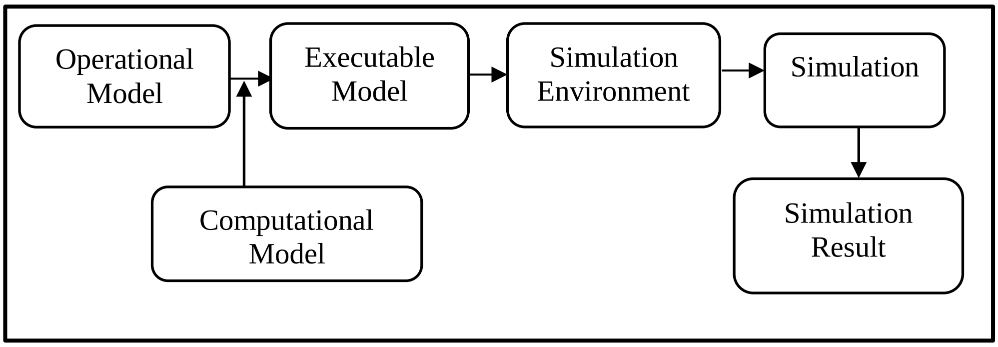


Figure 3.6. Simulation Stage Activities.

Moreover, the simulation result is essential in verifying if the mathematical equations obtained from the model are corresponding to the theories and models used in the study to prove the correctness of the model.

To achieve the simulation result, various activities are performed as shown in Figure 3.6. The executable model is the first activity in the simulation stage. This is translating the computational model into sets of codes using the numerical simulation environment (MATLAB). In the numerical simulation environment, the executable model is simulated by assigning selected cases or conditions to generate simulation traces. The simulation traces are the result of the simulation that depicts the behaviour of the computational model. The details of the computational model simulation are discussed in Chapter Five. For example, the simulation traces for equations 3.3 and 3.4 using the combinations of factors values as shown in Table 3.2 (also depicted in Figure 3.7 to 3.9). In this simulation, the following settings are utilized: ($0 \leq t \leq 500$) with $t_{max} = 500$ (to represent a set of training activities of the driver up to eight months).

The range (i.e., each time step) denotes the training hours where one (1) time step represents 5 hours of training. The level axis, which denotes the range values of *X* and *Z* in terms of high (1) and low (0) are determined.

Table 3.2

Examples of Values for Different Conditions of X

Factors	**High**	**Moderate**	**Low**
P	0.9	0.5	0.1
Q	0.8	0.5	0.1
R	0.8	0.5	0.1

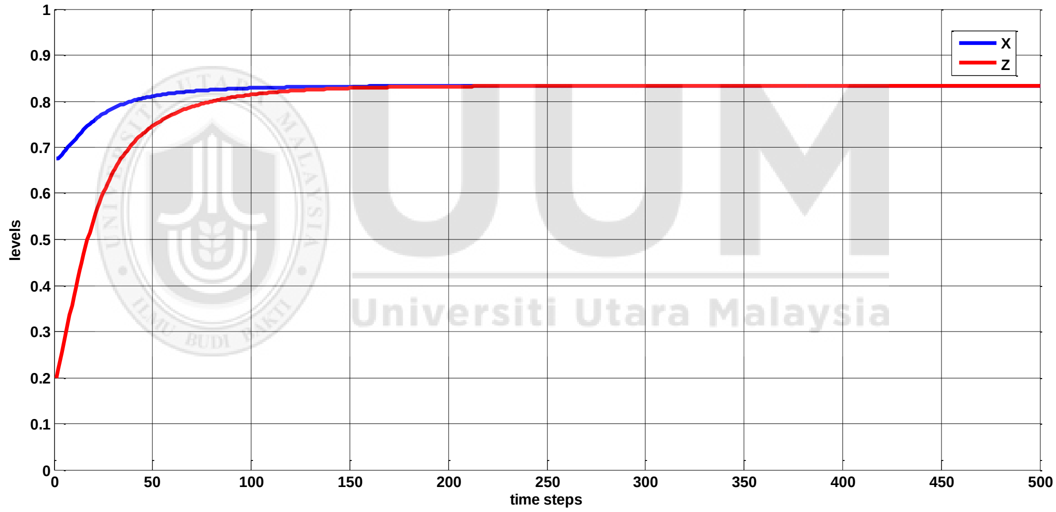


Figure 3.7. Simulation Traces showing a High Condition for X and Z.

From Figure 3.7 it can be seen that the combinations of *P*, *Q*, R and Z provide a simulation traces that stabilize as shown in Table 3.2.

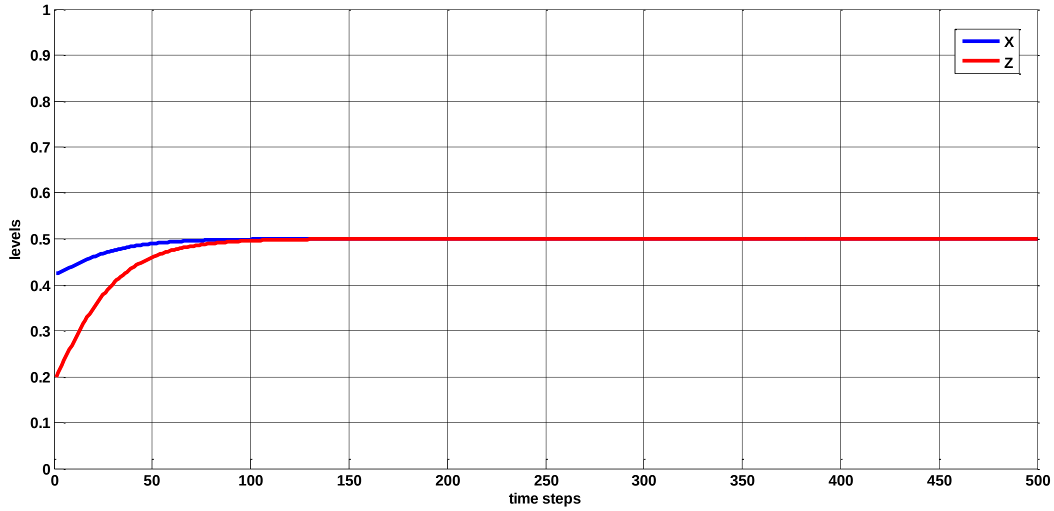


Figure 3.8. Simulation Traces showing Moderate Condition for X and Z.

In addition, the combinations of *P*, *Q*, *R* and *Z* provide a simulation traces as shown in Figure 3.8. This scenario stabilizes within moderate values. It explains the simulation traces of *X* and *Z* as presented in Table 3.2.

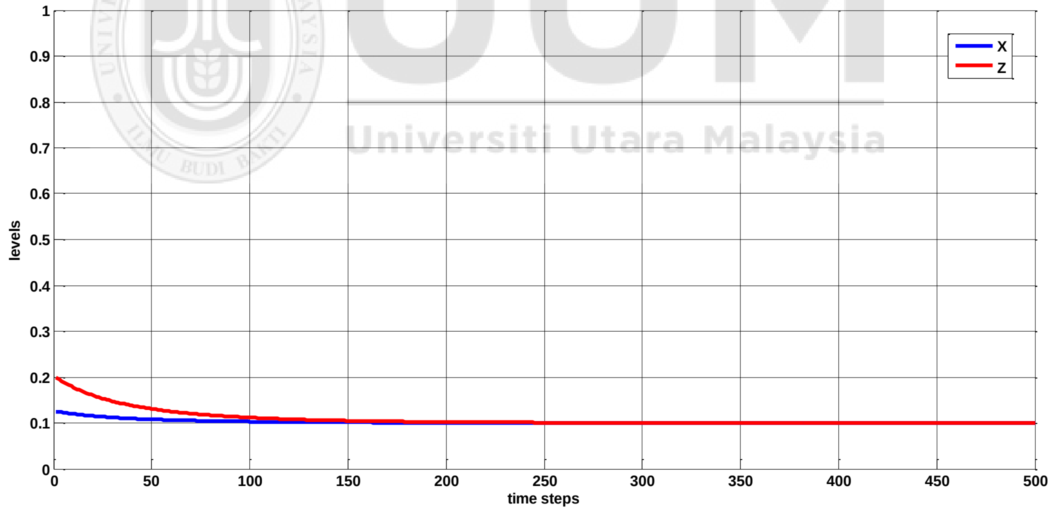


Figure 3.9. Simulation Traces for Low Condition in X and Z.

The low condition of *X* and *Z* is depicted in Figure 3.9 that shows the simulation traces as a result of combinations of low values of *P*, *Q*, and *R* (as presented in Table 3.2).

3.6 Evaluation Stage

This stage aims to ensure that the computational model is the actual representative of the phenomenon under investigation. The stage is divided into two sub-stages, namely verification and validation as shown in Figure 3.10. This stage addresses the fourth research objective in the study.

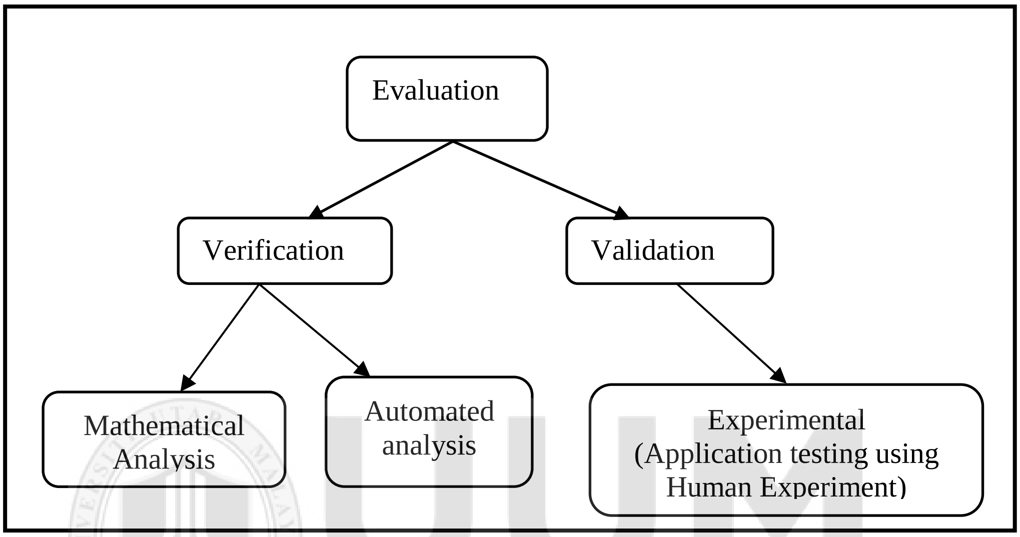


Figure 3.10. Evaluation Stage Activities

3.6.1 Verification Stage

Verification in this study is classified into two; mathematical analysis and automated analysis. The mathematical analysis is achieved using ordinary differential equations (Treur, 2016a, 2016b, 2016c) while automated verification is conducted using Temporal Trace Language (TTL) modal logic (Bosse, Merk & Treur, 2012). The two verification processes are further explained in Chapter Five.

3.6.1.1 Mathematical Analysis

This analysis ensures that all syntax and semantic representations utilized in computational models are reliable. They also ensure the correctness of the formalization of the computational models. According to Balakrishnan (2012), mathematical analysis can be numerical analysis, categorized into the functional analysis, real analysis, complex analysis, measurable analysis and differential equation analysis. Conversely, this study utilized numerical stability analysis (equilibria analysis) to check the stability of finite specifications in the computational hybrid model proposed. The analysis addresses problems of dynamic nature of the model under any small perturbations conditions, and it can identify flaws in any model even with a little disturbance (Treur, 2016b, 2016c). Moreover, adoption of this analysis in this study is because the analyses are used in many dynamic systems in relation to human systems as in prior studies such as (Treur, 2016a, 2016b).

For example, the analysis is implemented by setting the model derivative (or all derivatives) to zero which is stated in equations 3.5 and 3.6.

$$\frac{dy}{dx} = f(y) \qquad (3.5)$$

The constant (or equilibria) solutions of this differential equation are the roots of the equation.

$$f(y) = 0 \qquad (3.6)$$

Equillibria analysis is used to describe situations within the models where the values (continuous) approach a limit under certain conditions and stabilize. That is, if the dynamic of a model is defined by a differential equation, then the equilibria can be estimated by setting a derivative (or all derivatives) to zero.

3.6.1.2 Automated Verification

To verify whether the proposed model indeed generates results that adhere to related literature, a set of properties have been identified from related literatures. So, these properties show whether the model produces results that are coherent with the literature.

Also, by executing a large number of simulations and verifying these properties against the resulting traces, potential logical errors can easily be identified.

To allow the verification process to take place, these properties have been specified in a language called Temporal Trace Language (TTL). TTL is built on atoms referring to states of the world, time points, and traces. This relationship can be presented as a *state* $(\gamma, t, output(R))|=p$, which means that state property p is true at the output of role R in the state of the trace γ, at time point t. Where |= is a predicate symbol in the language which is used as infix notation. It is also comparable to the *Holds*-predicate in the situation calculus. Based on that concept, dynamic properties can be formulated using a hybrid sorted predicate logic approach over time, traces and states properties by using first-order logical connectives and quantifiers such as $\neg$, $\wedge$, $\vee$, $\Rightarrow$, $\forall$, and $\exists$ (Bosse et al., 2012).

For example in describing dynamic properties of complex processes such as SA creation, *time* and *traces* are considered by assuming a linearly ordered fixed time frame *T*. Using the simple example of dynamic properties of agent observation: For all traces γ, there is a time point t such that at time t agent A observes world state W. This informally stated dynamic property is formally expressed as follows:

$\forall\gamma$,:TRACES $\exists$t:TIME state(γ, t) |== observation(A, W). Moreover, the dynamic properties can be the form that relates a state at one point in time to a state at another point in time.

3.6.2 Validation Stage

At this stage, a real experiment is conducted by using a driving game simulator. The game simulator is a commercial software application to be incorporated in the desktop computers for the participants to play to ascertain if the computational model is proportional to the real behaviour of the driver in terms of rapid decision making in emergencies.

3.6.3 Validation Protocol

The validation process is conducted using validation protocols based on User-Centered Design (UCD) approach. The UCD approach is a process in which the needs, wants, and limitations of the end user of a product are given large attention at each stage of the design process. The protocol follows the approach in Figure 3.11

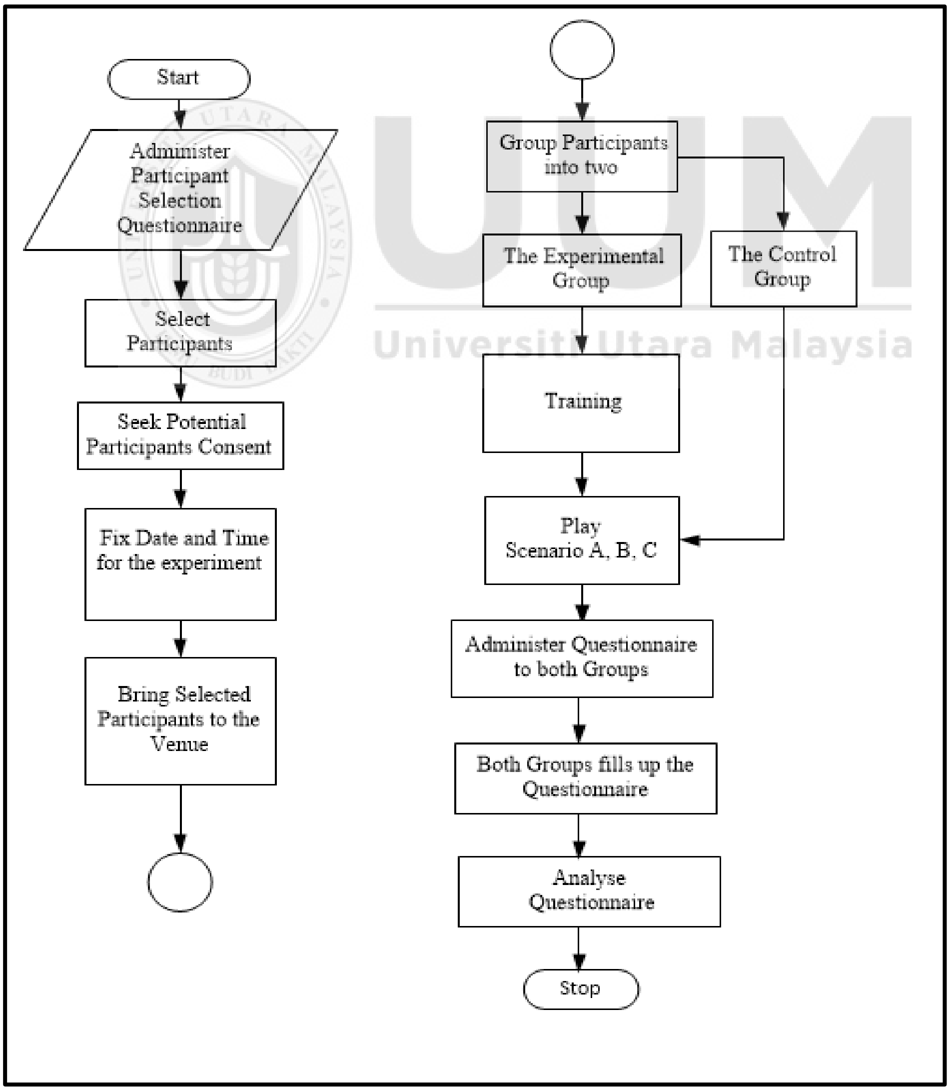


Figure 3.11. Validation Protocols for the Study

This study makes use of the validation protocols in Figure 3.11 to carry out the human experiment. The protocols are highlighted as follows:

To select the participants, questionnaires are administered at the College of Arts and Sciences (CAS) Universiti Utara Malaysia to the selected participants who fall under the criteria of the researcher that suit the study. After the participants are selected based on the criteria, then consent form are distributed to the selected participants. Later, a suitable date and time for the experiment are fixed to carry out the experiment and it is communicated to the selected participants. All the selected participants are brought to Human-Centered Computing Research Lab (HCC-RL) for the experiment. The participants are grouped into two, namely the experimental and control groups. The experimental group is trained using city-driving test while the control group is not trained. Given that the experimental group is trained, it is likely that the experimental group participants will perform better than the control group participants. Thus, this study states the following hypotheses with respect to the outcomes of training:

H0: Training improves driver’s prime decision making.

H1: Training does not improves driver’s prime decision making.

After the grouping, the participants (drivers) interact with the game simulator depending on their group. The game simulator which simulates series of conditions in driving, experiences and scenarios is installed into six different computers. Each computer has a scenario installed based on the SA model external factors that are mapped to the game simulator. These Scenarios are labelled as A, B, and C. After the two groups of participants have interacted with the three different scenarios set up in the city driving game simulator, a questionnaire based on the external and temporal factors of the Automaticity RPD training model is distributed to the participants. The questionnaire is divided into two parts: Part A deals with the demographic information of the participants and Part B consists of items on Driver Behaviour (DB) based on the training model. This is to evaluate the importance of the proposed model factors effectiveness to determine its effect on the automaticity of the driver to make effective decision especially during emergencies and to see if the simulation scenarios based on the model factors match the behaviour of the driver in terms of prime decision making in real life. Later, the participants answer the questionnaire based on their experiences and interactions with the game simulator. Thereafter, the questionnaire is analysed using statistical package for social sciences (SPSS).

3.7 Pre-testing and Pilot Study

An initial draft of the questionnaire was pretested before conducting the pilot study. The questionnaire was given to three experts to validate its items to determine if it possesses content and face validity (Creswell, 2014). The three experts were senior staff of Institute Memandu Mustika Muhibah Sdn. Bhd. Sintok, Malaysia. Sample of photos with one of the experts is shown in Appendix A. The questionnaire was also given to an English expert at the Language Centre, Universiti Utara Malaysia for grammatical checking process. All of the experts provided valuable inputs and corrections with regard to ambiguities, format, wording, simplicity and clarity of the items in the questionnaires that may cause confusion for the participants (Yaghmale, 2009). The experts' evaluation, corrections and suggestions were then reflected in the study questionnaire before administering it to the participants for the pilot study. This was done in order to ensure content validity and reliability of the questionnaire. The sample of the experts' evaluation questionnaire is shown in Appendix B.

Moreover, the researcher made some important observations before the pilot study and the observations were as follows: some of the participants did not answer the questionnaire based on their experience and interactions with the game simulator. Instead, they answered it based on their general driving experience. Therefore, the researcher instructed the participants that they should answer it strictly based on their experiences and interactions with the game simulator rather than using their general driving experiences.

Moreover, no protocol guideline was provided to guide the participants on how to perform the experiment during the pilot study. This affected the participants not to play the game up to a certain level where the system would give them an assignment that would form the basis of generated data. However, some participants played the game, but their data was not generated by the system. This suggests that protocol guide should be provided for the participants to guide them on how to perform the experiment.

Later, to verify the validity and reliability of the research instruments, a pilot test was carried out. This is because the scales adapted in this study were developed in different settings.

The pilot test was conducted before the main data collection. The main goal of the pilot test is to test how each item measuring the factors is reliable and consistent with the operational definition of the factors based on the participants' feedbacks (Zikmund-Fisher et al., 2010). Additionally, the benefit of the pilot study is to improve the questionnaire and strengthen the study when it comes to the analysis (Neuman, 2011, 2012). The pilot test follows the validation protocol approach in Figure 3.8 where the questionnaire used to select the participants was distributed and the potential participants were selected based on criteria. Six participants (drivers) including five males and one female both with experience and without experience were selected randomly. All the six participants had a valid driving licence and knowledge of computer usage and video gaming.

Subsequently, the responses from the participants were keyed in SPSS software to assess the reliability of the items adapted for measuring the understudied external and temporal factors of the proposed training model. Cronbach's alpha is used to assess the reliability and validity of the items employed in this study.

Table 3.3

Summary of Reliability Test

Items	**No of Items**	**Cronbach Alpha**
Basic Skills	8	0.874
Basic Practice	9	0.754
Sensory Ability	12	0.911
Driving Goals	3	0.996
Driving Intention	3	0.996
Potential Hazardous Information	4	0.869
Exposure on Task Complexity	8	0.937
Risk Perception	11	0.860
Driving Knowledge	4	0.950
Involuntary	4	0.797
Voluntary	4	0.797

The results of the Cronbach's alpha are presented in Table 3.3. According to Hair, Ringle and Sarstedt (2013), the threshold for acceptable Cronbach's alpha value is 0.70. According to the result presented in Table 3.3, the least Cronbach's Alpha value is 0.754 for basic practice which is above the suggested threshold. Therefore, these results indicate that the measures employed for measuring external and temporal factors in this study are reliable and valid, suggesting that the questionnaire is suitable for the main experiment.

In conclusion, Table 3.4 summarises the research methodology stages which includes the method utilized at each stage, the desire outcomes of the stages reflecting the four study objectives.

Table 3.4

Summary of the Research Stages

Stages of Research Methodology	**Methods**	**Outcomes**	**Research Objectives**
Domain model	Literature Review	Identified factors	1
Design model	Representation of factors relationship	Conceptual model	2
Operational model	Formal Representation of Factors	Computational Model	3
Simulation	Simulation Environment	Simulation Results	--
Evaluation	Verification using Mathematical Analysis and Automated Analysis (TTL); Validation using Human Experiment.	Evaluated model	4

3.8 Summary of the Chapter

This chapter discussed the study methodology employed to answer the four research questions as stated in chapter one. The present study adapted the approach by Drogoul et al. (2003) as the main study methodology. The main stages that made up the research methodology with their corresponding sub-stages assisted to achieve the four research objectives. The next chapter covered the development of the Computational-RDT model for prime decision making in driving.

CHAPTER FOUR
ENHANCEMENT AND COMPUTATIONALIZATION OF INTEGRATED DECISION-MAKING MODEL

4.0 Introduction

This chapter gives the detailed explanation on the enhancement and computationalization of IDM model for prime decision-making in driving domain.

4.1 Identification of Enhanced Integrated Decision-making Model Factors

In this study, thirty one (31) factors in an enhanced Integrated Decision-making Model (RDT) model were identified based on the literature review and empirical studies as stated in Chapter 2 and methodology in Chapter 3. Out of the thirty one (31) factors identified in this model, seven (7) factors are from the awareness component and twenty-four (24) are from the RPD training component of the model. These factors were further categorised into three different groups, namely external, instantaneous and temporal factors. The external (exogenous) factors are independent factors that contribute to other factors, while instantaneous factors are dependent factors that are time-bounded with no delay. In contrary, the temporal factors are time-bounded with delay. The categories of these factors are further elaborated in detailed in subsections 4.1.1, 4.1.2 and 4.1.3.

4.1.1 External Factors of the Enhanced Integrated Decision-making Model

There were nine (9) external factors identified in the enhanced IDM. Two (2) of the factors were classified under the awareness component of the enhanced IDM, namely *Environment and Expectations.* While seven (7) of the factors were classified under the

RPD training component of the enhanced IDM , namely *Basic practice*, *Basic skills, Sensory ability, Driver's goal, Potential hazardous information, Exposure on task complexity* and *Intention*. They determined the outcome of the relationship between the external and instantaneous process. See Table 4.4 for the two classifications.

In this study, *environment* refers to the surrounding in which car and driver operate. It is denoted as alpha (α). This definition is adapted from Hjälmdahl, Shinar, Carsten, & Peters (2011) and Shinar and Oppenheim (2011). The *expectation* is defined as knowledge of possible consequences or expectancies of the future (Klein, 2008). The *Basic practice* is the capacity of the driver to operate and control the vehicle (Freydier, Berthelon, & Bastien-Toniazzo, 2016). It follows by a set of *Basic Skills* to determine the operational competence of the driver (Imhoff, Lavallière, Germain-Robitaille, Teasdale, & Fait, 2017). *Sensory Ability* denotes the ability of driver to have cognitive, physical and visual functions to manipulate the vehicle (Anstey, Wood, Lord, & Walker, 2005). *Driver's goal* in this study refers to multiple driving aims that driver wants to achieve during the driving task (Dogan, Steg & Delhomme, 2011). *Potential Hazardous Information* refers to information concerning the potential hazards in the traffic (Borowsky et al., 2010; Crundall et al., 2012; Horswill, 2016; Huestegge & Böckler, 2016; Takahashi et al., 2007; Konishi et al., 2004). *Exposure on Task Complexity* refers to the complexity driver exposes to at the course of the interaction with the vehicle and environment (Grill, Osswald & Tscheligi, 2012). Lastly, the *intention* in the present study refers to a driver's mental state that translates his/her goals into reality (Moskowitz, 2013). The summary of the external factors of the RDT model is shown in Table 4.1.

Table 4.1

Summary of External factors of the Enhanced Integrated Decision-makingModel

Factors	Notation	Description	Related Theory/Models	References
Environment	*En*	The surrounding in which car and driver operate.	SA, TCI, UMD.	Endsley (1995, 2016); Fuller (2005); Hjälmdahl et al. (2011); Shinar and Oppenheim (2011).
Expectations	*Ep*	Knowledge of possible consequences or expectancies of the future.	SA, RPD, IDM	Endsley (1995, 2016); Klein (2008); Noyes (2012)
Basic Practice	*Bp*	The capacity to operate and control the vehicle	SA, TCI	Fuller (2005); Endsley (1995, 2016); Freydier et al. (2016)
Basic Skills	*Bs*	The operational competence of driver	SA, TCI	Imhoff et al. (2017)
Sensory Ability	*Sa*	The ability of driver to have cognitive, physical and visual functions to manipulate the vehicle	MM	Anstey et al. (2005)
Driving Goal	*Dg*	Multiple driving aims that driver wants to achieve during the driving task.	SA, RPD,TCI, IDM	Dogan et al. (2011)
Potential Hazardous Information	*Hi*	Information acquired regarding potential threads that might need urgent respond in the traffic environment during driving.	MP	Borowsky et al. (2010); Crundall et al. (2012); Horswill (2016); Huestegge and Böckler (2016)
Exposure on Task Complexity	*Tc*	The complexity driver exposes to at the course of the interaction with the vehicle and environment.	SA, TCI, RPD, IDM	Grill et al. (2012)
Intention	*In*	Driver's mental state that translates his goals into reality	SA, IDM	Moskowitz (2013).

Note: SA – Situation Awareness model, CMSA – Cognitive Model of Situation Awareness, RPD – Recognition-Primed Decision model, IDM – Integrated Decision-making Model for Pilot, TCI – Task-Capability Interface model, UMD - Unified Model of Driver Behaviour.

4.1.2 Instantaneous Factors of the Enhanced Integrated Decision-Making Model

Sixteen (16) instantaneous factors were identified in the enhanced IDM. Four (4) of the factors were classified under the awareness component of the enhanced IDM, namely O*bservation, Belief formation, Belief activation,* and *Performance of action*. Twelve (12) of the factors were classified under the RPD training component of the enhanced IDM model, namely *Practice, Acquired skill, Rehearsed experience, Driver ability, Driver's experience, Perception about hazard, Perception about task, Attention, Priming, Habitual-directed action, Goal-directed action* and *Acquired automaticity* as shown in Table 4.4. The definition of each factor as a concept is given as follows.

Observation refers to the ability of the driver to perceive elements in a driving environment such as road, traffic, obstacle, car condition and visibility (weather and light). The various elements to be observed by driver in a driving environment include *Road*, the road type, and its nature (dry, wet) where car is driven. *Traffic* refers to the density regarding cars per mile or km and the congestion in traffic may be observed while driving car on the road. *Obstacles* are the different complications that may be found along the road, such as stationary vehicles and other objects. *Car condition* represents the status of car, for example the engine may be faulty/good. *Visibility* that consists of the weather condition (clear/cloudy, rainy) may be observed on the road and the light condition (day/ night-time) where driving takes place. *Belief formation* is the ability of driver to form certainty of the observation made. Then, *belief activation* refers to the ability of driver to translate the certainty of observations into activation values of beliefs. *Performance of action* can be determined by the positive (safe) and negative (risky) confidence level of driver to decide. If the decision is safe, then the performance of action is *yes* (1), otherwise it is *no* (0). *Practice* is defined in this study as a method of developing the drivers' skills and knowledge that relates to specific useful competencies of the driving task. An *acquired skill* is a form of long-term skill while *basic skills* refer to short-term skill. Acquired skill denotes accumulated exposure of the basic skill over time which is acquired through experience and training to drive competently. *Rehearsed experience* is the accumulation of the experiences acquired from direct participation in the driving activity that is transferred into working memory (WM) and long-term memory (LTM). *Driver's ability* denotes the capability driver possesses in order to manipulate /operate car. *Driver's experience* means driver's accumulation of the reoccurrence of knowledge or skills acquired from direct participation in the driving activity.

Perception about hazard otherwise called hazard perception in other studies refers to a driver's ability to anticipate potentially dangerous situations on the road ahead (Horswill, 2016). *Perception about task* otherwise called task perception is defined as the way driver experiences task in potential traffic environment. *Attention* operationally refers to the ability of driver to perceive multiple items in parallel. *Priming* is a concept used in automaticity and is defined as a stimulus that makes the driver initiate response (unconscious and conscious responses) sequence during automatic processes. A *habitual-directed action* is a form of automaticity. In this study, it is referred to as action initiated by driver as an act of unconsciousness, and when action is repeated and sufficiently practiced, it becomes habitual action. A *goal-directed action* is a form of automaticity that is referred to as goal-dependent action. It relates to an action initiated by the driver as an act of conscious will. *Acquired automaticity* refers to process that occurs instantly within the limited time frame; hence, it is a short-term automaticity. Table 4.2 depicts the summary of the instantaneous factors of the RDT model.

Table 4.2

Summary of Instantaneous Factors of the Enhanced Integrated Decision-making Model

Factors	**Notation**	**Description**	**Related Theory/Models**	**References**
Observation	*On*	Ability to perceive elements in a driving environment.	SA,CMSA	Endsley (1995, 2016); Hoogendoorn et al. (2011)
Belief Formation	*Bf*	Ability to form certainty of the observation made.	CMSA	Hoogendoorn et al.(2011)
Belief Activation	*Ba*	Ability to translate the certainty of the observations into activation values of beliefs, which can be safe or risky.	CMSA	Hoogendoorn et al.(2011)
Performance of Action	*Pa*	Implementation of the decision taken by the driver.	SA, RPD and IDM	Endsley (1995,2016)
Practice	*Pc*	Method of developing the drivers' skills and knowledge that relates to specific useful competencies of the driving task.	SA, TCI	Fuller (2005)
Acquired Skills	*As*	Accumulated exposure of the basic skills.	TCI	Fuller (2005)
Rehearsed Experience	*Re*	Experiences acquired due to continuous driving routine that might decay overtime.	SA	Gazzaniga et al. (2012)
Driver Ability	*Da*	Capability driver possesses to manipulate /operate car.	SA, TCI	Endsley (1995, 2016); Fuller (2005).

Note: SA – Situation Awareness model, RPD – Recognition-Primed Decision model, RPDT-Recognition-Primed Decision Training Model, IDM – Integrated Decision-making Model for Pilot, TCI – Task-Capability Interface model, MM - Multifactorial Model and MP - Model of Processes, UMD - Unified Model of driver behaviour, WM- Working Memory, LTM- Long-Term Memory.

Table 4.2 Continued

Factors	Notation	Description	Related Theory/Models	References
Driver's Experience	*De*	Driver's accumulation of the reoccurrence of knowledge or skill acquired that result from direct participation in the driving activity.	SA, TCI, RPD, UMD, IDM.	Shinar and Oppenheim (2011); Oppenheim et al.(2010, 2012)
Perception about Hazard	*Hp*	Driver's ability to anticipate potentially dangerous situations on the road ahead.	MP	Horswill (2016)
Perception aboutTask	*Tp*	The way driver sees or experiences task in the potential traffic environment.	TCI	Fuller (2005)
Attention	*An*	The ability of driver to perceive multiple items in parallel accurately.	SA	Moskowitz (2013)
Priming	*Pg*	The stimulus that makes driver initiates response sequence in driving.	SA, IDM	Wheatley and Wegner (2001)
Habitual-directed action	*Hd*	Action initiated by driver as an act of unconsciousness while driving	SA, IDM	Moskowitz (2013) Wasserman and Wasserman (2016).
Goal-directed action	*Gd*	Action initiated by driver as an act of conscious willing while driving.	SA, IDM	Moskowitz (2013); Wasserman and Wasserman (2016).
Acquired Automaticity	*Aa*	Short-Term Automaticity.	SA, IDM	Panek et al. (2015)

4.1.3 Temporal Factors of the Enhanced Integrated Decision-making Model

Six (6) temporal factors were identified in the enhanced IDM based on the literature. One (1) factor called decision was classified in the awareness component of the enhanced IDM. The other five factors such as P*erception about risk*, *Driving* *knowledge, Involuntary automaticity, Voluntary automaticity and Experienced automaticity*, were classified under the RPD training component of the enhanced IDM model and the six determine the automaticity of the driver to perform effective decision-making. See Table 4.4 for the two classifications. The definition of each factor as a concept is given as follows.

Perception about Risk refers to the subjective experience of risk in potential traffic hazards (Rosenbloom et al., 2008), while *driving knowledge* is the ability of driver in knowing the traffic rules and regulations of the road. It is acquired mainly through practice and experience. *Involuntary automaticity* is operationally defined as behaviours that are unconsciously experienced (automatic behaviours) by driver during driving, whereas *voluntary automaticity* refers to behaviours that are consciously experienced (non-automatic behaviours) by driver while driving. *Experienced automaticity* refers to the long-term automaticity, as its process occurs for a long period. It denotes accumulated experience (exposure) of driver to make a prime decision. *Decision* is used to measure the confidence level of the driver, and it determines the performance of an action of driver. It is defined as the internal processes by which a course of action or inaction is selected from a set of alternatives. The summary of the temporal factors is shown in Tables 4.3.

Table 4.3

Summary of Temporal Factors of the Enhanced Integrated Decision-makingModel

Factors	**Notation**	**Description**	**Related Theory/Models**	**References**
Perception of Risk	*Rp*	Subjective experience of risk in potential traffic hazards.	TCI, MP	Rosenbloom et al. (2008)
Driving Knowledge	*Dk*	Knowledge of traffic rules and regulations of the road.	TCI, IDM	Stanton et al. (2007)
Involuntary automaticity	*Iv*	Unconscious and automatic behaviours experienced by driver.	SA, IDM	Wheatley and Wegner (2001); Wasserman and Wasserman (2016).
Voluntary automaticity	*Vy*	Conscious and non-automatic behaviours experienced by driver	SA, IDM	Wheatley and Wegner (2001); Wasserman and Wasserman (2016).
Experienced Automaticity	*Ea*	Long-term automaticity that denotes accumulated exposure of the acquired automaticity of driver.	SA, IDM	Wheatley and Wegner (2001); Wasserman and Wasserman (2016).
Decision	*Dc*	The internal processes by which the driver selects a course of action or inaction from a set of alternatives	SA	Smith (2016)

Note: SA – Situation Awareness model, RPD – Recognition-Primed Decision model, RPDT-Recognition-Primed Decision Training Model, IDM – Integrated Decision-making Model for Pilot, TCI – Task-Capability Interface model, MM - Multifactorial Model and MP - Model of Processes, UMD - Unified Model of driver behaviour, WM- Working Memory, LTM- Long-Term Memory.

From Table 4.1, 4.2, and 4.3 the factors identified based on cognitive and naturalistic decision making theories such as Endsley's, Naturalistic Decision Making theories and other related literatures are mostly the contribution of this study to the body of knowledge.

Table 4.4

Classification of the Enhanced Integrated Decision-making Model and its Factors

Classification of Factors	**Awareness Component**	**RPD Component**	**Enhanced IDM Factors**
External	1. Environment 2. Expectations	1. Basic practice 2. Basic skills, 3. Sensory ability, 4. Driver's goal, 5. Potential hazardous information, 6.Exposure on task complexity and 7.Intention	1. Environment 2. Expectations 3.Basic practice 4. Basic skills, 5. Sensory ability, 6. Driver's goal, 7.Potential hazardous information, 8.Exposure on task complexity and 9.Intention
Instantaneous	1.Observation 2.Belief formation 3.Belief activation 4.Performance of action	1. Practice, 2. Acquired skill, 3. Rehearsed experience, 4. Driver ability, 5. Driver's experience, 6. Perception about hazard, 7. Perception about task, 8. Attention, 9. Priming, 10. Habitual-directed action, 11. Goal-directed action and 12. Acquired automaticity	1.Observation, 2.Belief formation, 3.Belief activation, 4.Performance of action 5. Practice, 6. Acquired skill, 7. Rehearsed experience, 8. Driver ability, 9. Driver's experience, 10. Perception about hazard, 11. Perception about task, 12. Attention, 13. Priming, 14. Habitual-directed action, 15. Goal-directed action and 16. Acquired automaticity
Temporal	1. Decision	1. Perception about risk 2. Driving knowledge 3. Involuntary automaticity, 4. Voluntary automaticity and 5. Experienced automaticity,	1. Perception about risk, 2. Driving knowledge, 3. Involuntary automaticity, 4. Voluntary automaticity 5.Experienced automaticity, and 6. Decision.
Total Factors	**Seven (7)**	**Twenty four (24)**	**Thirty-one (31)**

Table 4.4 shows the summary of the classifications of the enhanced IDM (awareness and RPD training components) and its factors (external, instantaneous and temporal factors).

4.2 Enhancing the Conceptual Integrated Decision-making Model

In enhancing the conceptual IDM, training factors that are relevant for prime decision making were identified from the SA model and other related literatures. The enhancement was done on the RPD training component of the IDM using those training factors identified. The original IDM had six (6) training factors including experience, knowledge/rules, goals, complexity, intention and automaticity. In the enhanced IDM , the RPD component of the model had twenty four (24) training factors represented symbolically using nodes and flow arrows. The nodes represented the states and the flow arrow denoted the causal relationship between the states. The nodes and flow arrows formed the conceptual model. This conceptual model explicitly indicates interactions between factors and relationship involved based on cognitive theories e.g., Endsley theory of SA, Naturalistic Decision Making.

The causal relationships produced an enhanced conceptual IDM called Rabi's Driver Training (RDT) model as summarized in Figure 4.1 and Figure 4.2. The conceptual model is subdivided into generic and specific models for driving. In the generic model, the factors as constructs were expanded in this study in order to have a comprehensive model with training factors relevant for prime decision making particularly during demanding situations as shown in Figure 4.3. Some of the factors were connected with the exernal factors and were not grouped to avoid confusion. Therefore, the factors were expanded as follows: 1. Practice was elaborated to include *Basic practice (Bs)* and *Practice (Pc)*; 2. Ability was extended to have *Basic Skills (Bs), Acquired Skills (As)* and *Driver ability (Da)*; 3. *Experience* was expanded to include *Rehearsed experience (Re)* and *Driver's experience (De);* 4. *Perception of risk* was elaborated to include *Potential hazardous information (Hi), Perception about task (Tp), Perception about* *hazard (Hp)* and *Perception about risk (Rp)*; 5. *Automaticity* was elaborated to have Intention (In), Attention (An), *priming (Pg), habitual-directed action (Hd), goal-directed action (Gd), Acquired automaticity (Aa)* and *Experienced automaticity (Ea)*.

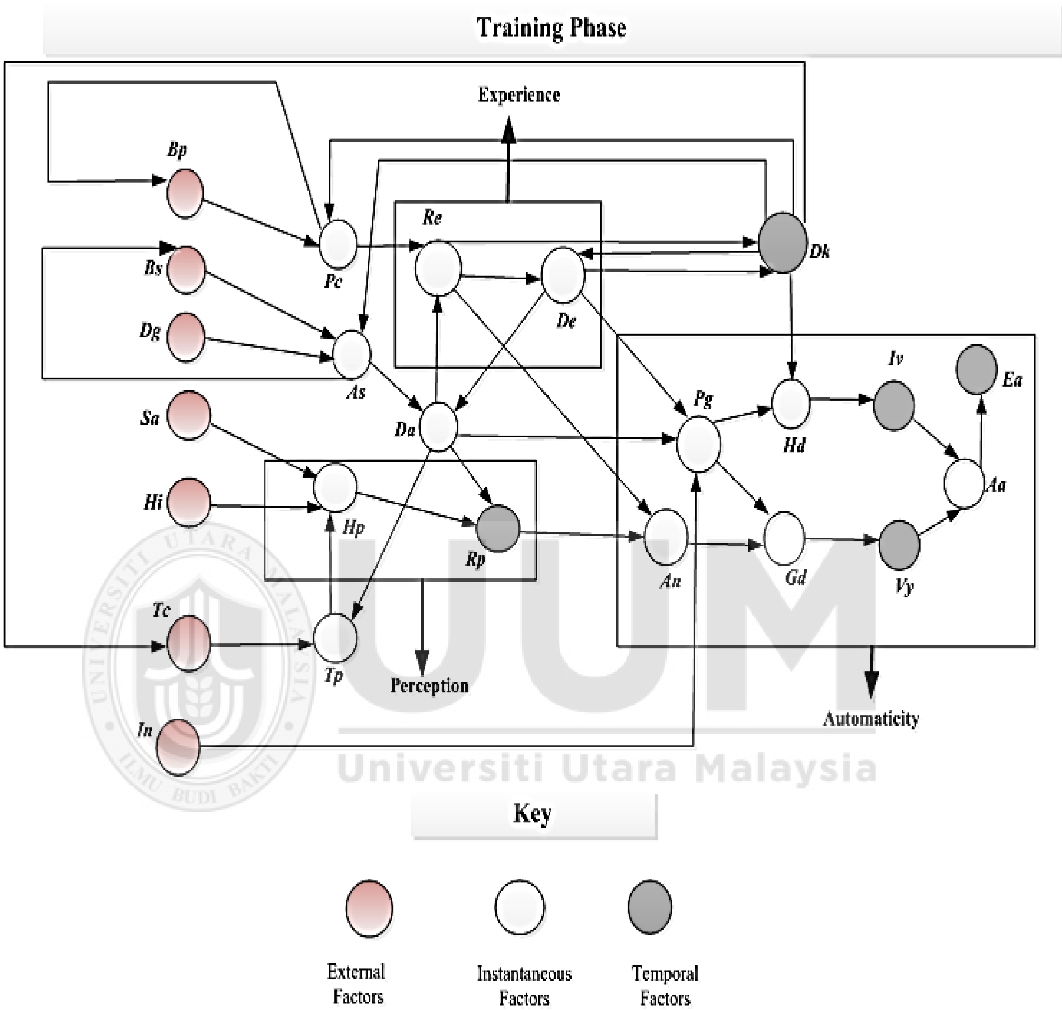


Figure 4.1. The Generic Conceptual RDT Model

In the specific conceptual RDT Model for driving the factors are not grouped as shown in Figure 4.2.

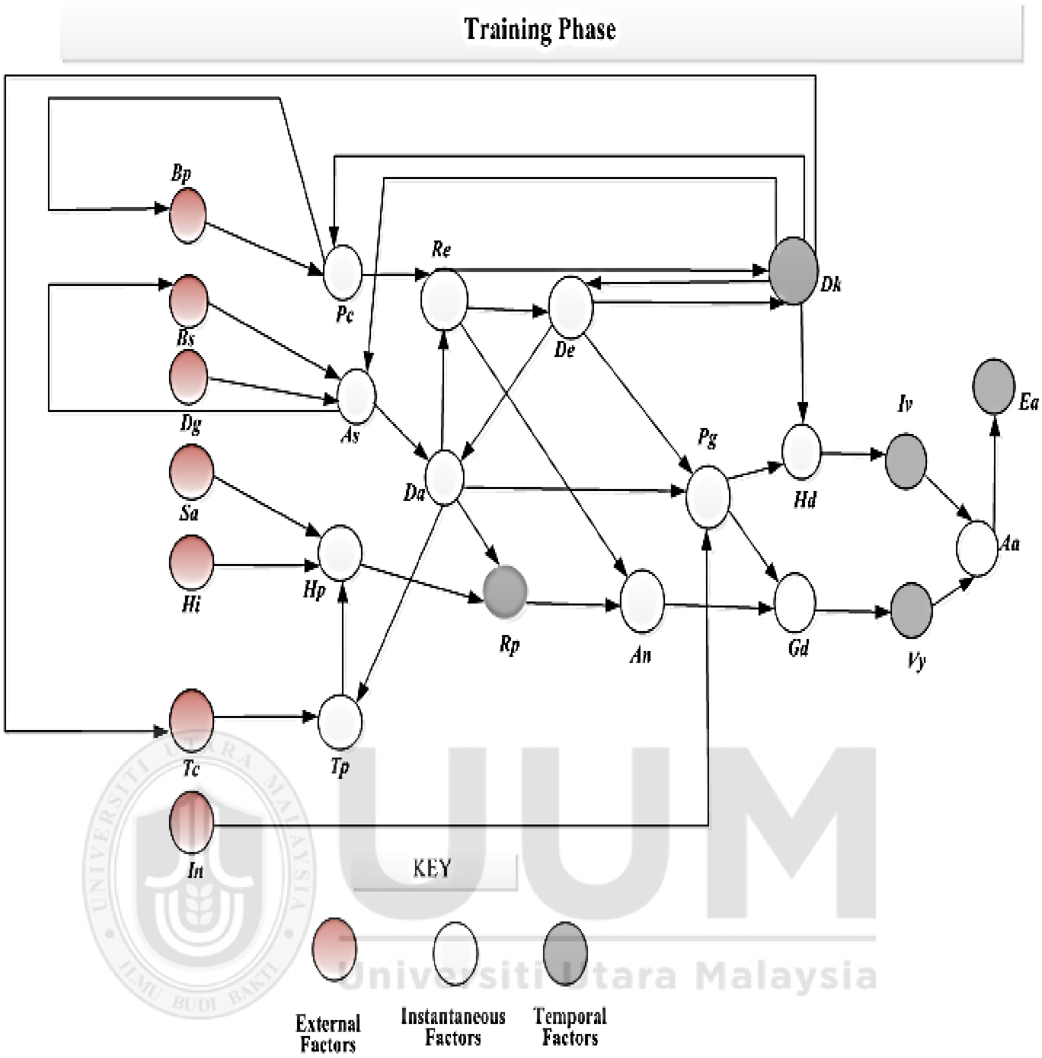


Figure 4.2. Conceptual RDT Model in Driving

Moreover, Figure 4.3 and Figure 4.4 presented the conceptual RDT model called Rabi's Driver Training (RDT) model that included training factors relevant for prime decision making. The conceptual RDT model is presented in two formats just as in the conceptual RDT model namely the generic model and the specific model for the driving domain as depicted in Figures 4.3 and 4.4, respectively.

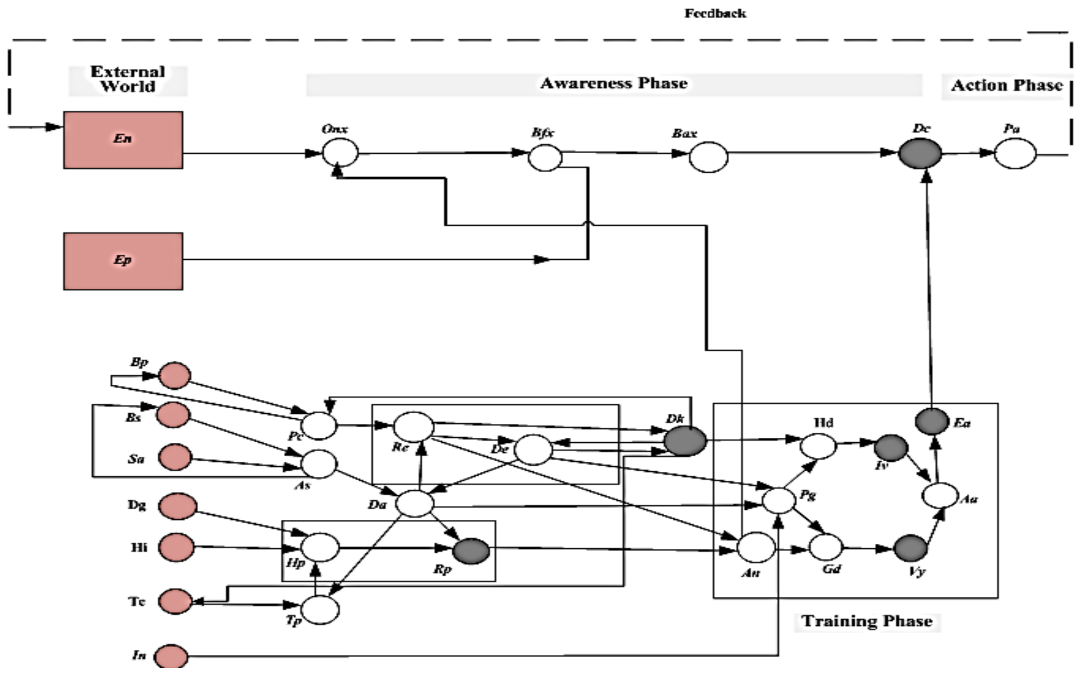


Figure 4.3. Generic RDT model for Prime Decision-Making

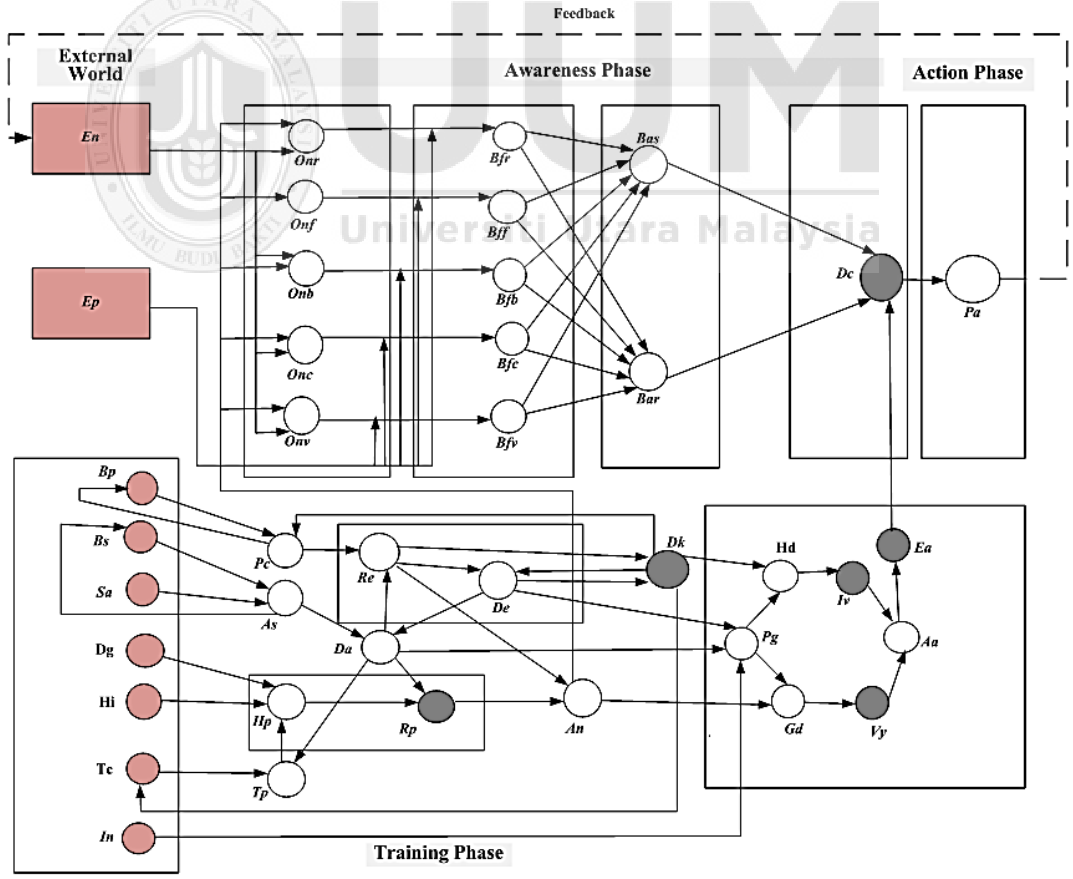


Figure 4.4. RDT model for Prime Decision-Making in Driving

From the Endsley theory of SA, three basic components including perception, comprehension and projection are further elaborated by the cognitive model of SA (Hoogendoorn et al., 2011). In their study, perception construct refers to an observation. Hence, this study makes use of observation to observe elements named *x* from the driving environment. The named elements *x* denoted road, traffic, obstacle, car condition and visibility. The next construct, comprehension is represented as belief formation for the current situation. Belief formation for the current situation is represented in this study by forming a belief on the elements *x* observed from the driving environment. Finally, projection is denoted as belief formation for a future situation. Then the belief formation for the current and future situation is translated into activation values of those beliefs and it is depicted in this study by forming a belief activation regarding the situation of the observed elements *x*. That is, after forming a belief regarding the observed elements, the driver then makes a judgement by forming belief activation and then decides. After making the decision, the driver implements the decision by acting (Performance of Action).

The factors, attention (*An*) and environment (*En*) causally influence observation (*On*). This is achieved by the aggregation of varying values of attention of the driver and the constant value assigned to the environment. However, belief formation is formulated by the positive contributions of observation and the values of expectation. The various beliefs for the elements are aggregated to form the belief activation (*Bax*). The belief activation can be either safe or risky situation. The two beliefs combined with automaticity to define the temporal value of decision, which determines the performance of action (*Pa*) of the driver. The performance of action gives feedback to the driving environment.

The difference between the generic and the specific models in Figure 4.5 and Figure 4.6 is in the awareness part of the models. In the specific model, the driver observes elements *x* mentioned and then, forms belief about the elements. Based on the belief formation, the driver then makes a judgement by forming belief activation whether the situation is safe or risky. Having made the judgement, driver acts by taking a decision. The decision of driver then determines his performance of action.

4.3 Formal Representation of the Conceptual Models

This section gives detail explanation of the concepts on the design of the RDT model formalization. The fundamental aim of this section is to obtain an executable computational model that is executed in a simulation environment for further interpretation of the model. Differential equation technique is used to represent the identified factors and its relationships. The formal models are simulated using a set of parameter values that range from 0 to 1. The set of parameters is used to regulate the computational models as explained in Section 4.3.1 and 4.3.2. The formalization of the conceptual awareness part and that of the RPD Training part of the RDT model is covered in this section.

4.3.1 Formal Representation of Awareness Component of the Enhanced Integrated Decision-making Model

The conceptual awareness component of the enhanced IDM is formulated into a set of formal equations that is implemented using simulation. This is explained in detail in chapter five of the study. The formalization of the model is done based on the studies by Bosse et al. (2009) and Treur (2016a, 2016b & 2016c). The formalization of the model factors is obtained with respect to time (t). The details on the formalization of the factors are given as follows.

a) Observation

Observation goes with paying attention to the environmental elements. Therefore, environment (*En*) and attention (*An*) contribute positively to observation (*On*). The more attention paid to the elements to be observed in the environment, the more its activation is enhanced into the memory. Otherwise, activation level decays and becomes difficult to recall. In this case, driver observes *x* elements, where x denotes road *(r)*, traffic *(f)*, obstacle *(b)*, car condition *(c)* and visibility *(v)*. These elements are observed through the environment, and the process of getting the information received from the environment into memory in the form of belief system to make a correct judgement is through attention. The judgement falls into two parts either the situation is safe or not safe (risky situation). Safe condition implies that all the five aforementioned elements are good (representing 1), and risky situation denotes that all the aforementioned elements are bad (representing 0), except obstacle in which the reverse is the case. Risk has three levels, namely low risk, moderate risk and high risk depending on the condition at each time frame. The detail explanation of risk levels is given in Chapter 5, section 5.3. The relationship of the three concepts: environment, attention and observation is shown in Figure 4.5

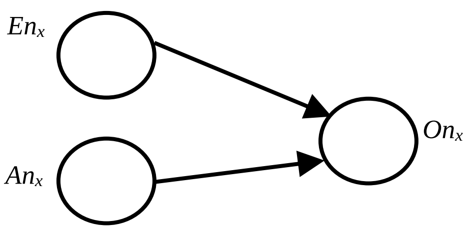


Figure 4.5. Causal Relationship of On with En and An

From Figure 4.5, *Enx* stands for the driving environment in which the elements (such as road, traffic, obstacles, car condition and the visibility) are observed. An_x stands for attention for the aforementioned elements, which differs in value. On_x stands for observation of the aforementioned elements in the driving environment. The formalization for computing the driver's observation of the various elements in the driving environment with respect to time (t) and alpha (α), where α ($0 \leq \alpha \leq 1$) is a constant parameter which represents the environment in which driver observes the aforementioned elements. These representations are shown in equations 4.1 to 4.5.

$$On_r\,(\mathrm{t}) = \alpha_{On_r}\,.\,An_r\,(\mathrm{t}) \tag{4.1}$$

$$On_f\,(\mathrm{t}) = \alpha_{On_f}\,.\,An_f\,(\mathrm{t}) \tag{4.2}$$

$$On_b\,(\mathrm{t}) = \alpha_{On_b}\,.\,An_b\,(\mathrm{t}) \tag{4.3}$$

$$On_c\,(\mathrm{t}) = \alpha_{On_c}\,.\,An_c\,(\mathrm{t}) \tag{4.4}$$

$$On_v\,(\mathrm{t}) = \alpha_{On_v}\,.\,An_v\,(\mathrm{t}) \tag{4.5}$$

Equations 4.1 to 4.5 present a perception in which the concept of observation is defined by the proportional contributions of what driver observes from the driving environment such as road, traffic, obstacles, car condition and visibility, and the level of attention given to those observed elements. The contributory mutual causal relationships between these two concepts (elements observed in the driving environment and the level of attention given to those same elements) determine the level of observation of the driver in the driving environment.

b) Belief Formation

For a driver to form certainty about observation, he/she should have an expectation and understand the significance of the current element or situation in line with driving goals. This enables the driver to make correct interpretation and judgement of a situation.

Hence, observation (*On*) and expectation (*Ep*) contribute positively to the driver's belief formation in this study. In this case, driver observes x elements as mentioned earlier. Figure 4.6 shows the relationship between the three concepts.

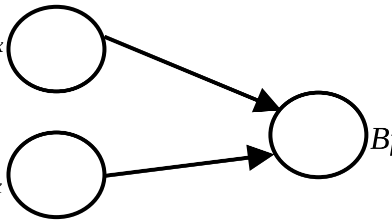


Figure 4.6. Causal Relationship of Bf with On and Ep

Accordingly, from Figure 4.6, On_x , Ep_x and Bf_x are observation, expectation and belief formation with respect to elements x, where $x = f(x_i \ldots\ldots\ldots x_n)$, where $x_i \ldots\ldots\ldots x_n$ are number of elements to be observed. The causal relationships that represent the driver's beliefs formation of those elements x observed are formalized and presented as follows:

$$Bf_r\,(\mathrm{t}) = On_r\,(\mathrm{t}).Ep_r\,(\mathrm{t}) \qquad (4.6)$$

$$Bf_f\,(\mathrm{t}) = On_f\,(\mathrm{t}).Ep_f\,(\mathrm{t}) \qquad (4.7)$$

$$Bf_b\,(t) = On_b\,(\mathrm{t}).Ep_b(\mathrm{t}) \qquad (4.8)$$

$$Bf_c\,(\mathrm{t}) = On_c\,(\mathrm{t}).Ep_c\,(\mathrm{t}) \qquad (4.9)$$

$$Bf_v\,(\mathrm{t}) = On_v\,(\mathrm{t}).Ep_v\,(\mathrm{t}) \qquad (4.10)$$

Equations 4.6 to 4.10 present a situation in which the concept of belief formation was defined by the mutual contributions of what the driver observed from the driving environment such as elements x and the level of expectancies (high/low) from those elements observed on the road. The value 1 indicates "high" while 0 indicates "low" level of those elements. The contributory mutual causal relationships between these two concepts (observation and expectation) determine the belief formation of the driver (safety or risky situation) in the driving environment.

c) Belief Activation

The certainty of the observation (belief formation) is classified into two, namely safe and risky situations depending on the input conditions for the observation. A mental model is essential in making such predictions. Hence, the belief activation is determined by the degree of certainty of the observation by the driver. The relationship is depicted in Figure 4.7 as follows.

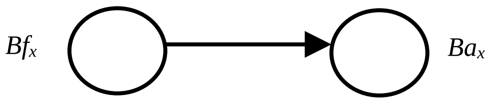


Figure 4.7. Causal Relationship of Ba with Bf

The relationship between the belief activation and belief formation is formalized using the logistic sigmoid function, which determines the gradual increment in speed (the changes in *y*-axis with respect to the *x*-axis) regarding the safe and risky driving conditions as follows:

$$Ba_s(t)=\frac{1}{1+e^{-\beta(P)}} \qquad (4.11)$$

where,

$$P = \sum_{i=1}^{i} \beta f_i * \omega_i$$

$$P = \sum_{i=1}^{i} \beta f_p * \omega_p$$

$$P = (Bf_r\,(\mathrm{t}).\,\omega_1 + Bf_f\,(\mathrm{t}).\,\omega_2 + Bf_b\,(\mathrm{t}).\,\omega_3 + Bf_c\,(\mathrm{t}).\,\omega_4 + Bf_v\,(\mathrm{t}).\,\omega_5)$$

$$\sum_{i=1}^{P} \omega_p = 1$$

Equation 4.11 denotes the formalization for computing the belief activation for a safe situation, where $\frac{1}{1+e^{-\beta(P)}}$ denotes logistic sigmoid function for belief activation for safe situation. The parameter β is the proportionality constant that represents update speed parameter and is assigned a value 1.

$Ba_r\,(t) = \frac{1}{e^{-\beta(1-(Q))}}$ (4.12)

where,

$Q = (Bf_r\,(\mathrm{t}).\,\omega_6 + Bf_f\,(\mathrm{t}).\,\omega_7 + Bf_b\,(\mathrm{t}).\,\omega_{8+}Bf_c\,(\mathrm{t}).\,\omega_9 + Bf_v\,(\mathrm{t}).\,\omega_{10}) \quad \sum_{i=1}^{Q} \omega_Q = 1$

Formalization of belief activation for the risky situation is shown in equation 4.12. In the sigmoid function $\frac{1}{e^{-\beta(1-(Q))}}$ for belief activation for the risky situation, β is allocated a constant value 1 and it signifies update speed parameter.

In equations 4.11 and 4.12, different weights is assigned to each element observed in the driving environment based on priority. Priorities are given to certain factors based on the importance attached to them. The weights are formed as a result of the certainty of the driver's observation himself. Although there could be situations in which an observer (driver) does not trust his/her observations fully (e.g. when the driver is stressed) and the weights may be assigned according to the extent to which the driver is inclined to trust those information sources (Aydoğan et al., 2014). In this study, in terms of belief activation for the risky situation, priority is given to an obstacle, followed by car condition and visibility, the road and traffic while in terms of belief activation for safety situation, priority is given to car condition and visibility, then obstacle, followed by road and traffic. In equations 4.11 and 4.12 that represent belief activation for safety situation and belief activation for the risky situation, respectively, ten (10) weights ω_1 to ω_{10} were assigned to each element observed in the driving environment. That is, ω_1 to ω_5 represent weights of the road, traffic, obstacle, car condition and visibility, respectively (they constitute belief activation for safe situations) while ω_6 to ω_{10}

represent weights of elements that constitute belief activation for risky situations. That is, ω_6 to ω_{10} represent weights of the road, traffic, obstacle, car condition and visibility, respectively. Based on the SA simulation execution using Matlab, the obstacles concerning belief activation for the safe situation are assigned a weight value equal to 0.2 while obstacles concerning belief activation for the risky situation are assigned a weight value equal to 0.4. Road and traffic are assigned 0.1 each for belief activation for safe and risky situations. Car condition and visibility are assigned weight values of 0.3 and 0.2 for belief activation for safe and risky situations, respectively. Those weights values assigned are to show the priority given to those elements. Hence, the weights indicating the priority of each element regarding belief activation for risky and safety situations are displayed in Table 4.5.

Table 4.5

Weight of Elements regarding Belief Activation for safe and risky situations

Elements	**Weight For Belief Activation for safe situation (ω_{bas})**	**Weight For Belief Activation for risky situation (ω_{bar})**
Road *(r)*	0.1	0.1
Traffic *(f)*	0.1	0.1
Obstacle *(o)*	0.2	0.4
Car Condition *(c)*	0.3	0.2
Visibility *(v)*	0.3	0.2

Equations 4.1 to 4.12 are the instantaneous equations that give the resultant process that leads to the development of the temporal equations. However, in awareness part of the IDM model, decision is the only temporal factor identified. Hence, its formalization process is presented as follows.

d) Decision

Decision *(Dc)* is triggered by the belief activation (Ba_x) of the aforementioned elements x that determines either safe or risky driving conditions in the driving environment. The causal relationship is depicted in Figure 4.8, and the formalization for this temporal factor is illustrated in equation 4.13.

$$Dc(t + \Delta t) = Dc(t) + \gamma_{dc}.\left(\sum Ba_x\,(\mathrm{t}) - Dc(t)\right).Dc(t).\left(1 - Dc(t)\right).\Delta t \qquad (4.13)$$

where γ_{dc} is a proportional parameter, represented as automaticity in the model. This change process is measured between t and $t + \Delta t$, where t is the time frame and Δt represents change interval in time (t).

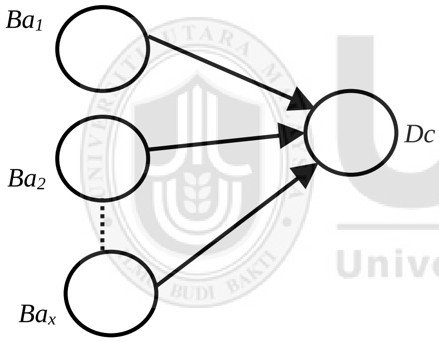


Figure 4.8. Causal Relationship of Dc with Ba_x

Equation 4.13 shows a relationship between belief activation of the driver either (safety or risk) and the confidence to make a decision. Based on this equation, belief activation for safety is inversely proportional to belief activation for risk, meaning that as the safety condition increases the risky condition decreases and vice versa. This determines the driver’s confidence to make a decision. If the level of the safe condition is high, so also the driver’s confidence to make a decision will be high. If it is low, the level of risky condition would be high, the confidence to make a decision will be low and vice versa. This implies that the driver's confidence to make a decision is determined by the activation of either safe or risky condition.

In the present study, the temporal factor decision can be used to measure the confidence level of the driver (Norman & Price, 2015). The study classified the confidence level of the driver within the range of 0 to 1 to decide, and Table 4.6 shows the summary of the confidence level classification.

Table 4.6

Summary of confidence level classification

Confidence Level	**Situation**	**Decision**	**References**
0 - 0.4	Risk	Low	(Chen, Zhou, Xiao, Deng, & Mahadevan, 2017; Vallin, Polyzoi, Marrone, Rosales-Klintz, Wisell, & Lundborg, 2016, Norman & Price, 2015).
0.5	Caution	Average	
0.6 – 1	Safe	High	

The classification is explained based on the situation of the environment that ranges from risk to safety. If the confidence level is 0 - 0.4, it means the situation is perceived as risky. Thus the driver has the low confidence to decide to perform an overtaking. Contrarily, if the confidence level is 0.6 – 1.0 it means the situation is perceived as safe, and the driver has high confidence to decide to perform an overtaking behaviour. The confidence level, 0.5 is perceived as a caution. Therefore, it is advisable for the driver to overtake cautiously.

4.3.2 Formal Representation of Recognition-Primed Decision Component of the Enhanced Integrated Decision-making Model

The conceptual RPD training component of the IDM is formalized into a set of equations. The formalisation nodes were designed using a set of parameters. The set of parameters were used to regulate or control the computational model. The details of the formalization of the model are given below.

a) Practice

Basic practice (*Bp*) and driving knowledge (*Dk*) contribute positively to the driver's practice. The two factors define the concept practice in this study, and the causal relationship of the three factors is depicted in Figure 4.9. Equation 4.14 shows the formalized causal relationships of the factors where γ_{pc} is a proportional parameter.

$$Pc(t) = \gamma_{pc}.Bp(t) + (1 - \gamma_{pc}).Dk(t) \quad (4.14)$$

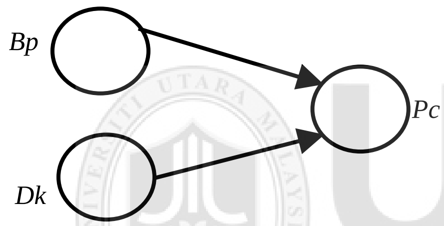


Figure 4.9. Causal Relationship of the Factors Contributing to Practice

b) Acquired Skills

Basic skills (*Bs*) and driver's goal (*Dg*) contribute positively to the driver's acquired skills (*As*), and the relationship is regulated by the driver's knowledge (*Dk*). The relationship of the three factors is depicted in Figure 4.10. The relationship is formalized in equation 4.15 where ω_{as1} and ω_{as2} are weight parameters.

$$As(t) = \beta_{as}.(\omega_{as1}.Bs(t) + \omega_{as2}.Sa(t)).(1 - \beta_{as}) \quad (4.15)$$

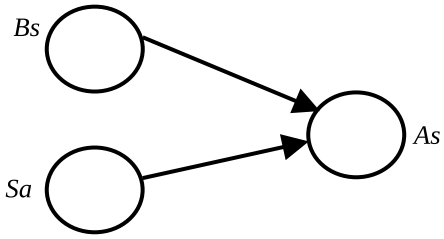


Figure 4.10. Causal Relationship of As with Bs, Sa and As

c) Perception about Hazard

Perception about hazard (*Hp*) is determined by three factors, namely driving ability (*Da*), potential hazardous information (*Hi*) and perception of the task (*Tp*). The driving ability and perception of task contribute positively to hazard perception, and potential hazardous information regulates the relationship. The relationship of the four factors is depicted in Figure 4.11. Equation 4.16 shows the formalization of the causal relationships of the factors where ω_{hp1} and $\omega_{hp2}$are weight parameters.

$$Hp(t) = [\omega_{hp1}.Dg(t) + \omega_{hp2}.Tp(t)].Hi(t) \quad (4.16)$$

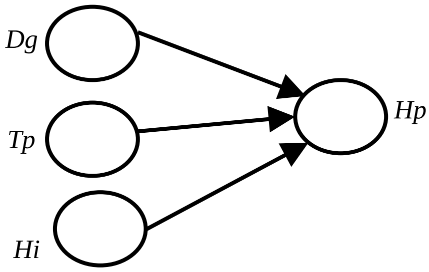


Figure 4.11. Causal Relationship of the Factors Contributing to Hazard Perception

d) Perception of Task

Driver ability (*Da*) and exposure to task complexity (*Tc*) influence perception about the task. The causal relationship of the three factors is shown in Figure 4.12. This is formalized in equation 4.17 where η_{rp} denoted proportional parameter.

$$Tp(t) = [\eta_{rp}.Da(t) + \left(1 - \eta_{rp}\right).Tc(t)] \quad (4.17)$$

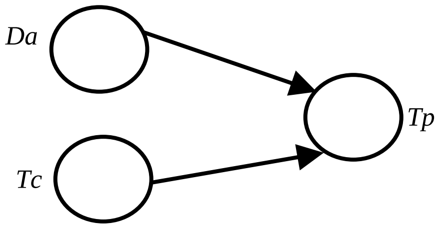


Figure 4.12. Causal Relationship of Tp with Da and Tc

e) Rehearsed Experience

Practice (*Pc*) and driving ability (Da) is said to influence the rehearsed experience of a driver positively. The causal relationship of the three factors is depicted in Figure 4.13, and it is formalized in equation 4.18 where γ_{re} is a proportional parameter.

$$Re(t) = [\gamma_{re}.Pc(t) + (1 - \gamma_{re}).Da(t)] \quad (4.18)$$

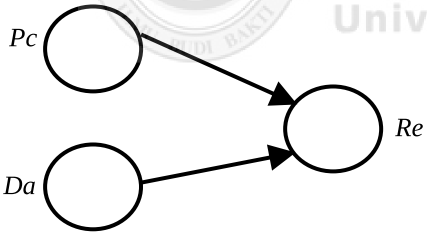


Figure 4.13. Causal Relationship of Re with Pc and Da

f) Driver's Ability

The driver's ability (*Da*) is positively influenced by the skills acquired (*As*) and experiences of the driver (*De*) in training. Figure 4.14.shows the relationship of the three factors. Equation 4.19 presents the formalization of the causal relationships of the three factors where ω_{da1} and ω_{da2} are weight factors.

$$Da(t) = \omega_{da1}.De(t) + \omega_{da2}.As(t) \quad (4.19)$$

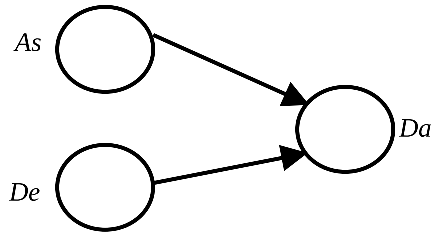


Figure 4.14. Causal Relationship of Da with As and De

g) Driver's Experience

The driver's experience (*De*) is positively influenced by rehearsed experience (Re) and driving knowledge (Dk). These causal relationships of the factors are denoted in Figure 4.15 and formalized in equation 4.20 where λ_{de} represents decay parameter.

$$De(t) = [\lambda_{de}.Re(t) + (1 - \lambda_{de}).Dk(t)] \quad (4.20)$$

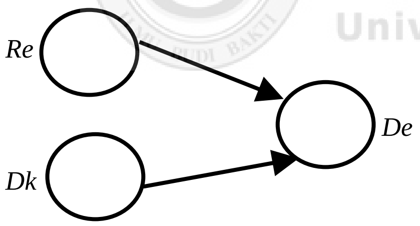


Figure 4.15. Causal Relationship of De with Re and Dk

h) Driving Knowledge

Rehearsed experience (Re) and driver experience (De) influence Driving knowledge positively. The relationship of the three factors is represented in Figure 4.16 and formalized in equation 4.21 where, γ_{dk} is denoted as speed factor, ω_{dk1} and ω_{dk2} are the weight parameters and λ_{dk} is a decay parameter.

$$Dk(t+\Delta t) = Dk(t) + \gamma_{dk}.\left[\left(Pos\left((\omega_{dk1}.Re(t) + \omega_{dk2}.De(t)) - Dk(t)\right).\left(1 - Dk(t)\right)\right) - Pos\left(-(\omega_{dk1}.Re(t) + \omega_{dk2}.De(t)) - \lambda_{dk}\right).Dk(t)\right].\Delta t \quad (4.21)$$

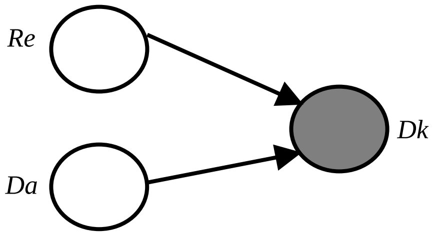


Figure 4.16. Causal Relationship of Dk with Re and Da

i) Perception of Risk

The two main factors that contribute positively to the perception of risk are the perception about hazard (*Hp*) and driver's ability (*Da*). Figure 4.17 shows the causal relationship of the three factors. These causal relationships are formalized in equation 4.22 where γ_{rp} is a proportional parameter. ω_{rp1} and ω_{rp2} are the weight parameters and $\lambda_{rp}$is a decay parameter.

$$Rp(t+\Delta t) = Rp(t) + \gamma_{rp}.\left[\left(Pos\left(\left(\omega_{rp1}.Hp(t) + \omega_{rp2}.Da(t)\right) - Rp(t)\right).\left(1 - Rp(t)\right)\right) - Pos\left(-\left(\omega_{rp1}.Hp(t) + \omega_{rp2}.Da(t)\right) - Rp(t)) - \lambda_{rp}\right).Rp(t)\right].\Delta t \quad (4.22)$$

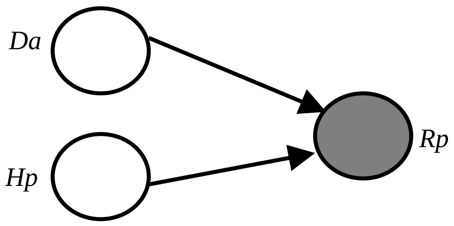


Figure 4.17. Causal Relationship of Rp with Hp and Da

j) Attention

Rehearsed experience (*Re*), and perception about the risk (*Rp*) contribute positively to the attention (*An*) of driver. The causal relationship of the three factors is depicted in Figure 4.18 and formalized in equation 4.23, where ξ_{an} denotes proportional parameter.

$$An(t) = [\xi_{an}.Rp(t) + (1 - \xi_{an}).Re(t)] \qquad (4.23)$$

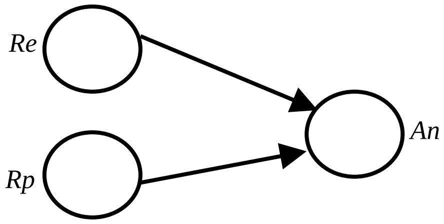


Figure 4.18. Causal Relationship of An with Re and Rp

k) Priming

Priming is influenced by three main factors, namely Driver's experience (De), Driver's ability (*Da*) and intention (*In*). Driver's experience and Driver's ability positively contribute to priming and the relationship is regulated by the intention of driver. Figure 4.19 shows the causal relationship of the three factors and is formalized in equation 4.24 where ξ_{pg} indicates proportional parameter.

$$Pg(t) = \left[\xi_{pg}.Da(t) + \left(1 - \xi_{pg}\right).De(t)\right].In(t) \qquad (4.24)$$

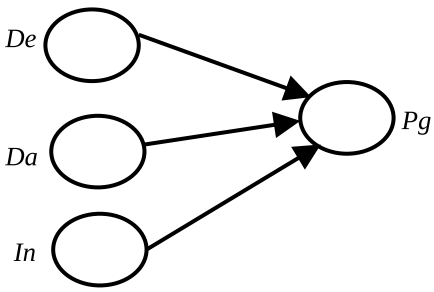


Figure 4.19. Causal Relationship of Pg with De, Da and In

l) Habitual-directed action

Habitual-directed action (Hd) is positively influenced by driving knowledge (*Dk*) and priming (*Pg*). The causal relationship of the three factors is represented in Figure 4.20 and is formalized in equation 4.25 where ω_{hd1} and ω_{hd2} are the weight parameters.

$$Hd(t) = \omega_{hd1}.Pg(t) + \omega_{hd2}.Dk(t) \quad (4.25)$$

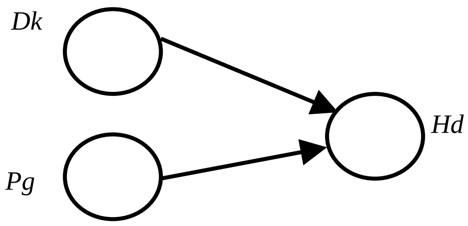


Figure 4.20. Causal Relationship of Hd with Dk and Pg

m) Goal-directed action

Priming (*Pg*) and attention (*An*) contribute positively to goal-directed action (Gd). In Figure 4.21 the relationship of the three factors is shown and the formalization is depicted in equation 4.26 where, ω_{gd1}, and ω_{gd2} are the weight parameters.

$$Gd(t) = \omega_{gd1}.An(t) + \omega_{gd2}.Pg(t) \quad (4.26)$$

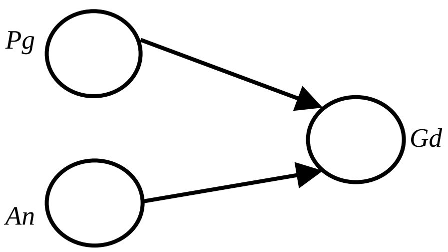


Figure 4.21. Causal Relationship of Gd with Pg and An.

n) Involuntary Automaticity

Involuntary automaticity (Iv) is positively influenced by habitual-directed action (*Hd*) only. The casual relationship between the two factors is depicted in Figure 4.22 and it is formalized in equation 4.27 where β_{iv} is a proportional parameter.

$$Iv(t+\Delta t) = Iv(t) + \beta_{iv}.\left[\left(Pos\left(\left(Hd(t) - Iv(t)\right)\right).\left(1 - Iv(t)\right)\right) - Pos\left(-\left(Hd(t) - Iv(t)\right)\right).Iv(t)\right] \quad (4.27)$$

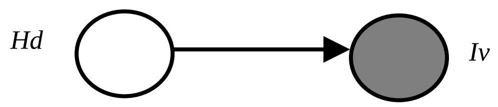


Figure 4.22. Causal Relationship of Iv with Hd.

o) Voluntary Automaticity

Voluntary automaticity (Vy) is positively influenced by goal-directed action (*Gd*). Figure 4.23 shows the causal relationship between the two factors and it is formalized in equation 4.28 where β_{vy} denotes proportional parameter.

$$Vy(t+\Delta t) = Vy(t) + \beta_{vy}.\left[\left(Pos\left(\left(Gd(t) - Vy(t)\right)\right).\left(1 - Vy(t)\right)\right) - Pos\left(-\left(Gd(t) - Vy(t)\right)\right).Vy(t)\right].\Delta t \quad (4.28)$$

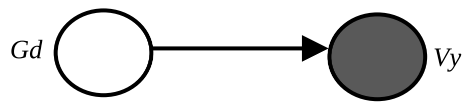


Figure 4.23. Causal Relationship of Vy with Gd

p) Acquired Automaticity

Involuntary (Iv) and voluntary (Vy) automaticity contribute positively to acquired automaticity *(Aa)*. The relationship of the three factors is shown in Figure 4.24 and, it is formalized in equation 4.29 where ω_{aa1} and ω_{aa2} are the weight parameters.

$$Aa = \omega_{aa1}.Iv(t) + \omega_{aa2}.Vy(t) \quad (4.29)$$

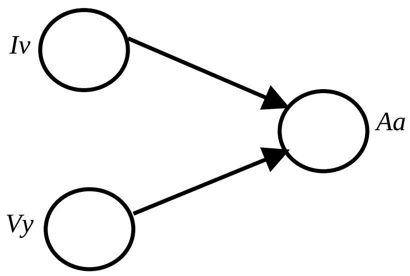


Figure 4.24. Causal Relationship of Aa with Iv, and Vy

q) Experienced Automaticity

Experienced automaticity *(Ea)* is positively influenced by the acquired automaticity. The causal relationship of the three factors is depicted in Figure 4.25. The formalization is shown in equation 4.30 where β_{ea} indicates proportional parameter.

$$Ea\ (t + \Delta t) = Ea(t) + \beta_{ea}.(Aa(t) - Ea(t)).Ea(t).\left(1 - Ea(t)\right) \tag{4.30}$$

Figure 4.25. Causal Relationship of Ea with Ae

r) Decision

Decision *(Dc)* is explained in subsection 4.3.1 as a temporal factor in awareness part of the RDT model. The decision was triggered by differences between safe and risky driving conditions and by the automaticity (experienced automaticity) of the driver. The causal relationship is depicted in Figure 4.26 and the formalization for the temporal factor is shown in equation 4.31 where γ_{dc} used as proportional parameter. It was represented as experienced automaticity (Ea) in the simulation.

$$Dc(t + \Delta t) = Dc(t) + \gamma_{dc}.\left(\left(\text{Bas (t)} - \text{Bar (t)}\right) - Dc(t)\right).Dc(t).\left(1 - Dc(t)\right).\Delta t \tag{4.31}$$

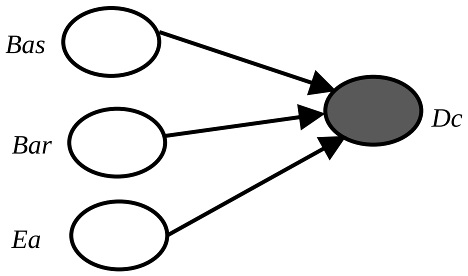


Figure 4.26. Causal Relationship of Dc with Bas, Bar, and Ea

4.4 Summary of the Chapter

This chapter presents the enhancement and computationalization of the IDM for primed decision-making in driving domain. The enhancement and computationalization of the IDM model is achieved in three stages. First is the identification of 31 factors of the RDT model. This was followed by the enhancement of conceptual IDM. Lastly, the formal representation of the conceptual RDT model was also achieved. These three stages were achieved in sections 4.1, 4.2 and 4.3 of this chapter. The next chapter presents the verification of the RDT model.

CHAPTER FIVE
VERIFICATION OF AN ENHANCED COMPUTATIONAL INTEGRATED DECISION-MAKING MODEL

5.0 Introduction

The fourth objective of this study is to evaluate the enhanced computational IDM (computational-RDT model). The evaluation of the computational-RDT model was conducted in two different stages. The first stage was the verification of the computational-RDT model by using simulation, mathematical and automated analysis methods. The second stage was the validation of the enhanced computational IDM (that was achieved in chapter 6). It was conducted by using human experiment to ensure the logical correctness of the enhanced computational model. In this chapter, the first stage (verification of the enhanced computational IDM) is part of the objective four and it is achieved in sections 5.1, 5.2 and 5.3.

Verification refers to the processes and techniques used to ensure that the models' specifications, assumptions, and the simulation results are correct. The aim is to ensure that the model is built right to achieve its designed and implementation objective. Therefore, to build the model right, mathematical and automated analyses were employed. The automated analysis was achieved by using Temporal Trace Language (TTL). The simulation technique was used in implementing the model by performing experiments in MATLAB simulation environment.

5.1 Simulation

Simulation provides insight into the robustness nature of a model, which depicts the eventual real effects of alternative conditions and concept variation in the enhanced model. Model should be robust if there are consistencies between the enhanced model simulation traces and the underpinning theories (Grimm et al., 2005). The simulation traces were obtained through the implementation of different driving situations for some selected cases out of the various instances. The simulation was conducted with respect to time *t* to provide insight into the sequential changes that occur to driver in specific case conditions. However, each of the cases developed had conditions based on scenarios that were implemented in the simulation environment.

5.1.1 Simulation Environment

The simulation environment was used to demonstrate the robustness of the model by visualizing the model execution with respect to underpinning cognitive and naturalistic decision making theories such as Endsley, Naturalistic Decision-Making and other related theories used in this study. The process was conducted by translating the equations generated from the RDT model into simulation traces. To explore patterns and traces that described the behaviour of driver, simulators was developed using equations generated from the enhanced model. The equations consist of regulating parameters that are explained in the next section.

5.1.2 Simulation Parameters

To perform simulation using MATLAB, several parameter values (setttings) of the RDT model factors were used to obtain real-life situation conditions of the selected case studies. This shows the simulated behaviours of the model for better insight into the functionalities of the model at different selected conditions. This study experimental parameters were obtained systematically to obtain the various estimations by following the guidelines in studies, such as Vidotto and Vicentini (2007), Vidotto, Massidda and Noventa (2010) and Vidotto (2013). An experiment was conducted to select and explore the best convergence based on the existing studies (Ding, 2014; Chen et al., 2012; Aster, Borchers & Thurber, 2011; Treur & Umair, 2011; Treur, 2016c; Vidotto et al., 2010) which suggested the use of 0.1 to 0.3 as low values, 0.4 to 0.6 as average values, and 0.7 to 1.0 as high values.

Moreover, the experimental parameter regulators used in this study were categorized into two different classes, namely the weight proportionality parameter and the proportional parameter (Speed Factor). The weight parameter is represented by (ω). For example, Vidotto and Vicentini (2007) suggested the weight value of 0.33 in the case of three concepts causal contributory factors. Another example of this parameter values was suggested by previous studies (Vidotto et al., 2010; Vidotto, 2013) to be 0.5 values for two simultaneous concepts. However, in the simulation example in (Treur, 2016b), all connection weights are 1, except that of $\omega_{responding} = 0.5$ and $\omega_{amplifying} = 0.5$ and they used the value 0.8 for the speed factors for all states. Weights are used to set priority and it is used when the factors have equal contribution while proportional factor parameter is used when the factors have different contributions in the causal relationship, they are all regulating parameter constants. Hence, this study adapted the parameter values (settings) used in Klein (2016b, Pg.24) through out the simulation experiment.

5.1.2.1 Simulation Parameter for the Awareness Component

The parameters used for the awareness part of the Computational-RDT model were functional parameters, known as speed factors and weight parameters. The functional parameters used for that part of the model are presented in Table 5.1 while the weight parameters are discussed in Chapter 4, Table 4.3.

Table 5.1

Simulation Regulating Parameters for the Awareness part

Symbol	Initialization Values	Type
α_{On_r}	0.8	Speed Factor
α_{On_f}	0.8	Speed Factor
α_{On_b}	0.8	Speed Factor
α_{On_c}	0.8	Speed Factor
α_{On_v}	0.8	Speed Factor
β_{Bas}	0.8	Speed Factor
β_{Bar}	0.8	Speed Factor
γ_{dc}	0.8	Speed Factor
Δt	0.3	Change Rate

5.1.2.2 Simulation Parameter for Recognition-Primed Decision Component

There are several functional and weight parameters used in the RPD component of the Computational-RDT model. The functional parameter shows how fast a state is changing upon causal impact while the weight parameter indicates the strength of the connection, often between 0 and 1, but sometimes also below 0 (negative effect). For example, the parameters were used for both the instantaneous and temporal relationships in that part of the model. Moreover, the temporal factors were derived based on the concept of differential equation used in Treur (2016b, 2016c). The temporal and instantaneous factors are time-bounded factors and evolve with respect to changes in time. The temporal factors have 0.1 as the initial value in the simulation environment, which is the starting point of the trajectory, to see the effect of changes that may occur. The change process in the temporal equations was measured in a time interval, i.e., the time step between t and $t + \Delta t$ where Δt is the small change or increase in time t.

The rate of change for all temporal specifications was determined by it flexibility rates. These parameters are presented in Table 5.2.

Table 5.2

Simulation Regulating Parameters for the Recognition-Primed Decision training component

Symbol	Initialization Values	Type
α_{re}	0.8	Speed Factor
α_{re}	0.8	Speed Factor
β_{bp}	0.8	Speed Factor
β_{bs}	0.8	Speed Factor
β_{tc}	0.8	Speed Factor
β_{iv}	0.8	Speed Factor
β_{vy}	0.8	Speed Factor
β_{ea}	0.8	Speed Factor
γ_{pc}	0.8	Speed Factor
γ_{re}	0.8	Speed Factor
γ_{dk}	0.8	Speed Factor
γ_{rp}	0.8	Speed Factor
ξ_{pg}	0.8	Speed Factor
ξ_{an}	0.8	Speed Factor
η_{tp}	0.8	Speed Factor
λ_{de}	0.01	Decay
λ_{dk}	0.01	Decay
λ_{rp}	0.01	Decay
Δt	0.3	Change Rate

In addition, Table 5.3 presents weight parameters used in the simulation experiments for the RPD training part of the Computational-RDT model. Examples of weight parameters used for the factors are ω_{da1}, ω_{da2}, ω_{hp1}, ω_{hp2}, etc. with $\sum\omega = 1$.

Table 5.3

Weight Regulating Parameters used in RPD training component

Factors	Weight Parameter One (ω_1)	Weight Parameter Two (ω_2)
Acquire Skill (*As*)	ω_{as1}	ω_{as2}
Driver's Ability (*Da*)	ω_{da1}	ω_{da2}
Potential Hazardous Information (*Hp*)	ω_{hp1}	ω_{hp2}
Driver's Knowledge (*Dk*)	ω_{dk1}	ω_{dk2}
Perception about Hazard (*Rp*)	ω_{rp1}	ω_{rp2}
Goal-directed action (*Gd*)	ω_{gd1}	ω_{gd2}
Acquired Automaticity (*Aa*)	ω_{aa1}	ω_{aa2}

The regulating functions in the equation are $(1-\beta_{bp})$, $(1-\beta_{bp})$, (1- γ_{pc}), (1- γ_{re}), (1- λ_{de}), $(1-\beta_{as})$, $(1-\xi_{pg})$, $(1-\xi_{an})$, $(1-\eta_{tp})$ & $(1-\beta_{tc})$. They were used to regulate the equations not to exceed the boundary limit that is one. Generally, this study made use of low values as ≤ 0.3, average values as 0.4 – 0.6, and high value as 0.7 – 1.0 for the simulation parameters. The differences in the simulation traces showed the unique differences in each driver's attribution (i.e., behaviour, personality, attitude and knowledge) with respect to time. The detailed description of the developed simulators for awareness part of the model, RPD training part of the model and the RDT model are presented in sections 5.3, 5.4 and 5.5, respectively. Appendix C shows the full simulator script code written in MATLAB.

5.1.3 Models Simulation Scenarios

The simulation of the model was divided into three, namely the simulation of the awareness component, simulation of the RPD component, and the simulation of the enhanced computational ID model.

5.1.3.1 Scenarios for the Awareness Component

In simulating the awareness component of the enhanced computational IDM, simulations conditions were used based on the five inputs factors (*road, traffic, obstacles, car condition, and visibility*) of the awareness component of the enhanced computational IDM model. In all the three awareness scenario simulations, time frame denoted as "*f*" was used to indicate the interval in time steps. With t_{max} = 500, where t_{max} represents maximum time frame of 500, and the 500 represents driving duration from the beginning to the end. Therefore, each time frame represents approximately 5 seconds. The time frame (500) is segmented into four time frames; *f*1, the first time frame ($0 \leq t \leq 125$); $f2$, the second time frame ($0 \leq t \leq 250$); $f3$, the third time frame ($0 \leq t \leq 375$); and $f4$, the fourth time frame ($0 \leq t \leq 500$). The simulation settings for the time frame are presented in Table 5.4.

Table 5.4

Situation Awareness Model Simulation Settings

Time Frame	**Interval Values**
f_1	0-125
f_2	126-250
f_3	251-375
f_4	376-500

Scenario conditions were also presented in the form of 0's and 1's in each time frame. One (1) means good and (0) means bad/poor for all the factors except obstacle in which the reverse is the case. This means that in case of obstacle, 1 means there is obstacle and 0 means no obstacle. This is shown in Table 5.5.

Table 5.5

Elements of Situation Awareness Model Scenario Conditions

Elements	**Values**	**Description**
Road (r)	1	Good
	0	Bad
Traffic (f)	1	Good
	0	Bad
Obstacle (o)	1	Bad (Obstacle present)
	0	Good (No obstacle present)
Car Condition (c)	1	Good
	0	Bad
Visibility (v)	1	Good
	0	Bad

In addition, when simulating the scenarios, values were generated for each time frame based on the combinational logic of 2^n, where n denoted the number of factors. Thus, in the awareness component of the IDM model, 2^5 was used where 5 represented the five factors that were used in all the three scenarios. Graphs were also generated based on each scenario conditions. Each scenario condition had three graphs (a), (b) and (c) that showed the safe/risky confidence level to decide, and performance of action of the car driver. The performance of action of the car driver is presented as low or high, where low indicates no [0] and high indicates yes [1].

Scenario One: The Low Risk Conditions

From Table 5.6, in the first and second time frames, all the driving conditions were good, and visibility was poor, respectively. The third and fourth time frames indicated that obstacle was on the road, and the road was bad, respectively. As a result of these conditions in all the time frames, it can be said that the scenario was good and hence, it can be described as a low-risk scenario.

Table 5.6

Low-Risk Conditions

Scenarios	**Factors**	**Time Frame Steps**			
#1		*f*1	*f*2	*f*3	*f*4
	Road	1	1	1	0
	Traffic	1	1	1	1
	Obstacles	0	0	1	1
	Car condition	1	1	1	1
	Visibility	1	0	1	1

Note: Each of these factors (Road, Traffic, Obstacles, Car condition and Visibility) takes the value 1or 0 to represent good or bad/poor, respectively except obstacle in which the reverse is the case.

At first time frame, all the driving conditions were good and as such, the safety level increased while the level of risk decreased as shown in Figure (5.1a). Driver had a high confidence level to decide as depicted in Figure (5.1b) due to an increase in the safety level and based on that, the driver's performance was high [indicated by yes (1)] as shown in Figure (5.1c).

In the second time frame, the risk level increased from the base-line (zero level) while the safety level decreased compared to the first time frame due to poor visibility as presented in Figure (5.1a). Therefore, driver's confidence level declined a bit as a result of an increase in the risk level as denoted in Figure (5.1b). Consequently, the driver's performance was high [indicated by yes (1)] due to higher safety level as compared to the risk level as depicted in Figure (5.1c).

The risk level was higher than the safe level in the third time frame due to the presence of an obstacle on the road as shown in Figure (5.1a). The higher level of risk caused a decline in the driver's confidence level to decide. The driver's confidence remains stable at certain level and then drastically decreased to the baseline as demonstrated in Figure (5.1b). As such, the driver's performance was low [indicated by no (0)] as shown in Figure (5.1c).

At the fourth time frame, Figure (5.1a) shows that safety and risk maintained the same level as in the third time frame due to bad road and the presence of obstacle. As such, driver had no confidence to decide; the confidence level remained at the baseline as demonstrated in Figure (5.1b). Based on this, the driver's performance was low [indicated by no (0)] as shown in Figure (5.1c).

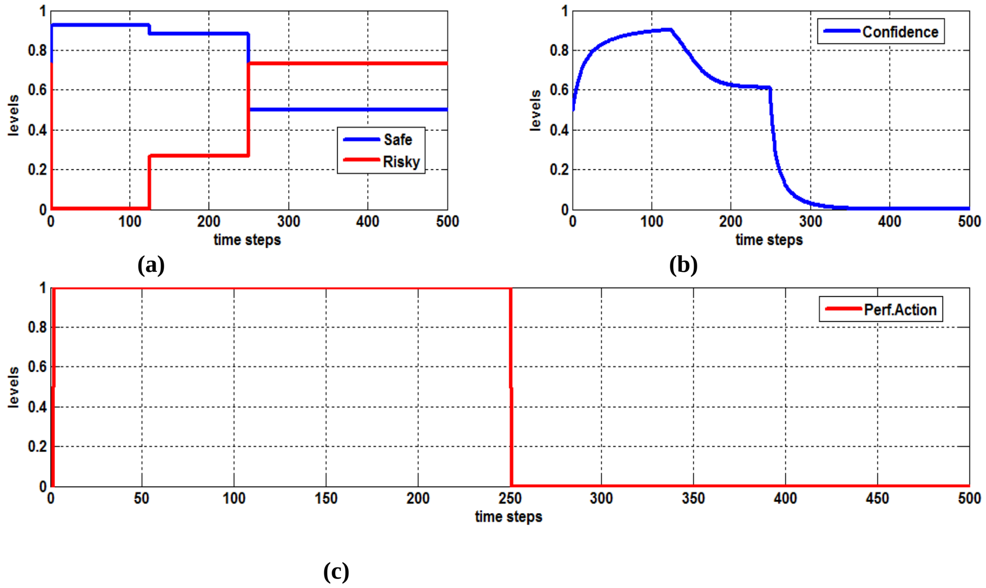


Figure 5.1. Simulation Result for Low-Risk Conditions

Scenario Two: The Moderate Risk Conditions

From Table 5.7, in the first time frame, the road was bad; there was traffic congestion, presence of obstacle and poor visibility. In the second and third time frames, the road was also bad, and traffic was congested, respectively. In the fourth time frame, all the driving conditions were bad. Based on these conditions in all the time frames, it can be concluded that the scenario was good and had a moderate risk.

Table 5.7

Moderate Risk Conditions

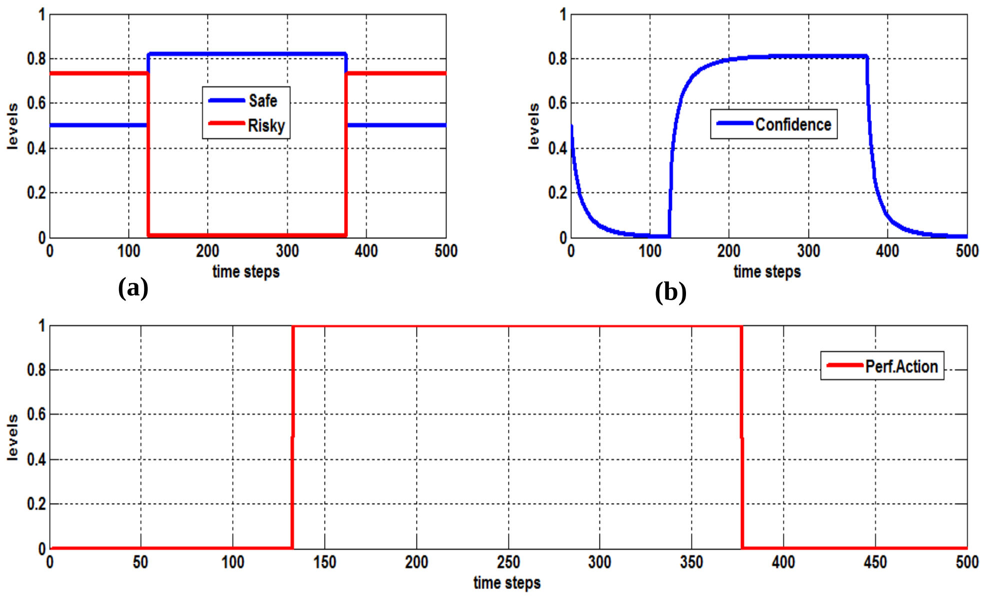
Scenarios	**Factors**	**Time Frame Steps**			
#2		f1	f2	f3	f4
	Road	0	0	1	0
	Traffic	0	1	0	0
	Obstacles	1	0	0	1
	Car condition	1	1	1	0
	Visibility	0	1	1	0

Note: Each of these factors (Road, Traffic, Obstacles, Car condition and Visibility) takes the value 1or 0 to represent good or bad/poor, respectively except obstacle in which the reverse is the case.

At the first time frame as shown in Figure (5.2a), the level of risk was more than the safety level due to the poor road, traffic congestion, presence of obstacle and poor visibility. As depicted in Figure (5.3b), driver had low confidence level to decide as a result of poor road, heavy traffic, presence of obstacle and poor visibility. Based on these, the driver's performance became low [indicated by no (0)] as shown in Figure (5.3c).

In the second and third time frame, the risk level decreased to the base-line (zero level) in proportion to the decrease in the level of safety due to poor road and heavy traffic, respectively. These conditions had less effect on the simulated driving behaviour of driver as compared to obstacle, car condition and visibility as presented in Figure (5.2a). Therefore, driver's confidence level increased in both time frames as shown in Figure (5.2b) because the road and traffic factors had less weight effect. Based on this, the driver's performance was said to be high [indicated by yes (1)] as shown in Figure (5.2c).

At the fourth time frame, the level of risk was higher than the level of safety because all the driving conditions were bad, as indicated in Figure (5.2a). As such, driver's confidence level decreased as demonstrated in Figure (5.2b). Hence, the driver's performance became low [indicated by no (0)] as shown in Figure (5.2c).



(c)

Figure 5.2. Simulation Result for Moderate Risk Conditions

Scenario Three: The High Risk Conditions

From Table 5.8, in the first time frame, all the driving conditions are bad except road condition while in the second time frame, the road is bad, and traffic is congested. The third time frame indicates that the car condition is bad and the visibility is poor while the fourth time frame shows that all the driving conditions are bad except that there is no traffic congestion. Therefore, the scenario is considered to be bad and highly risky.

Table 5.8

High-Risk Conditions

Scenarios	**Factors**	**Time Frame Steps**			
#3		f1	f2	f3	f4
	Road	1	0	1	0
	Traffic	0	0	1	1
	Obstacles	1	0	0	1
	Car condition	0	1	0	0
	Visibility	0	1	0	0

Note: Each of these factors (Road, Traffic, Obstacles, Car condition and Visibility) takes the value 1or 0 to represent good or bad/poor, respectively except obstacle in which the reverse is the case.

The scenario can also be understood from Figure (5.3). From Figure (5.3a), the first time frame depicts that all the driving conditions were bad and the level of risk was higher than the level of safety. This suggests that driver had low confidence level to decide due to the high level of risk as shown in Figure (5.3b). Based on this situation, the driver's performance can be described to be low [indicated by no (0)] as in Figure (5.3c).

The second time frame depicts that the risky level decreased almost to the base-line (zero) while the safe level increased due to poor road and congested traffic as in Figure (5.3a). As a result, the driver's confidence level increased as shown in Figure (5.3b) and the performance is high as indicated by yes (1). The driver's performance increased due to increase in the confidence level as shown in Figure (5.3c).

In the third and fourth time frame, Figure (5.3a), the level of risk increased more than the level of safety due to poor car condition and visibility in the former, and bad driving condition in the latter. As a result of the conditions as in Figure (5.3a), the driver's confidence level to decide declined to the base line as in Figure (5.3b). Hence, the driver's performance became low as indicated by no (0) for both time frames in figure (5.3c).

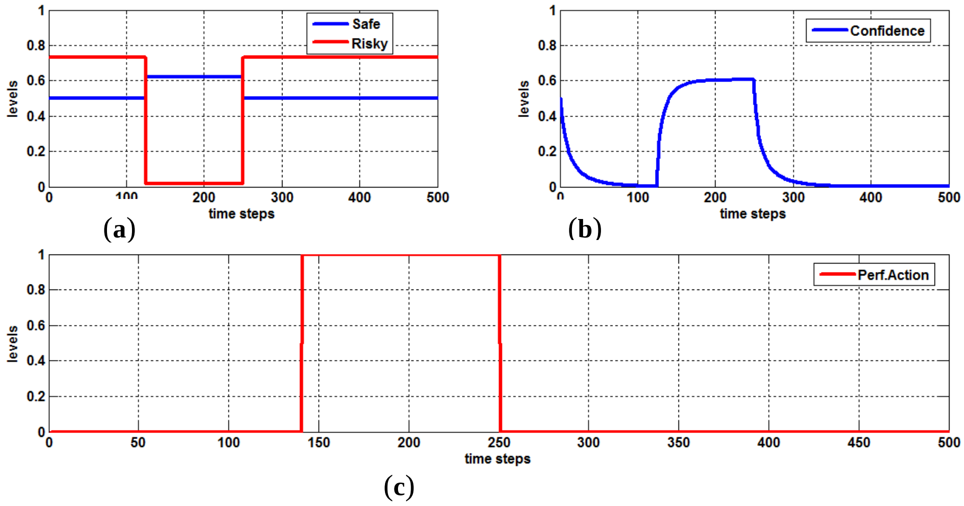


Figure 5.3. Simulation Result for High-Risk Conditions

5.1.3.2 Scenarios for the Recognition-Primed Decision Component

A simulator was developed using all defined formulas for experiment purposes, precisely to explore interesting patterns and traces that explained the behaviour of driver in the RPD training component of the enhanced IDM. Simulations conditions based on the input values of the seven factors of the training component of the model (*basic practice, basic skills, sensory ability, driver's goal, potential hazardous information, exposure on task complexity and intention*) are used. Each of the factors is assigned value of either zero (0) or one (1) where zero (0) means low, and one (1) means high for those inputs. In this simulation, the following settings are used: ($0\leq t \leq 500$) with t_{max} = 500 (to represent a set of training activities of the driver up to eight months). Each time step (i.e., range) denotes the training hours where one (1) time step represents 5 hours of training.

Scenario One: Skilful-Cautious Driver

The condition for Skilful-Cautious driver determined by the seven factors of the training model, namely *basic practice, basic skills, sensory ability, driver's goal, potential hazardous information*, *exposure on task complexity* and *intention* is (1111111). This implies that the driver's high training positively affects each of the factors. In this case, the driver was said to be skilful because of the positive impact of training on his basic practice, basic skill, and sensory ability.

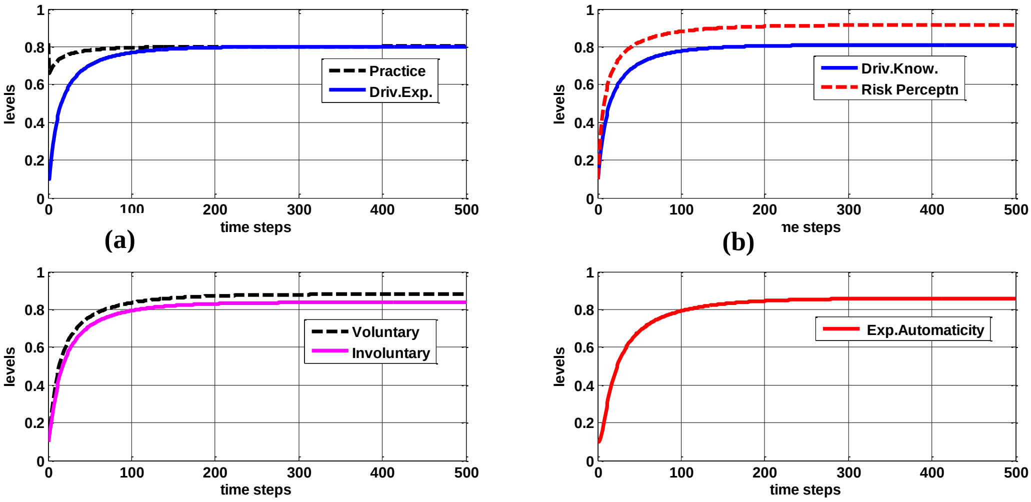
Table 5.9

Condition for Skilful-Cautious Driver

Scenario	Condition	Description	References
#1	1111111	A skilful driver who has been trained and exposed to driving task complexity has potential hazard information.	(Baughan et al., 2004; Endsley,2016; Moskowitz, 2013; Wheatley &Wegner, 2001).

Note: The seven input factors of the training model (basic practice, basic skills, sensory ability, driver's goal, potential hazardous information, exposure to task complexity and intention) are used. Each of the factors is assigned a value of either 0 or 1, where 0 means low/poor and 1 means high/good for those inputs.

In addition, driver is described to be Skilful-Cautious because a positive impact on the other mentioned factors makes driver to be cautious. The condition for Skilful-Cautious Driver is as in Table 5.9. In this scenario as shown in Figure (5.4a) that the driver's level of experience increased as the level of practice increased. The result is in line with Baughan et al. (2004) and Endsley (2016), and Figure (5.4b) indicates that the increase in the driver's knowledge increased the driver's perception of risk.



(a) (b) (c) (d)

Figure 5.4. Simulation Result for Skilful-Cautious Driver

In Figure (5.4c), involuntary automaticity level decreased with increase in the voluntary automaticity level, due to the influence of attention on the voluntary automaticity. Lastly, Figure (5.4d) shows that the experience automaticity level of the driver increased due to increase in the level of practice and experience. The statements made in Figures (5.4c) and (5.4d) are in accordance with the prior studies (Moskowitz, 2013; Wheatley & Wegner, 2001) and (Endsley, 2016) respectively.

Scenario Two: Skilful-Risk Taking Driver

The condition for Skilful-Risk taking driver determined by the seven factors of the training model, specifically *basic practice, basic skills, sensory ability, driver's goal, potential hazardous information, exposure on task complexity* and *intention* is (1110000). This suggested that high training of driver influenced his basic practice, basic skills and sensory ability and therefore, the driver was described to be skilful. However, the driver had low goal, low information on the potential hazard, low exposure to the driving task complexity and low intention, which implies risk-taking. Thus, the driver was said to be a skilful-risk taker. Table 5.10 shows the condition for Skilful-Risk Taking Driver.

Table 5.10

Condition for Skilful-Risk Taking Driver

Scenario	Condition	Description	References
#2	1110000	A skilful driver who has been trained has low potential hazard information, and exposure to driving task complexity.	(Deery, 1999; Brown & Groeger 1988; Wasserman & Wasserman, 2016)

Note: The seven input factors of the training model (basic practice, basic skills, sensory ability, driver's goal, potential hazardous information, exposure on task complexity and intention) are used. Each of the factors is assigned a value of either 0 or 1, where 0 means low/poor and 1 means high/good for those inputs.

In this scenario, Figure (5.5a) shows that the driver's level of experience increased with increase in the level of practice while Figure (5.5b) indicates that the driver's level of perception about risk decreased with a decrease in knowledge. In Figure (5.5c), involuntary automaticity level increased with a decreased in the voluntary level due to the influence of the driver's knowledge on the involuntary automaticity. Also, in Figure (5.5d), the experience automaticity level of the driver decreased (a bit lower) as a result of decreased in practice and experience levels. The statements made in Figures (5.5a, 5.5b, 5.5c & 5.5d) are in line with the previous studies (Baughan et al., 2004; Endsley, 2016), (Deery, 1999; Brown & Groeger, 1988), (Wasserman & Wasserman, 2016; Wheatley & Wegner, 2001) and (Endsley, 2016).

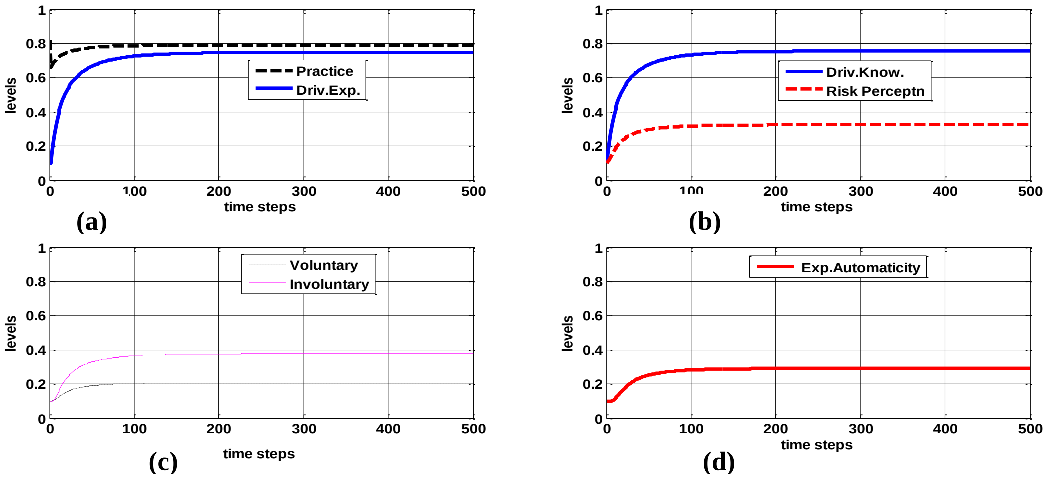


Figure 5.5. Simulation Result for Skilful- Risk Taking Driver

Scenario Three: Unskilful-Cautious Driver

The condition for Unskilful-Cautious driver based on the seven factors under consideration is (0011111). This denotes that low training level of the driver affected the driver's basic practice and basic skills. Hence, the driver is unskilful. However, the driver had good sensory ability and high goal, high information on the potential hazard, high exposure to the driving task complexity and high intention, suggesting that the driver was cautious. Therefore, the driver can be described as an Unskilful-Cautious driver. Table 5.11 presents the condition for Unskilful-Cautious Driver.

Table 5.11

Condition for Unskilful-Cautious Driver

Scenario	**Conditions**	**Description**	**References**
#3	0011111	The unskilful driver has not been trained, but acquired potential hazard information and has exposure to driving task complexity.	(Moskowitz, 2013; Endsley, 2016).

Note: The seven input factors of the training model (basic practice, basic skills, sensory ability, driver's goal, potential hazardous information, exposure on task complexity and intention) are used. Each of the factors assigned value of either 0 or 1, where 0 means low/poor and 1 means high/good for those inputs.

In this scenario, Figure (5.6a) shows that the driver's level of experience decreased with a decrease in the level of practice while Figure (5.6b) depicts that the driver's knowledge decreased with a decrease in the level of perception about risk. In Figure (5.6c), voluntary level decreased with a decrease in the attention level and the involuntary automaticity also decreased due to a decrease in the level of knowledge of the driver. Finally, Figure (5.6d) shows that the experience automaticity level of the driver decreased drastically due to a decrease in practice and experience levels. The statements in Figures (5.6a, 5.6b, 5.6c & 5.6d) are in accordance with the previous studies (Baughan et al., 2004; Endsley, 2016), (Deery, 1999; Brown & Groeger, 1988), (Moskowitz, 2013; Wheatley & Wegner, 2001) and (Endsley, 2016).

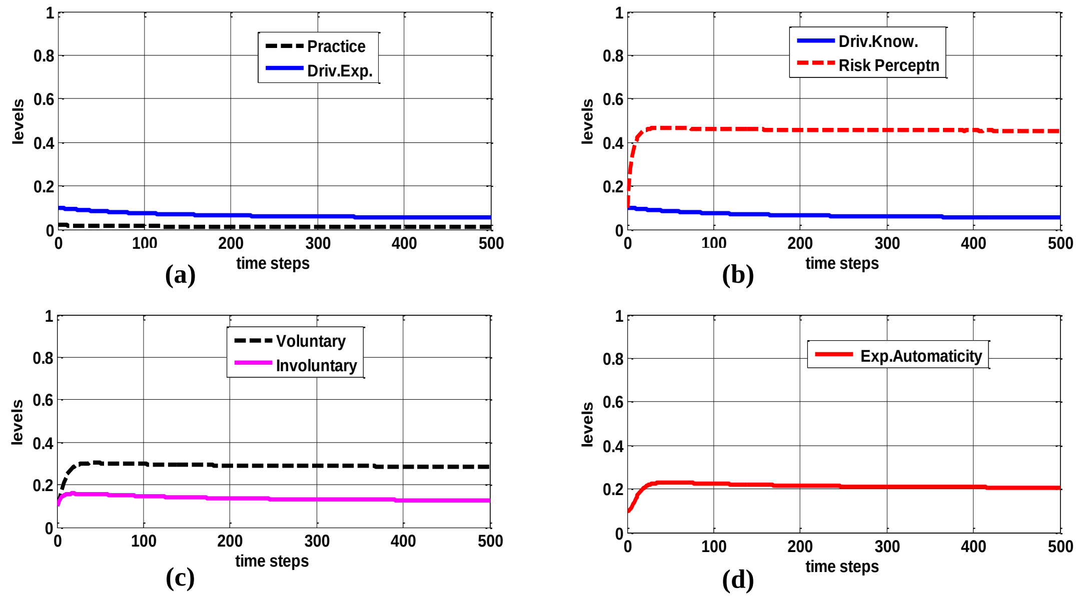


Figure 5.6. Simulation Result for Unskillful-Cautious Driver

5.1.3.3 Scenarios for the Enhanced Model

The scenarios and conditions for the enhanced computational IDM are presented in Table 5.12. Each scenario was presented with training and awareness conditions and were named long-term, medium-term and short-term training, respectively. Based on the conditions for each scenario, graphs were generated as shown in Figure 5.7, 5.8 and 5.9.

Scenario One: The Long-Term Training Exposure

In Scenario 1, Figure (5.7a) depicts that the driver's level of perception about risk increased with increment in driver's knowledge. However, the driver's level of perception about risk decreased to a certain level due to the effect of driver's low-level perception about potential hazardous information. The level eventually increased again due to good driving condition and skill of the driver. Figure (5.7b) indicates an insight into driver's experienced automaticity level through exposure to long-term training, which led to a high confidence level for decision. Figure (5.7c) relates that long-term training led to high performance of action by the driver.

Table 5.12

The Enhanced Integrated Decision-Making Conditions

Scenarios	Training conditions			Awareness conditions			Description
#1	1110111	1111011	1111111	11011			The driver receives more training compare to awareness.
#2	1110011	1110110		01011	10011		The driver receives equal proportion of training and awareness.
#3	1110101			00011	11111	11001	The driver receives less training compared to awareness.

Note: For training model, 7 input factors (basic practice, basic skills, sensory ability, driver's goal, potential hazardous information, exposure on task complexity and intention) are used. Each of the factors is assigned value either 0 or 1, where 0 means low/poor training and 1 means high/good training. For the awareness model, 5 input factors (Road, Traffic, Obstacles, Car condition and Visibility) are used where 1or 0 represent good or bad/poor, respectively with the exception of obstacle in which the reverse is the case.

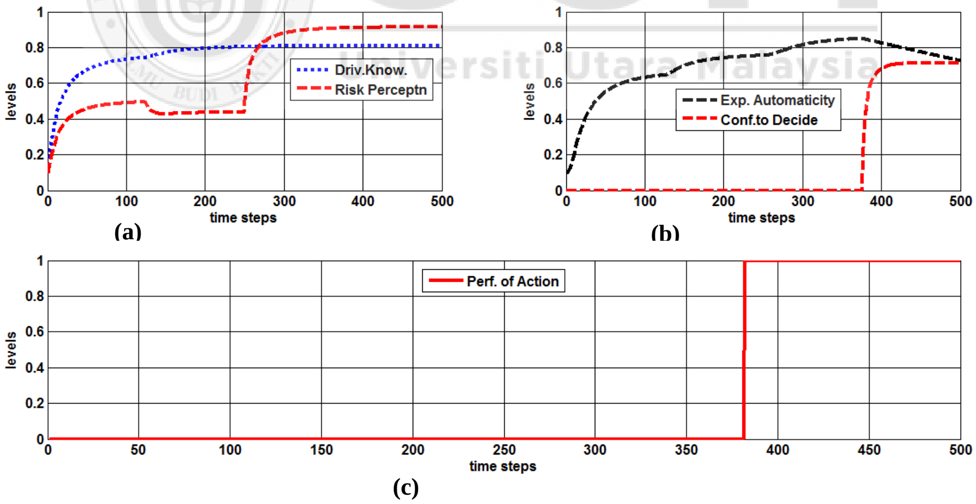


Figure 5.7. Simulation Conditions Results (for Scenario 1)

Scenario Two: The Medium-Term Training Exposure

In Scenario 2, Figure (5.8a) visualizes that the driver's level of perception about risk increased with proportional increase in driver's knowledge but the driver's level of perception about risk decreased a bit to a certain level due to the effect of driver's low level of potential hazardous information in the traffic environment. The driver's level of perception about risk eventually increased and became stable due to the skilfulness of the driver and other good driving conditions. Another result showed that experience automaticity of the driver decreased due to a short period of training. This led to low confidence level of the driver to make decision as it has been visualized in Figure (5.8b). Lastly, Figure (5.8c) provides a visual representation of driver's low performance due to a short period of training.

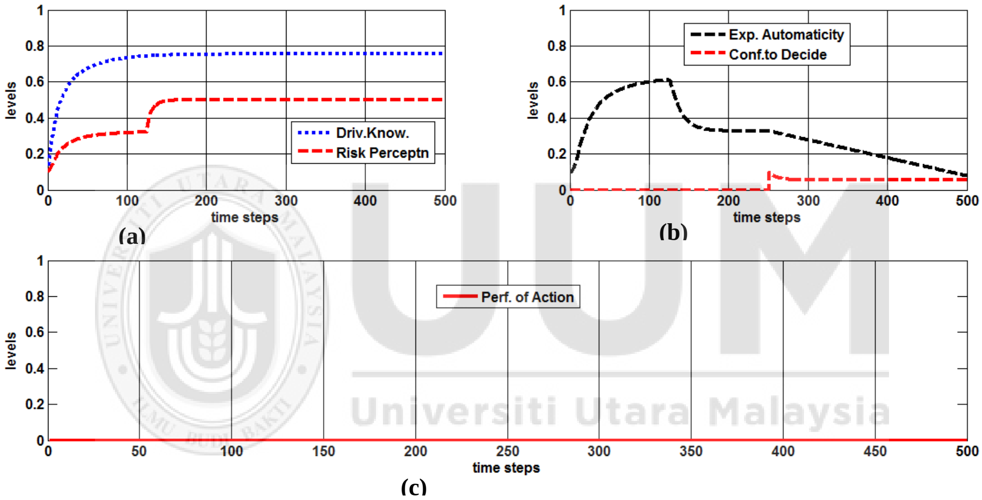


Figure 5.8. Simulation Conditions Results (for Scenario 2)

Scenario Three: The Short-Term Training Exposure

In Scenario 3, Figure (5.9a) indicates that the driver's level of perception about risk increased with proportional increase in driver's knowledge to a certain level and eventually decreased drastically due to a very short period of training. Result in Figure (5.9b) indicates that driver's experienced automaticity level decreased with a very short period of training, which led to a very low confidence level to make a decision. Result in Figure (5.9c) indicates that very short period of training led to lower performance of action by the driver.

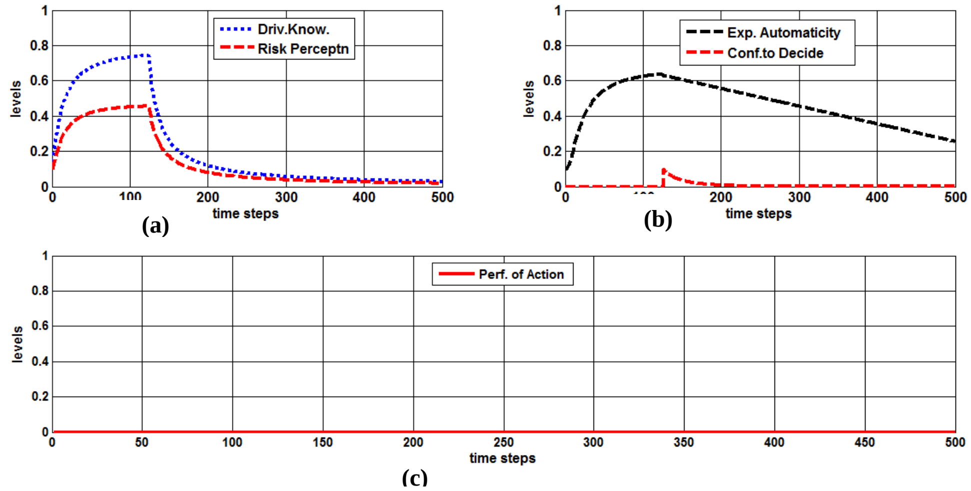


Figure 5.9. Simulation Conditions Results (for Scenario 3)

5.2 Mathematical Analysis

The mathematical analysis was conducted to verify the structural and theoretical correctness of the model. This study performed equilibrium analysis that described situations in which a stable situation had been reached. That is, if the dynamics of a system were described by a differential equation, then equilibrium levels can be estimated by setting a derivative (or all derivatives) to zero. One important thing to note is that an equilibrium condition is considered stable if the system always returns to it state after small disturbances. These equilibrium conditions indicate the correctness of the enhanced model that was pivoted on the model concept.

Mathematical analysis can be used to analyse the dynamic properties of dynamic models in order to understand the structural and correctness of the model through theoretical construct. Examples of such properties are as follows:

i. Values of the variables for which no change occurs (stationary points or equilibria);

ii. Certain variables in the model converge to some limit value (equilibria)

iii. Certain variables will show monotonically increasing or decreasing values over time (monotonicity)

iv. Situations occur in which no convergence occurs, but in the end a particular sequence of values is repeated all the time (limit cycle).

These equilibrium conditions are interesting to be explored, as it is possible to explain them using the knowledge from the theory or problem that is modelled. As such, the existence of reasonable equilibria is a sign of the correctness of the model. Moreover, the concept of mathematical analysis used in this study was derived from the concepts of the differential equation based on Treur (2016a, 2016b, 2016c). To obtain possible equilibrium values for the temporal factors, the study first described the temporal equations 4.21, 4.22, 4.27, 4.28, 4.30 and 4.31 previously presented in Section 4.3 Chapter Four. These are presented using differential equations 5.1, 5.2, 5.3, 5.4, 5.5 and 5.6. These six differential equations 5.1 to 5.6 provide the differential values for Driver's Knowledge (*Dk*), Perception about Risk (*Rp*), Involuntary Automaticity (*Iv*), Voluntary Automaticity (*Vy*), Experience Automaticity (*Ea*) and Decision (*Dc*), respectively.

$$\frac{dDk}{dt} = \gamma_{dk}.\left((\omega_{dk1}.Re + \omega_{dk2}.De) - Dk\right).Dk.(1 - Dk) \tag{5.1}$$

$$\frac{dRp}{dt} = \gamma_{rp}.\left(\left(\omega_{rp1}.Hp + \omega_{rp2}.Da\right) - Rp\right).Rp.(1 - Rp) \tag{5.2}$$

$$\frac{dIv}{dt} = \beta_{iv}.(Hd(t) - Iv).Iv.(1 - Iv) \tag{5.3}$$

$$\frac{dVy}{dt} = \beta_{vy}.(Gd - Vy).Vy.(1 - Vy) \tag{5.4}$$

$$\frac{dEa}{dt} = \beta_{ea}.(Aa - Ea).Ea.(1 - Ea) \tag{5.5}$$

$$\frac{dDc}{dt} = \gamma_{dc}.((Bas - Bar) - Dc).Dc.(1 - Dc) \qquad (5.6)$$

The symbols γ_{dk}, γ_{rp}, β_{iv}, β_{vy}, β_{ea}, γ_{dc} are proportional parameters (speed factors) while ω_{dk1}, ω_{dk2}, ω_{rp1}, ω_{rp2} are weight parameters, and both parameters are nonzero.

From equation 5.1 to 5.6, for any possible simulation results, the following cases can be distinguished:

$(Re + De) - Dk).(1 - Dk).Dk = 0$

$(Hp + Da) - Rp).(1 - Rp).Rp = 0$

$(Hd - Iv).(1 - Iv).Iv = 0$

$(Gd - Vy).(1 - Vy).Vy = 0$

$(Aa - Ea).(1 - Ea).Ea = 0$

$(Bas - Bar) - Dc).(1 - Dc).Dc = 0$

These cases can further be distinguished into the following:

$(Re + De = Dk) \vee (Dk = 1) \vee (Dk = 0)$

$(Hp + Da = Rp) \vee (Rp = 1) \vee (Rp = 0)$

$(Hd = Iv) \vee (Iv = 1) \vee (Iv = 0)$

$(Gd = Vy) \vee (Vy = 1) \vee (Vy = 0)$

$(Aa = Ea) \vee (Ea = 1) \vee (Ea = 0)$

$(Bas - Bar = Dc) \vee (Dc = 1) \vee (Dc = 0)$

Thus, it can be concluded that these are the points where the equilibrium can occur. That is, when $Re + De = Dk$, or $k = 1$,or $Dk = 0$. *B*y combining these three conditions, it can be re-written as a set of relationship in a form $(A \wedge D) \vee (A \wedge G)$:

$((Re + De = Dk) \vee (Dk = 1) \vee (Dk = 0)) \wedge$

$((Hp + Da = Rp) \vee (Rp = 1) \vee (Rp = 0)) \wedge$

$((Hd = Iv) \vee (Iv = 1) \vee (Iv = 0)) \wedge$

$((Gd = Vy) \vee (Vy = 1) \vee (Vy = 0)) \wedge$

$((Aa = Ea) \vee (Ea = 1) \vee (Ea = 0)) \wedge$

$((Bas - Bar = Dc) \vee (Dc = 1) \vee (Dc = 0))$

These expressions can be elaborated using distributive law as $(A \wedge D) \vee (A \wedge G) \vee (A \wedge J) \wedge (A \wedge M), \ldots, \vee (C \wedge R)$.

$(Re + De = Dk \wedge Re + De = Dk \wedge Hd = Iv \wedge Gd = Vy \wedge Aa = Ea \wedge Bas - Bar = Dc) \vee (Dk = 1 \wedge Rp = 1 \wedge Iv = 1 \wedge Vy = 1 \wedge Ea = 1 \wedge Dc = 1) \vee \ldots \vee (Dk = 0 \wedge Rp = 0 \wedge Iv = 0 \wedge Vy = 0 \wedge Ea = 0 \wedge Dc = 0)$.

The temporal factors were used to determine the possible combinations which resulted in value up to 3^6 (729) possible equillibrium points. Due to the large number of possible combinations, it made it difficult to provide a complete classification of equillibria. Typical cases were further analysed as follows:

Case 1: $(\boldsymbol{Hp + Da = Rp})$

$Hp = Rp - Da$ or

$Da = Rp - Hp$

First is to consider the factors that receive Rp as an input. For example, An receives Rp as an input. Therefore, by substituting $(Hp + Da = Rp)$ in equation (4.23), $An = \xi_{an} * Rp + (1 - \xi_{an}) * Re$ (4.23)

The result is as follows:

$$= Hp + Da + (1-1) * Re, \text{ assuming } \xi_{an} = 1$$

$$An = Hp + Da$$

$$An = Re$$

Assuming $\xi_{an} = 0.5$

$$An = 0.5 * Rp + (1 - 0.5) * Re,$$

$$An = 0.5 * Rp + 0.5 * Re,$$

$$An = 0.5 * (Rp + Re),$$

$$An = \frac{1}{2} * (Hp + Da + Re),$$

Assuming $\xi_{an} = 0$,

$$An = Re$$

Table 5.13 provides the summary of Rp Case one tested with variation of Xi of An

Table 5.13

Summary of Rp case one tested with variation of Xi of An

$\boldsymbol{\xi_{an} = 1}$	$\boldsymbol{\xi_{an} = 0.5}$	$\boldsymbol{\xi_{an} = 0}$
$An = Hp + Da$	$An = \frac{1}{2} * (Hp + Da + Re)$	$An = Re$

Case one depictes that perception about risk is influenced by the combination of driver‘s perception about hazard on the road and driver’s ability. From Table 5.13, when the case is tested with the parameter $\xi_{an} = 1$, (i.e., when ξ_{an} is high) the result indicated that driver’s level of attention was influenced by the driver’s perception about hazard combined with the driver’s ability. This implies that the level of attention of the driver depended on the perception level about task and driver’s ability and vice versa. When the case was tested with $\xi_{an} = 0.5$ parameter, (i.e., when ξ_{an} is moderate). The result showed that double the attention level of the driver on the road depended on the driver's perception about hazard on the road combined with the driver's ability and rehearsed experience. Similarly, when tested with parameter $\xi_{an} = 0$, (i.e., when ξ_{an} is low). The result indicated that driver's level of attention on the road depended on the driver's rehearsed experience.

Case 2: $(\boldsymbol{Rp = 0})$

Case 2 can be analysed by substituting $(Rp = 0)$ in equation (4.23),

$$An = \xi_{an} * Rp + (1 - \xi_{an}) * Re \qquad (4.23)$$

This gives the following results:

$= 1 * 0 + (1 - 1) * Re$, assuming $\xi_{an} = 1$

$An = 0$

$An = \xi_{an} * Rp + (1 - \xi_{an}) * Re,$

$= 0.5 * 0 + (1 - 0.5) * Re$, assuming $\xi_{an} = 0.5$

$An = 0.5Re$

$An = \xi_{an} * Rp + (1 - \xi_{an}) * Re,$

$= 0 * 0 + (1 - 0) * Re$, assuming $\xi_{an} = 0$

$An = Re$

The summary of Rp Case two tested with variation of Xi of An is provided in Table 5.14.

Table 5.14

Summary of Rp case two tested with variation of Xi of An

$\xi_{an} = 1$ **(High)**	$\xi_{an} = 0.5$ **(Moderate)**	$\xi_{an} = 0$ **(Low)**
$An = 0$	$An = \frac{1}{2} * Re$	$An = Re$

Case two depicts that perception about risk of the driver is low. From Table 5.14, when the case was tested with $\xi_{an} = 1$ parameter, the result suggested that attention level of the driver also became low and when tested with $\xi_{an} = 0.5$, the result indicated that doubled the driver's level of attention on the road depended on the driver's rehearsed experience. Likewise, when tested with $\xi_{an} = 0$, the result showed that driver's level of attention on the road was determined by the driver's rehearsed experience.

Case 3: $(\boldsymbol{Rp = 1})$

The study analyses Case 3 by substituting $Rp = 1$ in equation (4.23),

$$An = \xi_{an} * Rp + (1 - \xi_{an}) * Re \qquad (4.23)$$

And the following result is obtained:

$= 1 * 1 + (1 - 1) * Re$, assuming $\xi_{an} = 1$

$\mathrm{An} = 1$

$An = \xi_{an} * Rp + (1 - \xi_{an}) * Re,$

$= 0.5 * 1 + (1 - 0.5) * Re$, assuming $\xi_{an} = 0.5$

$An = \frac{1}{2}(1 + Re)$

$An = \xi_{an} * Rp + (1 - \xi_{an}) * Re,$

$= 0 * 1 + (1 - 0) * Re$, assuming $\xi_{an} = 0$

$An = Re$

The summary of Rp Case three tested with variation of Xi of An is presented in Table 5.15.

Table 5.15

Summary of Rp case three tested with variation of Xi of An

$\xi_{an} = 1$ **(High)**	$\xi_{an} = 0.5$ **(Moderate)**	$\xi_{an} = 0$ **(Low)**
$An = 1$	$An = \frac{1}{2}(1 + Re)$	$An = Re$

This case shows that perception about risk is high. Thus, from Table 5.15, when the case is tested with $\xi_{an} = 1$ parameter, the result indicated that attention of the driver on the road was also high and when tested with $\xi_{an} = 0.5$, the result showed that doubled the driver's level of attention on the road was determined by the high level of driver's rehearsed experience. Likewise, when tested with $\xi_{an} = 0$, the result suggested that driver's level of attention on road was determined by driver's rehearsed experience.

From the analyses of Case One, Two, and Three, when tested with different parameter values (1, 0.5 and 0), results suggested that risk perception of driver on the road was influenced by the increase in his level of attention. More so, when the risk perception of the driver was low, it indicated that his attention level was also low and vice versa. These findings were in line with the previous studies (Deery, 999; Rosenbloom et al., 2008).

Case 4: $(\boldsymbol{Hd = Iv})$

First, consider the factors that receive Iv as an input. It can be seen that Aa receives Iv as an input. Therefore, by substituting $Hd = Iv$ in equation (4.29),

$$Aa = \omega_{aa1} * Iv + \omega_{aa2} * Vy \qquad (4.29)$$

where, $\sum \omega = 1$, it gives the following:

$$Aa = (Iv + Vy)$$

$$Aa = (Hd + Vy)$$

$$Aa = Hd + Vy$$

Case 5: $(\boldsymbol{Iv = 1})$

The study analyses Case 5 by substituting $(Iv = 1)$ in equation (4.29),

$$Aa = \omega_{aa1} * Iv + \omega_{aa2} * Vy, \qquad (4.29)$$

where, $\sum \omega = 1$, the following is obtained:

$$Aa = (Iv + Vy)$$

$$Aa = 1 + Vy.$$

Case 6: $(\boldsymbol{Iv = 0})$

Similarly, Case 6 can be analysed by substituting $(Iv = 0)$ in equation (4.29),

$$Aa = \omega_{aa1} * Iv + \omega_{aa2} * Vy \qquad (4.29)$$

where, $\sum \omega = 1$, the result is as follows:

$$Aa = (Iv + Vy)$$

$$Aa = Vy$$

The summary of involuntary automaticity in Case Four, Five and Six is presented in Table 5.16.

Table 5.16

Summary of Involuntary automaticity, case four, five and six

$\boldsymbol{Hd = Iv}$	$\boldsymbol{Iv = 1}$ **(High)**	$\boldsymbol{Iv = 0}$ **(Low)**
$Aa = Hd + Vy$	$Aa = 1 + Vy$	$Aa = Vy.$

Case Four shows that the driver’s habitual-directed action was determined by the involuntary automaticity level of the driver when the driver was trained. In this case, the driver’s acquired automaticity level was influenced by the combination of driver’s habitual-directed action and the voluntary automaticity level. In case five, when the involuntary automaticity level of the driver was high, the resultant case was the high level of driver’s acquired automaticity that increased by the voluntary automaticity level. Similarly, when the involuntary automaticity level of the driver was low, the driver’s acquired automaticity level was determined by the voluntary automaticity level.

These three cases (4, 5 and 6) are in support of the results of the previous studies (Moskowitz, 2013; Wasserman & Wasserman, 2016; Wheatley & Wegner, 2001).

5.3 Automated Logical Analysis

This section deals with the verification of relevant dynamic properties of the cases considered in the enhanced model. For the automated verification, Temporal Trace Language (TTL) verification tool was used. TTL allows researchers to verify both qualitatively and quantitatively the model under analysis. TTL also has the ability to reason about time. The Temporal Trace Language (TTL) was used to perform automated verification of specified properties and states against generated traces. Many dynamic properties were formulated using a sorted predicate logic approach, based on the concept discussed in Chapter Three. The automated analysis further explained the awareness part of the IDM, and RPD Training part of the IDM in subsections 5.3.1 and 5.3.2, respectively.

5.3.1 Automated Analysis for the Awareness Component

Four cases were established based on the awareness component of the enhanced computational IDM model in the verified properties (VP1 to VP4). These properties were presented in semiformal and formal representations showing the application as regards to the cases presented:

VP1: Poor Visibility Leads to Lower Confident Level to Accelerate Car

$$
\begin{array}{l}
\forall \gamma\text{:TRACE, t1, t2:TIME, v1,v2,v3,v4, d:REAL, X:AGENT} \\
[\ \text{state}(\gamma, t1)\ \ |= \text{visibility}(X, v1)\ \& \\
\ \ \text{state}(\gamma, t1)\ \ |= \text{confident}(X, v2)\ \& \\
\ \ \text{state}(\gamma, t2)\ \ |= \text{visibility}(X, v3)\ \& \\
\ \ \text{state}(\gamma, t2)\ \ |= \text{confident}(X, v4)\ \& \\
\ \ t1 < t2 + d\ \&\ v1 > v3] \Rightarrow v2 > v4
\end{array}
$$

The first property case condition inferred that poor visibility as a result of poor/bad weather (rain) (Hess, Norton, Park & Street 2016; Hamdar, Qin, & Talebpour, 2016) and light (night) conditions (Charlton et al., 2006) lower the driver's confidence decision level to accelerate the car. The level of risk increases while the level of safety decreases because of poor visibility. Hence, the driver has low confidence level to decide and therefore, his action performed is low [indicated by no (0)] for the first and third time frames. This property is a significant attribute reflected in the case condition presented in Table 5.7 showing moderate risk condition and it is illustrated in Figure 5.2.

VP2: Belief about Safety Improves Confidence to Accelerate Car

∀γ:TRACE, t1, t2:TIME, R1,R2,R3,R4, d:REAL, X:AGENT
[state(γ, t1) |= belief_safety(X, R1) &
state(γ, t1) |= confident(X, R2) &
state(γ, t2) |= belief_safety(X, R3) &
state(γ, t2) |= confident(X, R4) &
t1 < t2 + d & R1 < R3] ⇒ R2≤ R4

The second property case condition shows that the driver's belief about safety increases his confidence level to decide to accelerate the car. This case condition is in accordance with the arguments of Hoogendoorn et al. (2011) and Aydoğan et al. (2014).

VP3: Monotonous Decreases of Confidence Level during Risky Conditions

∀γ:TRACE, t1, t2:TIME, V1,V2,V3,V4, d:REAL, X:AGENT
[state(γ, t1) |= belief_risky(X, V1) &
state(γ, t2) |= belief_risky(X, V2) &
state(γ, t2) |= confident(X, V3) &
t1 < t2 + d & V2 > V1] ⇒ V3≤ 0.2

The third property case condition shows that the level of risk monotonously decreases the drivers' confidence level to decide. This is explained using Table 5.7 and Figure 5.2. All the conditions presented in the first time frame were bad driving conditions with the exception of car condition that was presented as good condition. In this condition, the level of risk is higher than safety.

VP4: Variable v Between Boundaries

For all time points *t* between *tb* and *te* in trace γ if at *t* the value of *v* is *x*, then minimum value$<x$ $<$ maximum value.

$VP2 \equiv \forall\gamma$: TRACE, $\forall t$, tb, te:TIME, v:VAR, max, min:REAL [state(γ,t)|= has_value(v,x) & tb $\leq$ t $\leq$te $\Rightarrow$ min < x < max.

This formal specification can be used to check whether a variable stays between certain observed boundaries. For example, attention and belief activation should never be lower than 0 or higher than 1.

5.3.2 Automated Analysis for the Recognition-Primed Decision Component

The Automated verification for RPD component of the enhanced computational IDM is discussed in this section, as related to cases in subsection 5.1.3.2. Three cases are established based on the RPD training model in the verified properties (VP1 to VP3).

VP1: The Automaticity Level of the Driver Decreases with Decrease in Practice and Experience

VP1 $\equiv \forall\gamma$: TRACE, $\forall$t1, t2:TIME, $\forall$R1,R2,P1, P2, D1,D2:REAL
[state(γ,t1)|= has_value(practice_level, R1) &
state(γ,t2)|= has_value(practice_level, R2) &
state(γ,t1)|= has_value(experience_level, P1) &
state(γ,t2)|= has_value(experience_level, P2) &
state(γ,t1)|= has_value(automaticity, D1) &
state(γ,t2)|= has_value(automaticity, D2) &
t1 < t2 & R2 > R1 & P2 > P1] $\Rightarrow$ D1 $\geq$ D2

The first case condition suggested that if the driver had low practice time and experience, the automaticity level of the driver to make prime decision reduced as illustrated in Figure 5.6. This argument is in line with the studies of Panek et al. (2015) and Endsley (2016).

VP2: Monotonic Increase of Variable, v for Experience Improves Automaticity

For all time points t1 and t2 between tb and te in trace γ if at t1 the value of v is x1 and at t2 the value of v is x2 and t1 < t2, then x2 $\geq$ x1

VP4 $\equiv \forall\gamma$: TRACE, $\forall$t1, t2:TIME, $\forall$X1,X2:REAL
[state(γ,t1)|= has_value(v, X1) & state(γ,t2)|= has_value(v, X2) & tb $\leq$ t1 $\leq$ te & tb $\leq$ t2 $\leq$ te &
$\Rightarrow$ x2 $\geq$ x1

Similar with Panek et al. (2015) and Endsley et al. (2016) studies, the second case condition as shown in the formal specifications and illustrated in Figure 5.4 indicated that the automaticity level of the driver increased with increase in experience level.

VP3: Higher Attention Increases Voluntary Action

Individual's attention improves voluntary action (Gardner, 2012, 2015; Panek et al., 2015).

$$
\begin{aligned}
&\text{VP2} \equiv \forall\gamma\text{: TRACE, } \forall\text{t1, t2:TIME, } \forall\text{F1,F2,H1,H2, d:REAL}\\
&[\text{state}(\gamma,\text{t1})|= \text{attention(F1) \&}\\
&\ \text{state}(\gamma,\text{t1})|= \text{voluntary(H1) \&}\\
&\ \text{state}(\gamma,\text{t2})|= \text{attention(F2) \&}\\
&\ \text{state}(\gamma,\text{t2})|= \text{voluntary(H2) \&}\\
&\ \text{t2} \geq \text{t1 +d \& F1 > 0.6 \& F1< F2]} \Rightarrow \text{H2 > H1}
\end{aligned}
$$

In line with Moskowitz (2013), and Wheatley and Wegner (2001), the third case condition showed that the voluntary automaticity level of driver increased with increase in the level of his attention.

5.4 Summary of the Chapter

This chapter explained in detail the verification of an enhanced computational ID (Computational-RDT) model that was categorized into simulation, mathematical and automated analysis. The simulation was used for the implementation of the model in which the simulation traces showed the behaviour of driver in a particular condition in adherence to literature. The mathematical analysis was based on stability points by checking the values of the stability points of dynamic factors observed in the simulation experiments. The automated analysis was achieved based on Temporal Trace Language (TTL). Therefore, the verification of the Computational-RDT model was achieved in section 5.1, 5.2 and 5.3.

CHAPTER SIX
VALIDATION OF AN ENHANCED COMPUTATIONAL INTEGRATED DECISION-MAKING MODEL

6.0 Introduction

The fourth objective of this study is to evaluate the enhanced computational IDM (Computational-RDT model). The evaluation of the Computational-RDT model is conducted in two different stages. The first stage is verification of the Computational-RDT model (which is achieved in Chapter 5) by using simulation, mathematical and automated analysis methods. The second stage, which is validation of the computational RDT model, is achieved in sections 6.1 and 6.2 of this chapter. This is conducted by using human experiment where an adapted application (City Car Driving simulator) features were mapped with the external factors of the awareness component of the ID model to perform the experiment, and a questionnaire was also designed based on the external and temporal factors of the RPD training component of the IDM to validate the Computational-RDT model. This is to ensure the logical correctness of the enhanced model. Evaluation is an important process that helps to ensure that models and simulations are correct and reliable. It also ensures that the model produces results that actually represent the phenomenon under investigation.

6.1 Validation of an Enhanced Computational Integrated Decision-making Model

To validate the enhanced computional IDM (Computational-RDT) achieved in this study, an experimental design was conducted. Previous studies have demonstrated the appropriateness of experimental design for validating computational-RDT model, such as the RPD and SA models (Liu et al, 2009). The experimental design in this study involves only a post-test experiment. The purpose of the post-test is to examine the effectiveness of model factors in order to see if the simulation scenarios based on the model factors match the behaviour of the driver in real life domain. The experiment determines how these factors affect drivers' prime decision-making during emergencies. That is, it determines the influence of the training the driver had with the game simulator on the automaticity of the driver to make effective prime decision particularly during emergencies, which eventually enhances the drivers' performance of action. The following sections present the instrument used, procedures, and the data analysis for this experiment.

6.1.1 Instrument

In order to validate the participants' automaticity for effective prime decision making during emergencies, a questionnaire was designed as the instrument. The instruments were adapted from the validated items derived from previous studies. The questionnaire consisted of eleven (11) factors having sixty-six (66) items. A cover letter in front of the questionnaire explains the purpose of the research; it introduces the researcher and informs the participants that all information given by them shall be treated confidentially. The questionnaire is divided into two different sections. Section A deals with the demographic information of the participants such as age, gender, marital status, level of education, years of driving experience, and years holding a valid driving license. Section B consists of items on Driver Behaviour (DB) based on the external and temporal factors of the training model. Both sections contained instructions on how to fill up the questionnaire.

There are eleven (11) factors in section B, namely basic skills, basic practice, sensory ability, driving goal, driving intention, potential hazardous information, exposure to task complexity, perception about risk, driving knowledge, involuntary automaticity, and voluntary automaticity with each factor having items that measure them. For example, basic skill is measured by eight (8) items (Cox, Reeve, Cox, & Cox,2012; Lajunen & Summala, 1995; Lin et al., 2014; Patrick, 2016), basic practice is measured by nine (9) items (Tajvar et al., 2015), sensory ability is measured by twelve (12) items related to Vision and Night Driving Questionnaire (VND-Q) (Kimlin, 2016; Feng, Marulanda,& Donmez, 2014). In addition, literaure has measured driving goal by three (3) items (Chen, Gully, Whiteman, & Kilcullen, 2000; Dogan et al., 2011), driving intention by three (3) items (Moskowitz, 2013), potential hazardous information by four (4) items (Crundall et al., 2012; Huestegge, 2017; Konishi et al., 2004; Takahashi et al., 2007). Other factors such as exposure to task complexity is measured by eight (8) items (see Grill et al., 2012), perception about risk is measured by eleven (11) items (Rosenbloom et al., 2008), driving knowledge is measured by four (4) items (Okafor, Odeyemi & Dolapo, 2013; Phanindra & Chaitanya, 2016). Also, involuntary automaticity is measured by four (4) items (Verplanken & Orbell, 2003; Panek et al., 2015) and finally, voluntary automaticity is measured by four (4) items (see Verplanken & Orbell, 2003; Panek et al., 2015).

Moreover, the Cronbach Alpha of each factor was presented in Table 3.3, Chapter Three. The importance of each item measuring each factor is to validate the effectiveness of the designed model factors to determine the effect of training on the automaticity of the driver for make prime decision-making, especially during emergencies. In addition, it is to see if the simulation scenarios based on the model factors match the behaviour of the driver in terms of prime decision making in real life domain.

The participants rated the importance of each of these factors after interacting with the game simulator using an eleven-point-scale. The rating scale is from (0-10), with (0-5) indicating Low and (6-10) indicating High (Son, Choe, Kim, Hong, & Kim, 2016; Karstoft, Nielsen, & Nielsen, 2017; Sung et al., 2017). In each case, low means poor/bad decision while high means good/correct decision.

6.1.2 Experimental Procedures

The validation process was done using validation protocols based on user-centred design (UCD) approach and explained using Figure 6.1.

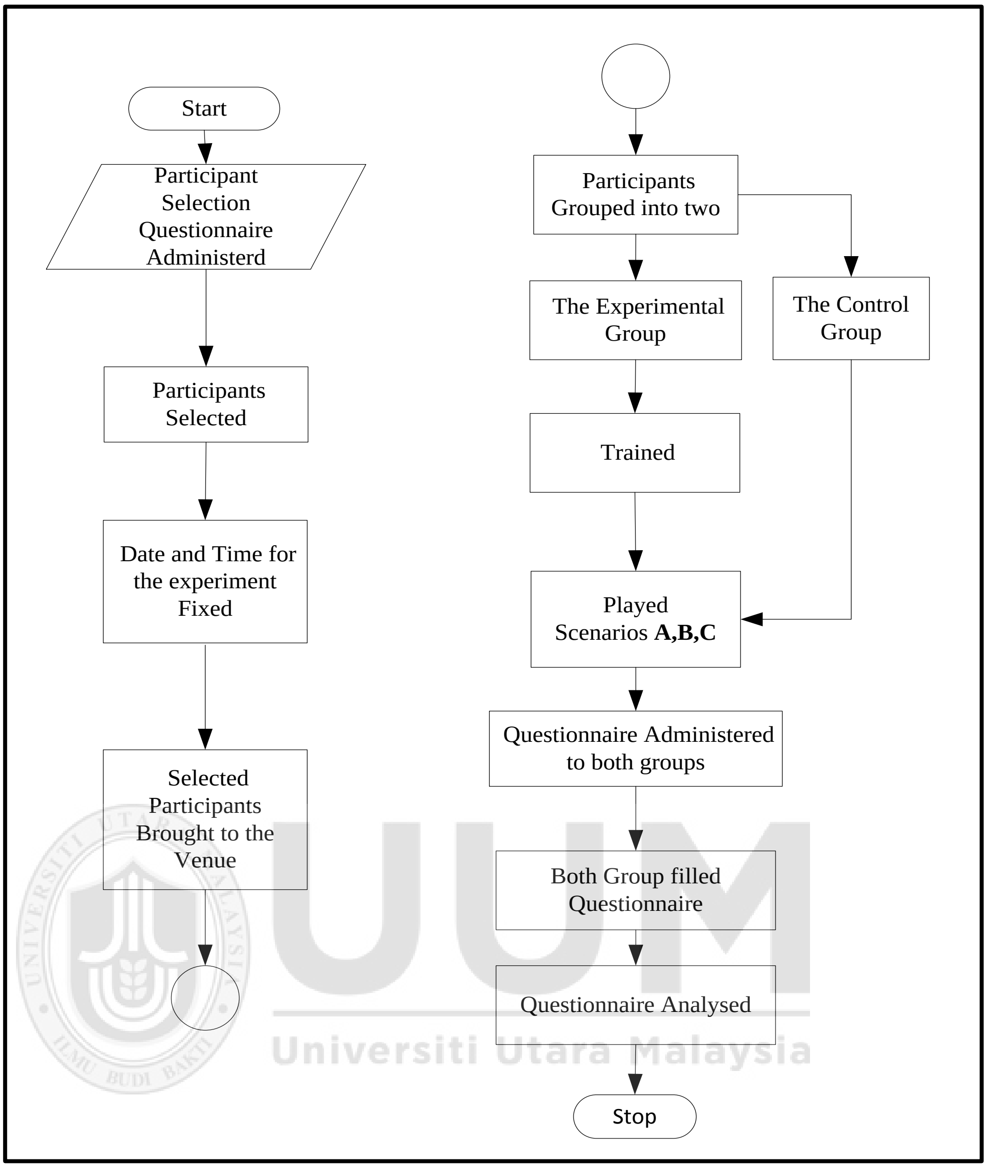


Figure 6.1. Validation Process Flowchart

6.1.2.1 Selection of Participants

Representativeness is an important factor in selecting participants in an experimental study (Babbie, 2010). Hence, in experimental research, researchers focus more on the representativeness of their participants ahead of other randomization techniques. Babbie (2010) added that in experimental research design, representativeness of participants is more crucial than the sample size. Therefore, to ensure representativeness of the participants in this study, the participants were selected using the criteria, namely valid driving licence, driving experience of more than 5 years for experienced drivers, and less than 1 year for inexperienced drivers, and minimum driving covering 5,000 Km mileage per year. In addition, the participants were middle-age drivers (23 to 53 years old), having knowledge of computer, video gaming, driving game simulator, and having willingness to play the game simulator. These criteria are in line with prior studies (Bellet et al., 2011; Hjälmdahl et al., 2011). For this purpose, fifty (50) questionnaires were distributed at the College of Arts and Sciences (CAS), Universiti Utara Malaysia to select participants who fulfilled the aforementioned criteria. Hence, the sample of the questionnaire for selecting participants is written in English and Bahasa Malaysia as shown in Appendix D.

Out of the fifty distributed questionnaires, thirty-seven were returned to the researcher. Among those returned, thirty (about 81%) participants were males and seven (about 19 %) participants were females as shown in the pie chat in Figure 6.2.

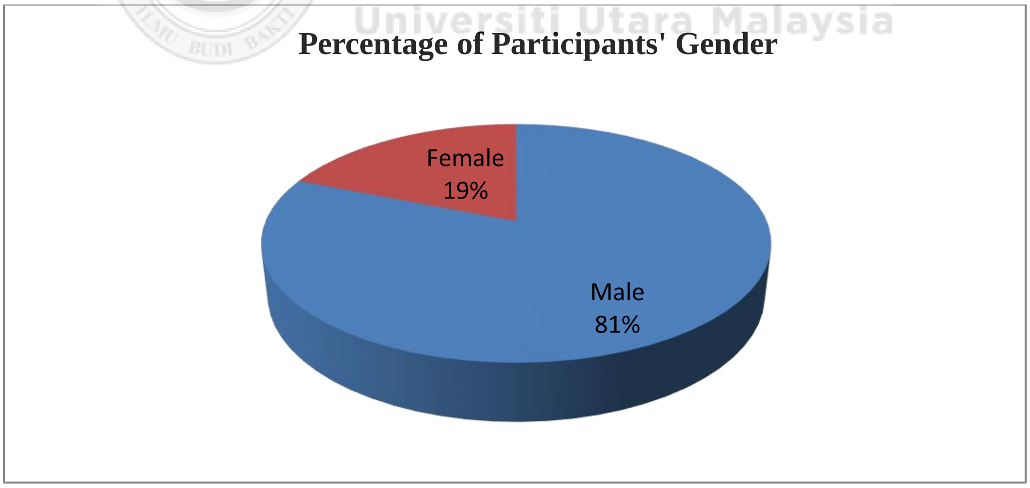


Figure 6.2. Percentage of Participant’s Gender

Concerning the participants’ age group, they were middle age drivers (23-53) years. According to the questionnaire’s report, nineteen (about 51%) participants were less than thirty years, fourteen (about 38%) participants were between thirty to thirty-nine years, while four (about 11%) participants were between forty to forty-nine years. Hence, the three ranges of the age group fall within the middle ages of the participants as presented in Table 6.1 and the percentage scores are presented in a pie chart form in Figure 6.3.

Table 6.1

Summary of Participants' Age Group

Age Group	Frequency	Per cent	Valid Per cent	Cumulative Per cent
<30	19	51.4	51.4	51.4
30-39	14	37.8	37.8	89.2
40-49	4	10.8	10.8	100.0
Total	37	100.0	100.0	

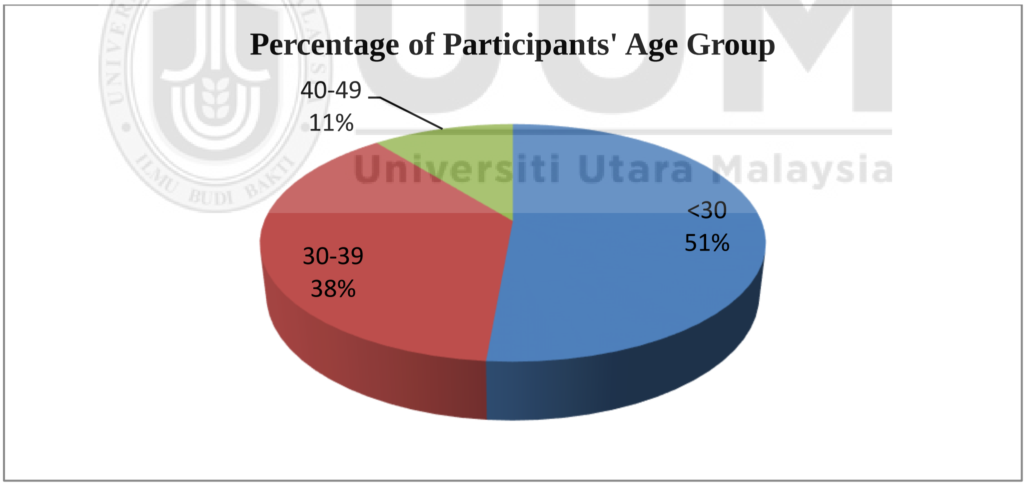


Figure 6.3. Percentage of Participants' Age Group

In terms of the driving experience, twelve (about 32%) participants had less than 1 years' experience, five (about 14%) participants had 1 to 5 years' experience, while twenty (about 54%) participants had greater than or equal to 6 years' experience. Table 6.2 and Figure 6.4 show the participants' years of driving experience and the percentage scores in a pie chart, respectively.

Table 6.2

Summary of Participants' years of Driving Experience

Driving Experience	Frequency	Per cent	Valid Per cent	Cumulative Per cent
<1 Year	12	32.4	32.4	32.4
1-5 Years	5	13.5	13.5	45.9
>=6 Years	20	54.1	81.1	100.0
Total	37	100.0	100.0	

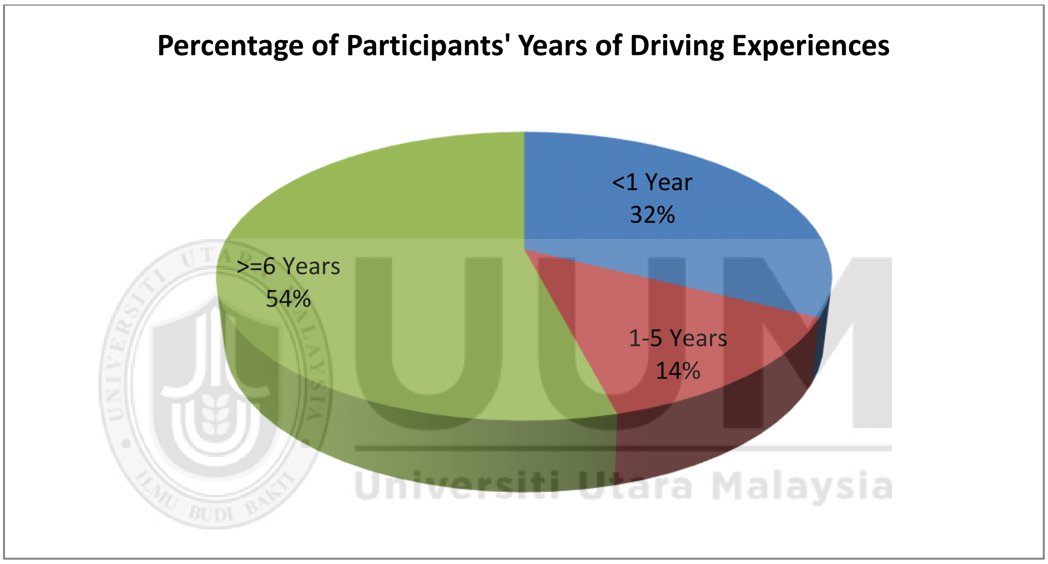


Figure 6.4. Percentage of Participants' Years of Driving Experiences

With respect to the participants' records on Mileage per year, seventeen (about 46%) participants covered less than five thousand kilometres per year while twenty (about 54%) participants covered greater or equal to five thousand kilometres per year. Table 6.3 shows the participants' annual mileage, and Figure 6.5 indicates the percentage scores in a pie chart form.

Table 6.3

Summary of Participants' Annual Mileage

Annual Mileage	Frequency	Per cent	Valid Per cent	Cumulative Per cent
<5,000 km	17	45.9	45.9	45.9
>=5,000 km	20	54.1	54.1	100.0
Total	37	100.0	100.0	

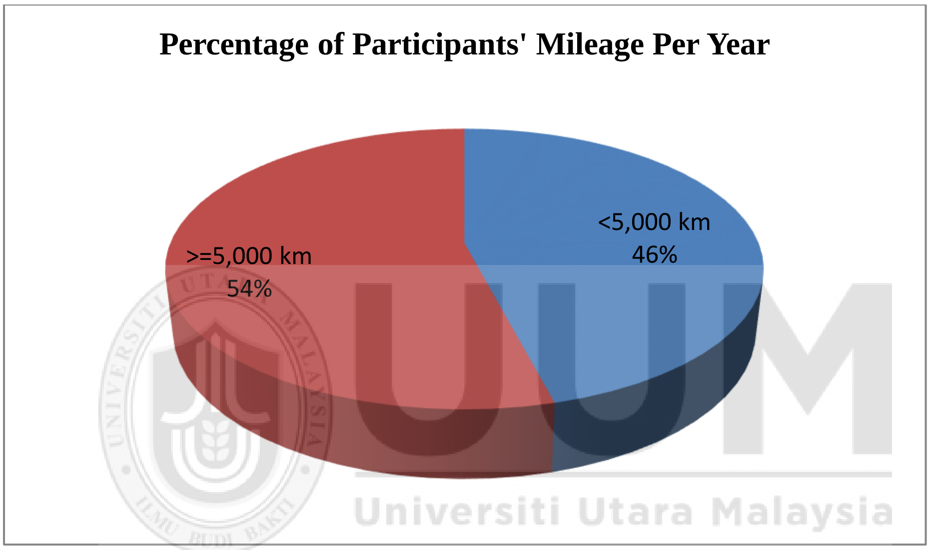


Figure 6.5. Percentage of Participants' Mileage per year

Concerning the participants that had valid driving licences, it was shown that twenty-one (about 57%) participants had valid driving licences, and sixteen (about 42%) participants had none. Table 6.4 indicates the participants that had valid driving licences and those that had none. Their percentage scores are shown in Figure 6.6 in a pie chart form.

Table 6.4

Summary of Participants with Valid Driving Licences

	Frequency	Per cent	Valid Per cent	Cumulative Per cent
Yes	21	56.8	56.8	56.8
No	16	42.3	42.3	100.0
Total	37	100.0	100.0	

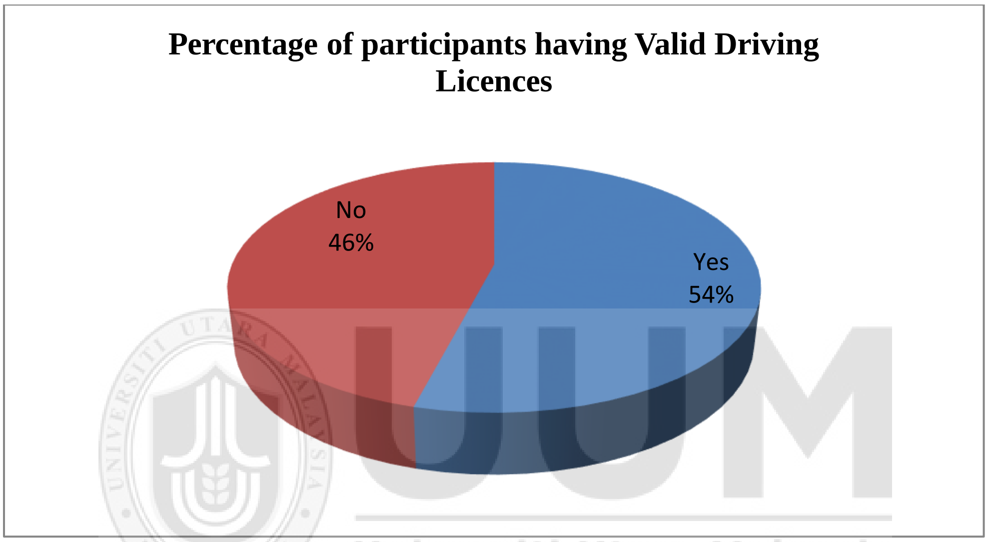


Figure 6.6. Percentage of Participants having Valid Driving Licences

Concerning the participants having knowledge of desktop driving simulator, it was found that twenty-four (about 65%) participants had previously used desktop driving simulator while thirteen (about 35%) had not used it before. Table 6.5 displays the statistics of the participants having knowledge of desktop driving simulator, while Figure 6.7 shows their percentage scores in a pie chart format.

Table 6.5

Summary of Participants having Knowledge of Desktop Driving Simulator

Desktop Driving Simulator	**Frequency**	**Per cent**	**Valid Per cent**	**Cumulative Per cent**
Yes	24	64.9	64.9	64.9
No	13	35.1	35.1	100.0
Total	37	100.0	100.0	

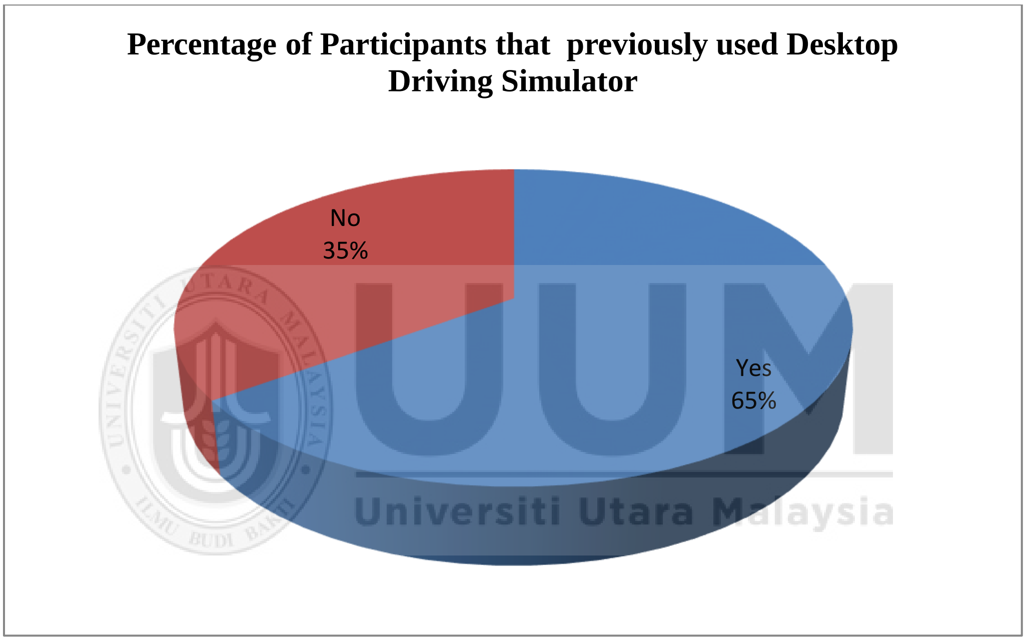


Figure 6.7. Participants that had knowledge of Desktop Driving Simulator

In terms of participants that had knowledge of video game, it was indicated that thirty (about 81%) participants had previously played a video game while seven (about 19%) had not played any video game previously as shown in Table 6.6. Correspondingly, the percentage scores of those participants are presented in a pie chart in Figure 6.8.

Table 6.6

Summary of Participants that had Knowledge of Video Game

Play Video Game	Frequency	Per cent	Valid Per cent	Cumulative Per cent
Yes	30	81.1	81.1	81.1
No	7	18.9	18.9	100.0
Total	37	100.0	100.0	

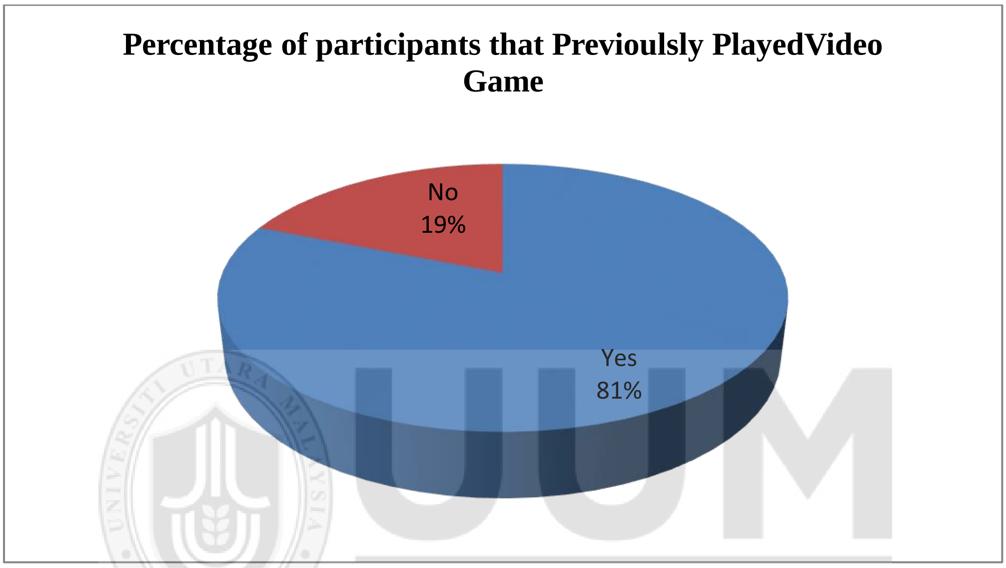


Figure 6.8. Percentage of Participants that Previously Played Video Game

With respect to the percentage of participants using computer weekly, it was found that almost all participants had been using computer weekly with the exception of only one (about 3%) participant had not used a computer on a weekly basis. This signified that almost all the participants were computer literates as presented in a pie chart in Figure 6.9. The analysis of the data collected for the selected participant as presented in Tables 6.2 - 6.6 enables the study to focus on the selection criteria. The analysis indicates that all the participants recruited for this experimental study have the same characteristics, which satisfy the criteria for the experiment.

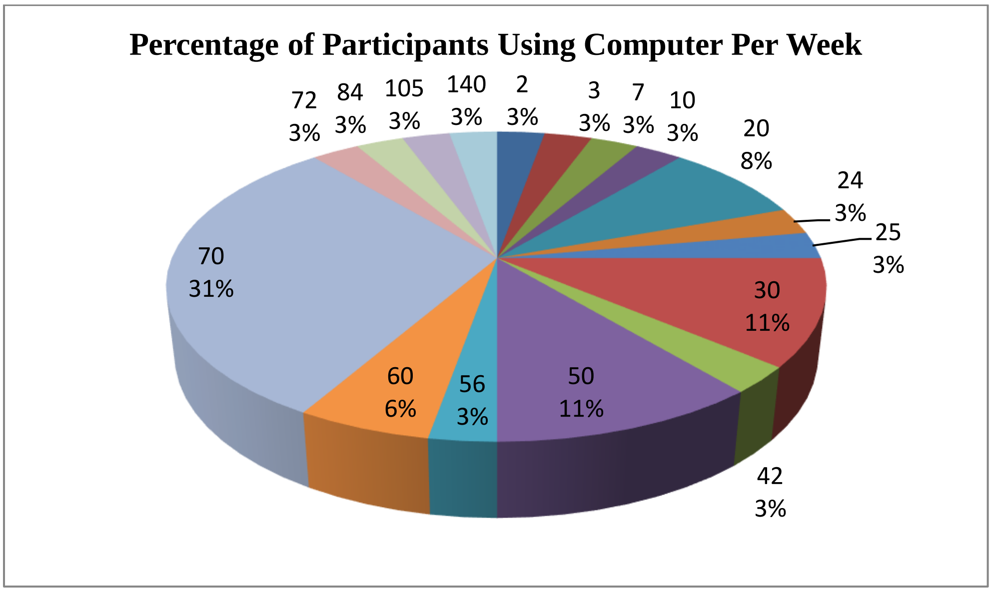


Figure 6.9. Percentage of Participants using Computer Weekly

6.1.2.2 Consent Form

After the participants were selected based on the criteria, then the consent form was administered to the selected participants. The consent form has the following details: 1. Purpose of the research study experiment. 2. What you will be asked to do in the study experiment. 3. Required time for the experimental group and control group participants. 4. Date & time for the experiment. This was left open until decided by the researcher. 5. Venue. 6. Risks. 7. Benefits/ compensation. 8. Confidentiality. 9. Voluntary participation. 10. Right to withdraw from the study. 11. Permission to snap and use photos. 12. Whom to contact if you have questions about the study experiment and participant’s name, signature and date. This is to ensure that the participants have full knowledge of the experimental study; they agree to the conditions and willing to participate. The sample of the consent forms in both English language and Bahasa Malay translated version is shown in Appendix E.

6.1.2.3 Date and Time

A suitable date and time for the experiment was fixed to carry out the experiment and was communicated to the selected participants via their contacts information.

6.1.2.4 Participants

Twenty participants were selected in this experiment in line with the previous studies (e.g., Bellet et al., 2011; Kaber, Zhang, Jin, Mosaly, Garner, 2012; Liu et al., 2009) that had discussed driver behaviour. Among the participants selected, eighteen were males, and two were females of middle age (23 to 53 years old). In addition, all the twenty participants were experienced drivers (i.e., driving experience >5yrs) had valid driving licences, and covered a minimum of 5,000 km mileage per year in driving. The demographic information of the participants is shown in Appendix F.

6.1.2.5 Venue of the Experiment

All selected participants were brought to Human-Centered Computing Research Lab (HCCRL) for the experiment. The experiment room was very quiet, conducive and convenient for the participants for the smooth interaction with the game application.

6.1.2.6 Grouping of Participants

The participants selected for the experiment were grouped into two using simple randomization technique (Suresh, 2011). For example, the researcher used a shuffled deck of cards method by writing 1 to 20 in small pieces of paper. One (1) to ten (10) represented experimental group participants while eleven (11) to twenty (20) represented the control group participants. The small pieces of paper were then moulded and put into small container. Each participant then picked one of the moulded papers.

The use of a shuffled deck of cards method is in line with the previous studies (Daddis & Brunell, 2015; Maxfield, Patil & Cunningham, 2016). The experimental group participants were trained using city-driving test during the experiment while the control group were not trained; they played the free driving test in the game simulator.

6.1.2.7 Participants Interaction with the Simulator

At this stage, the participants (drivers) interacted with the game simulator. The game simulator has two main stages, career driving and free driving. The game simulator simulates series of fictitious driving, experiences and scenarios (good, average and bad driving conditions). These driving conditions (scenarios) are based on the simulation scenarios used in MATLAB as explained in Chapter 5. Each of these scenarios was labelled A, B, and C and configured into six different PCs that the participants used, with each PC having a scenario configured based on the model external factors mapped inside the game simulator. Thereafter, all the participants (experimental and control groups) created their profiles in the simulator to store their individual information. However, before the participants interacted with the simulator, protocol (user) guide was provided for the two groups of participants (experimental and control groups) on how to perform the experiment. The details of the protocol guide are shown in Appendix G.

The experimental group played both of the two stages (career driving and free driving), while the control group played only the free driving stage. In the free driving stage, the three different scenarios consisting of different conditions in driving environment are set up. These include road, traffic, obstacles, car condition and visibility. The photos of participants who interacted with the game simulator were taken, and permissions were given by the participants to the researcher to use these pictures as evidence of participation. Appendix H displays this evidence.

After the two groups of participants had interacted and played with the three different scenarios in the city driving game simulator, questionnaire based on the external and temporal factors of the designed model were administered to the participants to fill. The participants filled the questionnaire based on their experiences and interactions with the game simulator. See Appendix I for the sample of the post-test questionnaire both in English and in Bahasa Malaysian translated version. Thereafter, the questionnaire was analysed using statistical package for social sciences (SPSS).

6.1.3 Data Analysis

In this subsection, the study discusses the results of simulator and questionnaire. The results are based on descriptive analysis. Scenarios of prime decision-making and summary of the subsection are also discussed.

6.1.3.1 Simulator Results Discussion

The simulator results were obtained for the twenty (20) participants involved in the experiment, ten (10) participants each for both control and experimental group. The experiment record consists of distances the driver covered without committing any traffic violation. These traffic violations are classified into "no violations (NV)", "no major violations (NMV)", and "no accident (NA)" while driving the game simulator.

Table 6.7

Summary of scenarios settings in simulator

Scenarios	Traffic Density Measurement (%)
A	0 - 20 (Low Traffic)
B	41 - 60 (Average Traffic)
C	81 - 100 (High Traffic)

These violations were recorded for one session because the participants played the game only once. Hence, the setting of the scenarios in the simulator was based on their traffic density measurements as shown in Table 6.7.

Table 6.8

Participants' Simulator Traffic Records for Scenario A

SCENARIO A (EXPERIMENTAL GROUP)			
PARTICIPANTS	**NV (miles)**	**NMV (miles)**	**NA (miles)**
1	0.50	0.51	0.84
2	0.50	0.51	0.72
3	0.61	0.90	1.22
4	0.35	0.49	0.54
5	0.17	0.39	1.44
6	0.49	2.54	8.16
7	0.32	0.44	0.81
8	0.06	0.07	0.13
9	0.05	0.06	0.06
10	0.53	0.81	0.84
Mean score	**0.358**	**0.672**	**1.476**
SCENARIO A (CONTROL GROUP)			
PARTICIPANTS	**NV (miles)**	**NMV (miles)**	**NA (miles)**
1	0.28	0.58	0.67
2	0.24	1.11	0.77
3	0.36	0.36	0.86
4	0.21	0.34	1.05
5	0.55	1.44	0.83
6	0.30	0.46	0.60
7	0.20	0.35	0.81
8	0.46	0.87	0.87
9	0.33	0.33	0.86
10	0.54	0.54	0.86
Mean scores	**0.347**	**0.638**	**0.818**

Note: The participants are categorised into experimental and control groups

The data for the ten participants, each from both experimental (EXP) and control (CTRL) groups in scenarios A, B and C is presented in Table 6.8, 6.9, and 6.10, respectively.

Table 6.9

Participants' Simulator Traffic Records for Scenario B

SCENARIO B (EXPERIMENTAL GROUP)			
PARTICIPANTS	**NV (miles)**	**NMV (miles)**	**NA (miles)**
1	0.60	0.60	0.60
2	0.30	0.50	0.55
3	0.53	0.98	1.89
4	0.39	1.14	0.74
5	0.27	0.35	2.11
6	0.17	0.41	0.75
7	0.50	0.50	0.57
8	0.20	0.34	0.40
9	0.19	0.55	0.78
10	0.27	0.91	0.91
Mean scores	**0.342**	**0.628**	**0.930**
SCENARIO B (CONTROL GROUP)			
PARTICIPANTS	**NV (miles)**	**NMV (miles)**	**NA (miles)**
1	0.01	0.01	0.01
2	0.33	1.62	1.62
3	0.26	0.45	0.56
4	0.21	0.44	0.48
5	0.35	0.86	0.86
6	0.51	1.26	2.71
7	0.39	1.14	0.74
8	0.12	0.38	0.74
9	0.32	0.32	0.52
10	0.25	0.52	0.52
Mean scores	**0.275**	**0.70**	**0.876**

Note: The participants are categorised into experimental and control groups

Table 6.10

Participants' Simulator Traffic Records for Scenario C

SCENARIO C (EXPERIMENTAL GROUP)			
PARTICIPANTS	**NV (miles)**	**NMV (miles)**	**NA (miles)**
1	0.69	0.62	0.82
2	0.56	0.46	0.81
3	0.59	0.61	0.82
4	0.50	0.50	0.65
5	0.73	0.72	3.01
6	0.69	0.78	1.52
7	0.58	0.61	0.71
8	0.65	0.55	0.76
9	0.51	0.47	0.62
10	0.63	0.61	0.78
Mean scores	**0.613**	**0.593**	**1.05**
SCENARIO C (CONTROL GROUP)			
PARTICIPANTS	**NV (miles)**	**NMV (miles)**	**NA (miles)**
1	0.11	0.14	0.14
2	0.17	0.22	0.22
3	0.21	0.21	0.27
4	0.20	0.39	0.53
5	0.39	0.45	0.67
6	0.12	0.19	0.29
7	0.40	0.76	1.06
8	0.41	0.77	0.83
9	0.16	0.25	0.25
10	0.41	0.46	0.60
Mean scores	**0.258**	**0.384**	**0.486**

Note: The participants are categorised into experimental and control groups

The data was analysed using Statistical Tools for Social Sciences (SPSS). The result was presented using bar chart as shown in Figure 6.10. It showed the violations recorded against the distance covered in miles, comparing control and experimental groups in scenarios A, B and C. Moreover, No Violation (NV), No Major Violation (NMV), and No Accident (NA) were represented in light blue colour, dark red colour, and green colour, respectively.

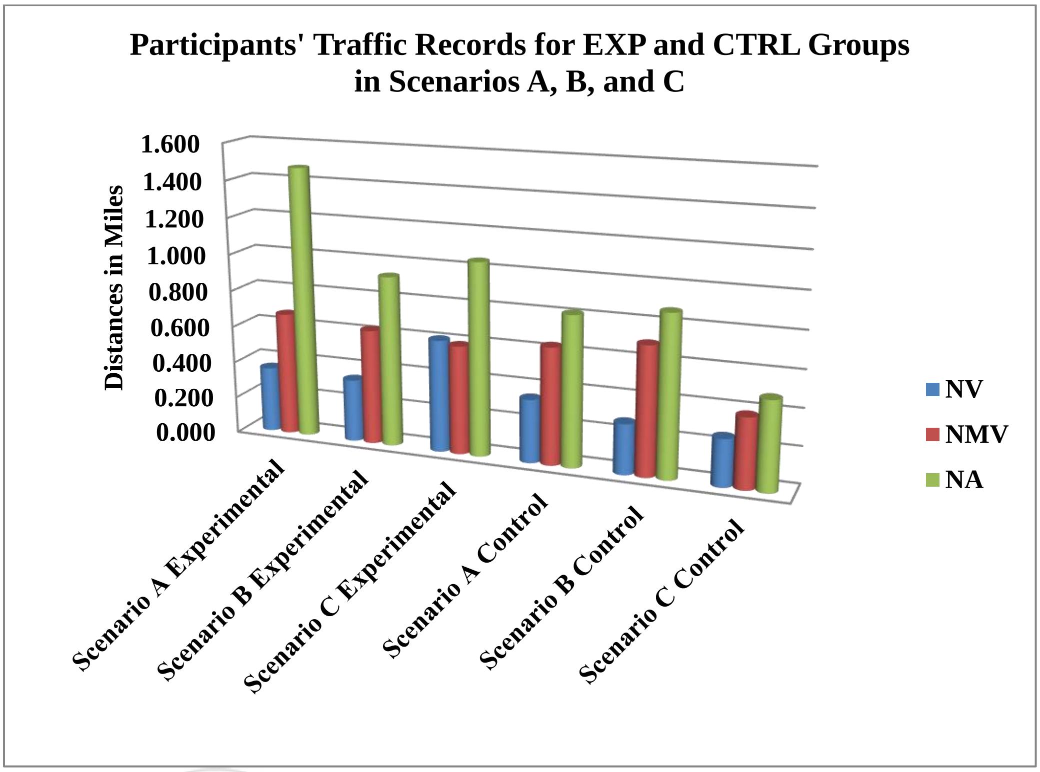


Figure 6.10. The violations recorded by groups' participants in all scenarios

The experimental group participants have the distance mean scores of 0.358, 0.342 and 0.613 for committing "no violation" in traffic under scenarios A, B, and C, respectively. The mean scores of the experimental group participants under all the scenarios are greater than the mean scores of the control group participants, which are 0.347, 0.275 and 0.258 for scenarios A, B, and C, respectively. Based on these scores, it can be concluded that the experimental groups performed better than the control group participants in terms of longer distance covered without violation of traffic.

With respect to the measurement of "no major violation" in traffic, the experimental group participants have the distance mean scores of 0.672, 0.628 and 0.593 for scenarios A, B, and C respectively while those of the control group participants are 0.638, 0.700 and 0.384 for scenarios A, B, and C respectively. Based on the distance mean scores of the two groups, the experimental group participants covered longer distance with “no major violation” committed compared to the control group participants under scenarios A and C. However, the distance mean scores covered with “no major violation” for control group participants under scenario B is longer than that of the experimental group participant. This result is not surprising in the sense that scenario B is a normal situation with conditions such as daytime, normal traffic flow and good visibility. Therefore, any of the participants from the two groups has the tendency to perform better under this scenario.

Regarding the measurement of “no accident” in traffic, the experimental group participants have the mean scores of 1.476, 0.930 and 1.050 under scenarios A, B, and C, respectively while the control group participants have the mean scores of 0.818, 0.876 and 0.486 under scenarios A, B, and C, respectively. Based on these scores, it can be concluded that experimental group covered longer distance with “no accident” committed compared to the control group participants under scenarios A, B and C. On the whole, it can be concluded that the experimental group participants performed better than the control group participants in terms of longer distances covered without committing major violations of traffic, or having accident in traffic.

To test the significant level of the difference between experimental and control groups, this study employs independent-sample t-test. Table 6.11 presents the results of the independent sample t-test together with the Levene’s test for equality of variance. The Levene’s test of equality of variance suggests that if the test is significant at the 5% level, it means that the assumption of equal variance is violated and the “equal variance not assumed” is used. Conversely, if the significant value of Levene's Test for Equality of Variances is not significant at the 5% level, one can conclude that the assumption of equal variances is not violated and for this reason, “equal variances assumed” are used (Coakes, 2013; Field, 2009; Pallant, 2010). The independent t-test of equality is used to determine the significant difference between the experimental and control groups in relation to ‘No Violation’, ‘No Major Violation’ and ‘No Accident’ for the three scenarios A, B and C.

The results presented in Table 6.11 for scenario A and B suggested that the values of Levene's Test for Equality of Variances are not significant for ‘No Violation’, ‘No Major Violation’ and ‘No Accident’. Since the values were greater than 5% it can be concluded that the assumption of equal variances is not violated and therefore, equal variances assumed are used. The corresponding results of t-test using the P-value for ‘No Violation’, ‘No Major Violation’ and ‘No Accident’ are lesser than 2.0 or P > 0.05 and thus, they are not significant at 5%. Hence, this implied that there was no significant difference in each of ‘No Violation’, ‘No Major Violation’ and ‘No Accident’ between the experimental and control groups for scenarios A and B.

The results in Table 6.11 for scenario C suggested that the significant value of Levene's Test for Equality of Variances indicated the P- value 0.009 for ‘No Violation’. Since this value is less than 5% it can be concluded that the assumption of equal variances is violated and for this reason, equal variances not assumed are used. The corresponding result of t-test = 7.479 with the significant value = 0.000. Since the significant value is lesser than 5%, it is concluded that there is significant difference in ‘No Violation between the experimental and control groups. Also for scenario C in Table 6.11, Levene's Test for Equality of Variances is significant at 5% level (p-value 0.031) for ‘No Major Violation’. This suggests that the assumption of equal variances is violated and therefore, equal variances not assumed are used. The result of t-test value is 2.629 with the significant value of 0.017. The significant value, lesser than 5%, suggests that there is significant difference in ‘No Major Violation between the experimental and control groups.

Table 6.11 shows that for scenario C, Levene's Test for Equality of Variances is insignificant at 5% with p value equals to 0.191 for ‘No Accident’. This means that there is no violation of the assumption of equal variances and hence equal variances assumed are used. The t-test result is equal to 2.247 with p-value equals to 0.037 indicating that there is a significant (at the 5% level) difference in ‘No Accident’ between the experimental and control groups.

Furthermore, in scenario C Table 6.11, for experimental groups, the mean scores (0.613), (0.593) and (1.050) for ‘no violation’, ‘no major violation’ and ‘no accident’, respectively are higher than the mean values (0.258), (0.384), and (0.486) of control groups for ‘no violation’, ‘no major violation’, and ‘no accident’, respectively. This result shows that scenario C is a high-risk scenario having bad driving conditions such as pedestrian and traffic density of 100%, and many obstacles. In addition, the participants under this scenario drove at night and when it was raining thereby facing visibility problems due to bad weather condition.

Table 6.11

Participants' Simulator Results for Test of Mean Difference

Violations	Group	Participants	Mean	Levene's Test for Equality of Variances		t-stat	p-value
				F	Sig.		
No Violation (A)	Experimental	10	0.457	2.793	0.112	1.849	0.081
	Control	10	0.347				
No Major Violation (A)	Experimental	10	0.672	0.653	0.430	0.134	0.895
	Control	10	0.638				
No Accident (A)	Experimental	10	1.476	4.220	0.055	0.871	0.395
	Control	10	0.818				
No Violation (B)	Experimental	10	0.342	0.517	0.481	1.014	0.324
	Control	10	0.275				
No Major Violation (B)	Experimental	10	0.628	4.352	0.051	-0.396	0.697
	Control	10	0.700				
No Accident (B)	Experimental	10	0.930	0.182	0.675	0.178	0.861
	Control	10	0.876				
No Violation (C)	Experimental	10	0.613	8.571	0.009	7.479	0.000
	Control	10	0.258				
No Major Violation (C)	Experimental	10	0.593	5.484	0.031	2.629	0.017
	Control	10	0.384				
No Accident (C)	Experimental	10	1.050	1.843	0.191	2.247	0.037
	Control	10	0.486				

Note: The tests are performed for Scenarios, A, B and C

However, scenario A and B are associated with good driving conditions such as pedestrian and traffic density of 0-50%, and less obstacles. Under these scenarios, there was no visibility problem and the participants drove during the day time when the weather condition was clear. The results indicate that in scenario C, there are significant differences between the experimental and control groups in terms of 'no violation', 'no major violation' and 'no accident'. This suggests that scenario C being the high-risk scenario requires the expertise of the participants.

In this case, the influence of training is paramount because of the complexity of scenario C. In addition, the results indicated that in scenario C, the mean scores for ‘no violation’, ‘no major violation’ and ‘no accident’ were greater for experimental groups than for the control groups. This implies that training plays an important role in making better decision by drivers in experimental group as compared to those in control group. These results support the earlier stated null hypothesis (H0 in Chapter 3), which states that training improves driver’s prime decision making.

6.1.3.2 Validation of the Enhanced Computational Integrated Decision-making Model

This section discusses the analysis of participants’ responses obtained through questionnaire designed based on the RPD training part of the IDM external and temporal factors to validate the the Enhanced Computational IDM (Computational-RDT) model. The responses of the participants from the two groups are analysed using Statistical Tools for Social Sciences (SPSS), and the results are presented in Tables 6.12 and 6.13. The two tables contain the external and the temporal factors discussed in Chapter Four, subsections 4.2.1 and 4.2.2.

Table 6.12

Mean Scores for the Experimental Group

	P1	**P2**	**P3**	**P4**	**P5**	**P6**	**P7**	**P8**	**P9**	**P10**	**Mean**
Basic Skills	6.63	7.50	7.50	7.25	7.13	7.88	7.38	7.25	8.50	5.88	7.29
Basic Practice	6.33	6.44	6.78	7.22	6.44	6.22	6.56	6.78	6.89	6.00	6.57
Sensory Ability	4.50	5.00	6.00	4.58	5.08	5.58	4.33	5.42	5.33	4.92	5.08
Driving Goal	9.00	7.00	8.00	9.00	8.00	9.00	9.00	9.00	9.00	9.00	8.60
Driving Intention	9.00	7.00	8.00	9.00	8.00	9.00	9.00	8.00	9.00	9.00	8.50
Potential Hazardous Information	8.00	7.50	8.00	9.25	7.50	8.25	7.75	8.75	9.00	6.75	8.08
Exposure on Task Complexity	8.25	8.25	8.25	8.00	7.50	7.75	8.25	8.75	9.25	6.75	8.10
Risk Perception	7.73	7.73	7.45	7.91	8.00	7.27	8.18	7.73	8.27	6.91	7.72
Driving Knowledge	9.25	9.00	9.25	9.00	8.50	9.50	9.50	9.00	9.50	9.00	9.15
Involuntary	7.50	7.50	8.00	7.00	8.50	7.75	7.50	7.50	7.00	7.25	7.55
Voluntary	2.50	2.50	2.00	3.00	1.50	2.25	2.50	2.50	3.00	2.75	2.45
Mean	7.15	6.86	7.20	7.38	6.92	7.31	7.27	7.33	7.70	7.65	

Table 6.12 and Table 6.13 show the mean scores of individual participants in experimental group and the control group, respectively for each of the eleven (11) factors based on the items used to measure them. According to the results presented in both tables, there were clear indications that the mean scores values for all the factors in Table 6.12 are higher than values presented in Table 6.13. This suggested that training given to the experimental group participants reflected in their responses to the questionnaire. For instance, in the case of driving knowledge, the mean score (9.15) of the experimental group participants is higher (6.58) than that of the control group. In addition, the driving knowledge as a factor had the highest mean score among all the factors in the experimental group. The higher mean value obtained from the driving knowledge indicated that the experimental group participants had a clear understanding of traffic rules, traffic signs and signals, that minimized the risk of accident. This evidence was consistent with the argument of Zaidi, Paul, Mishra and Srivastav (2016)

that abiding by traffic rules could lead to less or no accident. Therefore, training of drivers is important for prime decision making, in particular, during emergencies.

Table 6.13

Mean Scores for the Control Group

	P1	**P2**	**P3**	**P4**	**P5**	**P6**	**P7**	**P8**	**P9**	**P10**	**Mean**
Basic Skills	5.38	6.00	4.13	6.13	6.00	6.50	5.88	6.25	6.38	6.25	**5.89**
Basic Practice	6.11	4.78	4.22	5.00	5.33	5.56	4.78	5.00	5.33	5.67	5.18
Sensory Ability	5.00	3.83	3.92	4.00	3.75	4.00	2.67	2.92	3.17	3.17	5.12
Driving Goals	7.00	7.00	6.00	6.00	6.00	6.00	6.00	7.00	7.00	6.67	6.47
Driving Intention	7.00	7.00	6.00	6.00	6.00	6.00	6.00	7.00	7.00	6.67	6.47
Potential Hazardous Information	6.75	6.75	5.50	7.50	7.25	6.50	6.25	6.00	6.25	6.50	6.53
Exposure on Task Complexity	6.38	5.25	5.38	6.38	6.25	6.00	6.38	6.38	6.38	6.75	6.15
Risk Perception	6.27	5.64	6.00	6.45	7.00	6.09	5.45	5.82	5.64	6.73	6.11
Driving Knowledge	6.75	6.75	6.50	6.75	7.00	6.50	6.5	6.25	6.50	6.25	6.58
Involuntary	6.50	6.25	5.50	6.50	7.50	6.00	6.25	6.50	6.50	6.50	6.40
Voluntary	3.50	3.75	4.50	3.50	2.50	4.00	3.75	3.50	3.50	3.50	3.60
Mean	6.06	5.73	5.24	5.84	5.87	5.74	5.45	5.69	5.79	5.88	

Similarly, the risk perception mean score of the experimental group participants is higher than that of the control group participants. This indicates that the experimental group participants have a higher tendency to avoid, recognize, and handle risk (Rosenbloom et al., 2008). However, the results for the voluntary automaticity factor, that captured the conscious automaticity of the participants, revealed that the experimental group had lower mean score compared to the control group participants. The reason being that for any prime decision making, the participant needed to operate independent of conscious control. Hence, training enhances the automatic actions of the participants (E.g., matching of clutch and changing of gear) during driving.

Furthermore, the mean score for the driving goal of the experimental group participants is higher than that of the control group participants. This is because the experimental participants can manage multiple goals (e.g., safety and time saving) while driving. This result is in line with Dogan et al.’s (2011) assertion that drivers’ behaviours are regulated with their goals of which safety has the highest priority.

The factor related to participants’ exposure to task complexity for the experimental group participants has higher mean score than the control group. This revealed that the participant in the experimental group could handle complex tasks such as accelerating, activating a direction indicator, braking, changing gear, checking surrounding for unsafe situations, maintaining lane and steering (Grill et al., 2012). In fact, the ability of the experimental group to handle task complexity enables drivers to attain multiple goals. Further analysis on the mean scores of all the participants in each of the factors with regard to the items that measure them for both the experimental and control groups are presented in Figures 6.11 using bar chart.

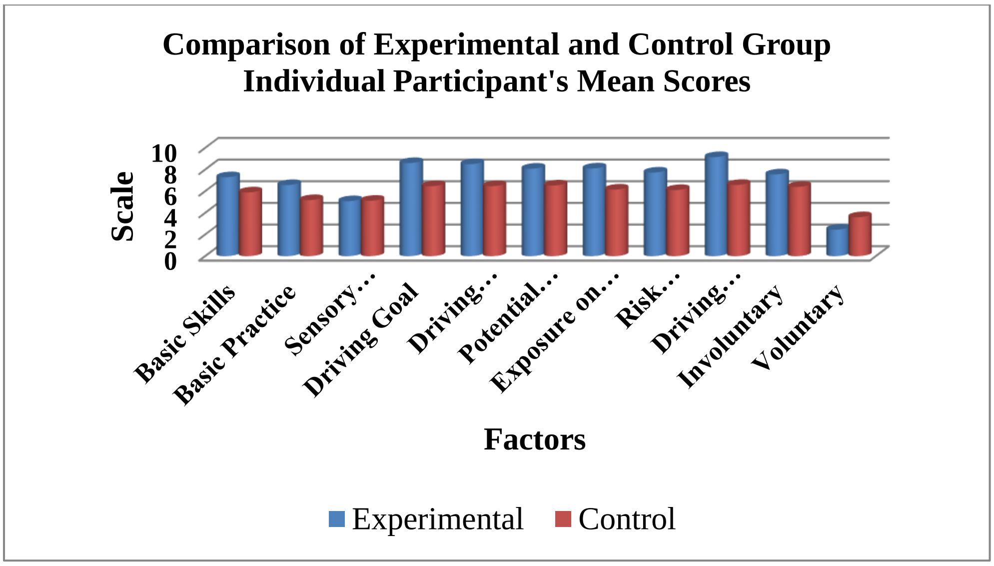


Figure 6.11. Mean scores of factors for the experimental and control group

Table 6.14 presents the independent sample t-test for the comparison between the experimental and control group participants in relation to the following factors: Basic Skills, Basic Practice, Sensory Ability, Driving Goals, Driving Intention, Potential Hazardous Information, Exposure to Task Complexity, Risk Perception, Driving Knowledge, Involuntary automaticity, and Voluntary automaticity.

The results in Table 6.14 indicates that the values of Levene's Test for Equality of Variances are not significant at 5% for all the factors, suggesting that there is no violation of assumption of equal variances. Hence, equal variances assumed are employed. The corresponding values of t-test for almost all the factors are greater than 5.0, indicating that they are significant at the 1% level. This suggests that there is significant difference in each of the factors between the experimental and the control groups.

Furthermore, for basic skills, basic practice, sensory ability, driving goals, driving intention, potential hazardous information, exposure to task complexity, risk perception, driving knowledge, involuntary automaticity factor and voluntary automaticity factor, the mean scores for the experimental group were higher than those for the control group. Therefore, the findings from the analysis of participants' responses based on questionnaire indicated the influence of training on the experimental group participants that made them have better decision-making skill as compared to control group.

Table 6.14

Results of Independent Sample Test

Factors	Group	Participants	Mean	Levene's Test for Equality of Variances		t-test for Equality of Means	
				F	Sig.	t-stat	p-value
Basic Skills	Experimental	10	7.29	0.001	0.982	4.50	0.000
	Control	10	5.89				
Basic Practice	Experimental	10	6.57	1.546	0.23	6.81	0.000
	Control	10	5.18				
Sensory Ability	Experimental	10	5.08	0.626	0.439	5.29	0.000
	Control	10	3.64				
Driving Goals	Experimental	10	8.60	0.58	0.456	7.84	0.000
	Control	10	6.47				
Driving Intention	Experimental	10	8.50	1.618	0.22	7.42	0.000
	Control	10	6.47				
Potential Hazardous Information	Experimental	10	8.08	0.773	0.391	5.10	0.000
	Control	10	6.53				
Exposure on Task Complexity	Experimental	10	8.10	0.463	0.505	7.43	0.000
	Control	10	6.15				
Risk Perception	Experimental	10	7.72	0.69	0.417	7.77	0.000
	Control	10	6.11				
Driving Knowledge	Experimental	10	9.15	0.771	0.391	20.6	0.000
	Control	10	6.58				
Involuntary	Experimental	10	7.55	0.000	1.000	5.37	0.000
	Control	10	6.40				
Voluntary	Experimental	10	2.45	0.000	1.000	-5.37	0.000
	Control	10	3.60				

Note: Independent sample test comparing experimental and control group participants

The findings obtained by this study is consistent with the proposition made earlier in Chapter 3, as indicated by H0, which states that training improves driver's prime decision making.

6.1.3.3 Scenarios of Prime Decision-Making

The two critical decisions in prime decisions making are *panic stop* and *sudden swerve* to another direction (Leland, 2008). This is obtainable in the game simulator used in this experimental study where the participants take these decisions at a point in time when playing the game simulator. These prime decisions are as a result of two obstacles (car and pedestrian). These obstacles make the situation become an emergency. The flowchart diagrams in Figures 6.12 and 6.13 explain the two obstacles. Figure 6.12 illustrates pedestrian as an obstacle, while Figure 6.13 illustrates car swerving as an obstacle.

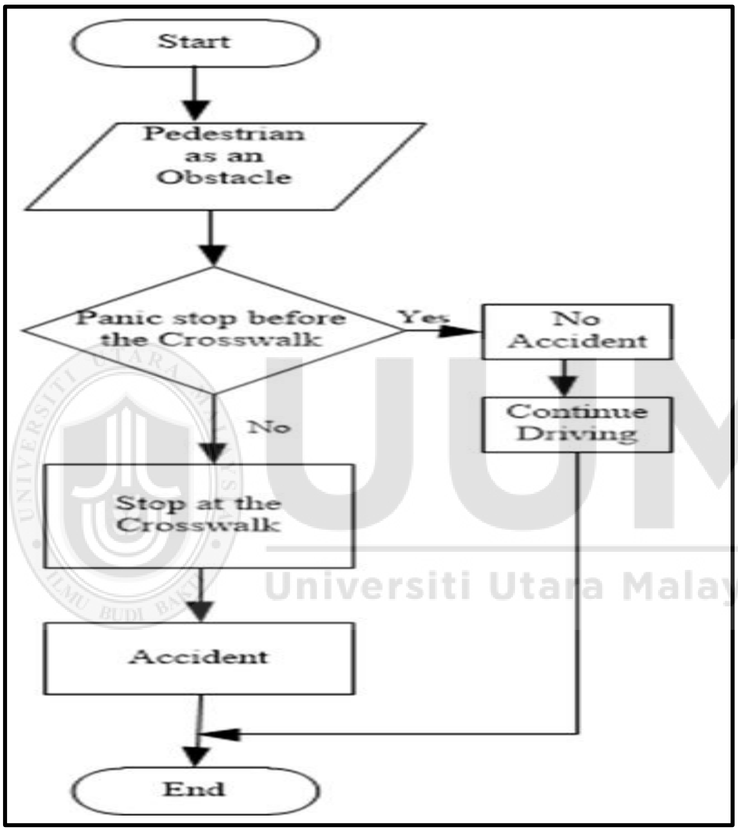


Figure 6.12. Flowchart diagram of pedestrian as an obstacle

Based on the flowchart in Figure 6.12, the pedestrian supposes to cross the road at the crosswalk (pedestrian crossing). However, in an instance whereby the pedestrian crosses the road at a wrong place (at the traffic light junction or the roundabout etc.), this is considered as an obstacle. It causes the participant to make human logical decision to make a panic stop. In this case, the participant supposes to stop before the crosswalk for the pedestrians to cross the road successfully, to avoid an accident. However, if the participant stops at the crosswalk, this leads to accident (pedestrian accident) by hitting the pedestrians crossing the road.

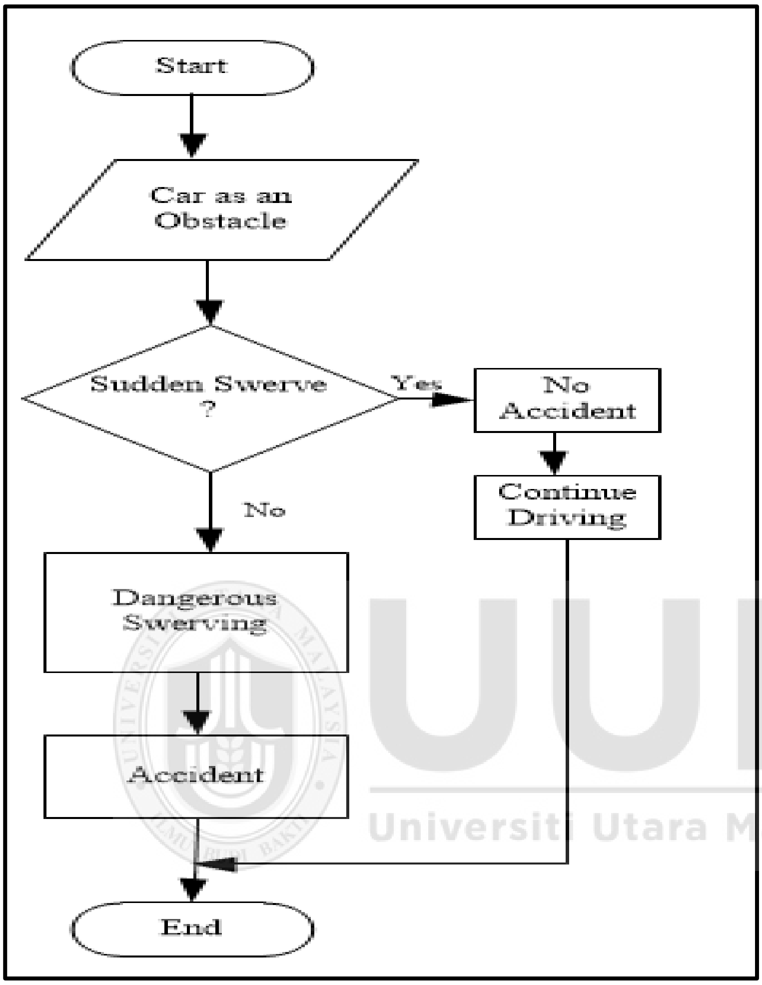


Figure 6.13. Flowchart diagram of car overtaking as an obstacle

In Figure 6.13, the participant swerves for good human logical reasoning to avoid accident. For example, when the participant is driving, another car suddenly crosses over and overtakes the participant car with lesser speed. In that situation, the participant cannot apply brake due to the nature of the traffic where other cars were behind the participant's cars. As such, the participant has to decide to make sudden swerve to another direction. However, if the participant makes sudden swerve to another direction, he/she can continue driving. Otherwise, if dangerous swerving is made, he/she is likely to be involved in an accident by hitting another car, or with another car that pulls out from any direction in the traffic during the swerving process. Based on the aforementioned two logical decisions, the designed model in this study is further explained using computational reasoning approach. This enables the researcher to see how the designed model can reason out. The computational reasoning is viewed from two perspectives. On the one hand, it is the computational reasoning with situation awareness part of the IDM, and on the other hand, it is the computational reasoning with RPD training part of the model.

The conceptual SA part of the IDM external factors is mapped with the game simulator features based on driving conditions. The driving conditions are categorized into three scenarios (A, B, and C). To explain the reasoning process, the results obtained from the game simulator in scenario C are used. This is because all the conditions mapped with the simulator in scenario C were bad/risky driving conditions except the car condition that was good for the three scenarios used in the simulator settings.

As earlier shown in Table 6.10, the participants' records of the experimental and control group in scenario C contain the distances the participants covered while driving the game simulator without committing violations (NV), major violations (NMV) and accident (NA). In this scenaro, the fourth participant from the experimental group has the lowest distance covered while the fifth participant has the highest. From the control group, the first participant and the seventh participant have the lowest (0.39) and highest (2.22) distances covered, respectively. This implies that the lower the distance covered by the participant, the poorer the decision made and the higher the distance covered by the participant, the better the decision made by the participant. For example using scenario C from Table 6.10, the fifth participant from the experimental group make two good human logical decisions based on the participant distance scores, 0.73, 0.72 and 3.01 for no violations (NV), no major violations (NMV) committed and no accident (NA), respectively using the simulator. The two good human logical decisions of the participant are: 1) the participant carefully performed sudden swerve to another direction successfully and continued driving rather than making dangerous swerving that might lead to accident. 2) The participant made a panic stop, and successfully stopped before the crosswalk for the pedestrians to cross the road successfully rather than hitting the pedestrian (i.e., the participant avoided hitting the pedestrian). These logical decisions of the participant are triggered by the factors involved in the conceptual RDT model. From the SA part of the IDM , the decisions of the participant are triggered using backward engineering process. The participant decisions are as a result of the belief activation for safety that is higher than the belief activation for risk. The believe activation for safety is as a result of the belief formation of elements observed from the driving environment such as road, traffic, obstacle and visibility. The belief formation is done based on the elements observed from the driving environment and the expectation of the same elements. The observation of the elements is triggered by the environment and the attention of the driver on these same elements.

In addition, from the RPD training part of the IDM for the experimental group presented in Table 6.12 subsections (6.2.3.2), the same participant five from the experimental group makes good decisions based on the mean scores that measure the model factors using questionnaire. The participant good decisions are facilitated by these factors. For example, experienced automaticity (that is, long-term automaticity) is prompted by acquired (short-term automaticity) automaticity that is triggered by voluntary (1.50) and involuntary (8.50) automaticity. In addition, the involuntary automaticity is triggered by a habitual-direction action that is also a form of unconscious automaticity, while voluntary automaticity is stimulated by a goal-directed action that is a form of conscious automaticity. The habitual-direction action is prompted by driving knowledge (8.50) and priming factor. The goal-directed action is activated by priming and attention of the driver on the elements in the environment. The driver's knowledge is prompted by rehearsed experience and driver's experience while priming is stimulated by driver's experience, driver ability and intention (8.00). The attention of the driver is stimulated by rehearsed experience and risk perception (8.00) while his/her experience is triggered by knowledge (8.50), and rehearsed experience. Risk perception is prompted by driver ability and perception about hazard while his/her ability is stimulated by his/her experience and acquired skills. In addition, rehearsed experience is prompted by driver's ability and practice while practice is triggered by driving knowledge (8.50) and basic practice (6.44). More so, acquired skill is prompted by basic skill (7.13) and sensory ability (5.08) while perception about hazard is stimulated by driving goal (8.00), potential hazardous information (7.50) and perception about task. Perception about task is triggered by exposure to task complexity (7.50) and driver's ability while exposure to task complexity is facilitated by driving knowledge (8.50). In general, based on the integration of the two models and the participant scores, the participant from experimental group performed good logical decisions to swerve suddenly to another direction successfully, and to avoid hitting the pedestrian.

However, concerning the control group under the same scenario C, the first participant from this group make two poor/incorrect and illogical decisions based on the enhanced IDM (called RDT model). The simulator distance scores results are presented in Table 6.10 and the RPD training part of the IDM factors mean scores for the control group are presented in Table 6.13. From Table 6.10, the first participant from control group has distance scores of 0.11, 0.14 and 0.14 for no violations (NV), no major violations (NMV) committed and no accident (NA) in traffic, respectively. From the RPD training part of the ID model using backward engineering reasoning process, the decisions of the participant one (1) from this control group are also triggered by the similar factors as those of experimental group, although with different scores as shown in Table 6.13.

Based on the distance scores gained by the participant, it can be said that, one, the participant made dangerous swerving to another direction thereby causing an accident (i.e. crashed into another car), and two, the participant did not stop before the crosswalk, thereby hitting the pedestrian that was crossing the road (i.e., caused pedestrian accident). The two aforementioned decisions made by the participants are illustrated in Appendix J.

Conclusively, in the SA part of the IDM, training reflects on the decision making of drivers (participants). The training given to the drivers of experimental group influenced him/her to make correct/good decision, particularly in scenario C as compared to the control group participants. Similarly, in the RPD training part of the IDM, training also reflects on the decision making of drivers (participants) in the questionnaire results. The training of the drivers influenced the correct/good decision making of experimental group as compared with the control group participants. Hence, the integration of the two models influences the decision making of drivers (participants).

6.2 City Car Driving Simulator

The City Car Driving Simulator Home Edition (City Car Driving, 2017), which is a car simulator game called 3D instructor, is adapted in this study to validate the proposed model. It is a Russian game developed by Havok.com Inc. The simulator is designed to assist users to feel the car driving in a big city or country under different conditions.

The game simulator uses advanced car physics to achieve a realistic car feeling and a high-quality render engine for graphical realism. Pedestrians, cars, and roads are created to make the players feel they are driving a real car in a real city. Several studies (Craye & Karray, 2015; Craye, Rashwan, Kamel & Karray, 2016; Dicke, Jakus, Tomazic & Sodnik, 2012; Yang, Liang & Chang, 2016; Yang, Liang, Chang & Lin, 2015) have used the City Car Driving Simulator to compare and identify individual driving behaviour. The justification for choosing the City Car Driving Simulator is that it has several strengths or advantages over other shelf simulators such as The Open Racing Car Simulator TORCS (Wymann, Espié, Guionneau, Dimitrakakis, Coulom & Sumner, 2000) and Systems Technonology Inc. interactive driving simulator (STISIM) (Allen, Stein, Aponso, Rosenthal & Hogue, 1990). As a 3D game simulator, it is used to synthesize almost realistic 3-D road scenes with dynamic traffic streams where a virtual driver drives a car in the simulation system. This system embodies the driver behaviour of quality, meeting the criteria for comparing and identifying the driver's driving behaviour; the system modifies car physics so that one can have a very customizable and expandable simulator (Yang, Liang, & Chang, 2016; Yang, Liang, Chang & Lin, 2015).

The City Car Driving simulator must importantly supported the integration of the external factors of the SA components of the ID model that has been used in the experiment to train the experimental group participants. This show that the simulator provides basic driving skills training (City Car Driving, 2017) that serves as advantage to the experimental group participants compared to the control group participants.

The simulator supports the simulation of multiple driving environments, such as different regions of a city centre, a motorway or a highway. It also enables a variety of different driving routes and traffic intensity conditions to assist and form basic driving skills (Dicke, Jakus, Tomazic, & Sodnik, 2012). In addition, it enables driver to be accustomed to car controls by learning how to operate correctly with the wheel and pedals, how to confidently switch to the appropriate gear, and how to properly employ steering techniques (Dicke et al., 2012).

More so, the car simulator makes it possible to train basic physical car driving skills, remember road signs and traffic lane markings, learn how to drive through signalled and unsupervised crossings, drive on several types of road under various outdoor conditions such as weather, light, and traffic conditions (Craye, Rashwan, Kamel & Karray, 2016). Furthermore, the car simulator allows the training of various types of parking, and other manoeuvres. The quality of the graphics along with the wide view displayed offers the driver a realistic driving experience (Craye et al., 2016).

The City Car Driving Simulator is appropriate for simulating driving scenarios and experiences because of the possibility of manipulating all the important factors that influence prime decision-making process in driving by the computational RDT model.

For instance, in the simulator, the environmental factors such as the road, traffic, obstacles and weather/light conditions are adjusted to be in line with the experiment requirement. In addition, the adapted simulator supports many real driving features and conditions that are explained in detailed as shown in a table in Appendix K. And the system requirement to run the application is shown in Appendix L.

6.2.1 Mapping Driving Scenarios with Situation Awareness model Factors and Application Features

The game simulator features are mapped to the external factors of the SA components of the enhanced ID model. There are three driving scenarios set up based on the external factors that are in line with the three simulated scenarios in a simulation environment using MATLAB as in Chapter 5, subsection 5.3. The three driving scenarios set up are good driving conditions (low risk), average driving conditions (moderate risk) and bad driving conditions (high risk). The three different driving scenarios consist of different conditions in driving environment that includes road, traffic, obstacles, car condition and visibility. The mapping of the three driving scenarios with the game driving simulator is shown in Table 6.15.

Table 6.15

Mapping Driving Scenarios with the SA model Factors and Application Features

Scenarios		Factors	Main Application Features	Sub-Application features
Low Risk	Good Driving Conditions	Environment	Area (New City)	▪ New district
		Road	Route Generation	Assignment Type ▪ Free routes ▪ Violation are inadmissible ▪ Minor Violation are admissible ▪ Limitation with points. Parameters ▪ Frequency of assignment (Very rare) ▪ Maximum length (2.5Km) ▪ Minimum length (2Km) ▪ Point limit (10).
		Traffic	Traffic	▪ Vehicular traffic density (0%) ▪ Traffic behaviour (Cautious traffic). ▪ Pedestrian traffic density (0%)
		Obstacle	Emergency situations on the road.	▪ Dangerous change of traffic (Rare). ▪ Emergency braking of the car ahead (Rare). ▪ Dangerous entrance of the vehicle to the oncoming lane (Rare). ▪ Pedestrian crossing the road in a wrong place (Rare). ▪ Appearance of traffic controller at the crossroads (Rare). ▪ Breaking of traffic light (Rare).
		Car	Transport	▪ Standard ▪ Vehicle ▪ Colour ▪ Gear System
		Visibility	Season/Weather/ Time of the day	Summer/Clear/Day

Note: The driving scenarios are mapped to the external factors of the SA components of the IDM model and the application features

Table 6.15 Continued

Scenarios	Factors	Main Application Features	Sub-Application features	Scenarios
Moderate Risk	Average Driving Conditions	Environment	Area (New City)	▪ New district
		Road	Route Generation	Assignment Type ▪ Free routes ▪ Violation are inadmissible ▪ Minor Violation are admissible ▪ Limitation with points Parameters ▪ Frequency of assignment (Very rare) ▪ Maximum length (2.5Km) ▪ Minimum length (2Km) ▪ Point limit (10)
		Traffic	Traffic	▪ Vehicular traffic density (50%) ▪ Traffic behaviour (Usual traffic). ▪ Pedestrian traffic density (50%)
		Obstacle	Emergency situations on the road.	▪ Dangerous change of traffic (Often). ▪ Emergency braking of the car ahead (Often). ▪ Dangerous entrance of the vehicle to the oncoming lane (Often). ▪ Pedestrian crossing the road in a wrong place (Often). ▪ Appearance of traffic controller at the crossroads (Often). ▪ Breaking of traffic light (Often).
		Car	Transport	▪ Standard ▪ Vehicle ▪ Colour ▪ Gear System
		Visibility	Season/Weather/ Time of the day	Summer/Clear/Day

Table 6.15 Continued

Scenarios	Factors	Main Application Features	Sub-Application features	Scenarios
High Risk	Bad Driving Conditions	Environment	Area (New City)	▪ New district
		Road	Route Generation	Assignment Type ▪ Free routes ▪ Violation are inadmissible ▪ Minor Violation are admissible ▪ Limitation with points Parameters ▪ Frequency of assignment (Very Often) ▪ Maximum length (2.5Km) ▪ Minimum length (2Km) ▪ Point limit (10)
		Traffic	Traffic	▪ Vehicular traffic density (100%) ▪ Traffic behaviour (Aggressive Traffic). ▪ Pedestrian traffic density (100%)
		Obstacle	Emergency situations on the road.	▪ Dangerous change of traffic (Very Often). ▪ Emergency braking of the car ahead Very Often). ▪ Dangerous entrance of the vehicle to the oncoming lane (Very Often). ▪ Pedestrian crossing the road in a wrong place (Very Often). ▪ Appearance of traffic controller at the crossroads (Very Often). ▪ Breaking of traffic light (Very Often).
		Car	Transport	▪ Standard ▪ Vehicle ▪ Colour ▪ Gear System
		Visibility	Season/Weather/ Time of the day	Autumn/Rainy/Night

6.2.2 Simulator Stages

The City Car Driving Simulator Home Edition has two main stages: The career driving stage (where drivers are trained) and free driving stage (where drivers drive under various conditions without training).

6.2.2.1 The Career Driving stage

In the career driving stage, the drivers are assumed to be receiving training lessons in a virtual driving school. In the simulator, there are tasks to be achieved, such as car starting and shifting of gear (training), slalom (zigzag), *U*-turn, garage, turns, hills, track test and city driving test. However, for this study, city driving test is chosen and used to train the experimental group participants. It is one of the training tasks used in city car driving simulator. A driver is trained in the virtual city. The virtual instructor gives the trainee the driving directions to follow; when the trainee completes the task and parks the car at the finished point without violating the driving rules and regulations and without exceeding the permissible violation score, then, the driver is said to be successful. This gives the trainee (driver) the achievement “city driving test”. Moreover, for the trainee to receive the achievement “fastest of all” he should complete the task without violations and in less than 24 minutes.

6.2.2.2 The Free Driving stage

In the free driving stage, the driver drives in a virtual city based on the scenario set up to achieve the study objective. The driving scenarios are set up based on the model external factors particularly the awareness model external factors. The free driving is used for both experimental and control group in this study.

6.3 Summary of the Chapter

This chapter gave detail explanation on the validation of an enhanced computational IDM (Computational-RDT) using human experiment. This was accomplished by using an adapted application (game driving simulator). The game driving simulator features were mapped with the external factors of the awareness component of the IDM to evaluate the Computational-RDT model validity. In addition, a questionnaire was designed based on the external and temporal factors of the RPD training component of the IDM model to validate the Computational-RDT model.

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CHAPTER SEVEN
CONCLUSION

7.0 Introduction

This chapter presents a general overview of the study's focus and objectives that have been achieved. It also presents the contributions of the study and provides suggestions on area of focus for future studies's investigation. In particular, Section 7.1 of this chapter summarizes the conclusions drawn from the previous chapters in line with the stated objectives of this study while Section 7.2 presents the implications of the study's results. In Section 7.3 the limitations of the study are discussed while Section 7.4 provides, as a suggestion, the future work direction.

7.1 Revisiting Research Objectives

This study presents an enhanced computational IDM (Computational-RDT) in driving domain that assists driver in making prime decision. There are four objectives of this research as presented in Chapter 1, namely; 1) to identify the training factors relevant for Prime Decision-Making in driving domain, 2) to enhance the IDM by including relevant training factors to have a comprehensive conceptual model, 3) to computationalise the enhanced ID model in order to have a model with a reasoning ability to backtrack, and 4) to evaluate the enhanced computational IDM by verification and validation analyses. These objectives have been achieved and the details were explained in Chapter Four, Five and Six.

Research Objective #1:

The first research objective is to identify training factors relevant for Prime Decision-Making in driving domain. Therefore, this study presented a total of thirty-one (31) factors, seven (7) factors from the awareness component and twenty-four (24) from the RPD training component of the RDT model. These factors were summarized in Tables 4.1, 4.2 and 4.3 in Chapter 4 Section 4.1. The factors were obtained based on related theories of SA and other related literatures as explained in Chapter Four. In addition, previous related studies were reviewed to guide in obtaining these appropriate factors. This becomes imperative due to challenging and complex nature of the prime decision making within the driving domain. Chapter 4 (Section 4.1) described the detailed pertinent to this objective.

Research Objective #2:

The second objective is to enhance the Integrated Decision-making Model (IDM) by including relevant training factors to have a comprehensive conceptual model. To accomplish this objective, the obtained training factors relevant for prime decision making from the SA model and other related literatures were used to enhance the RPD training component of the IDM where the relationships of the factors based on theories of SA, NDM and other theories were used to form a conceptual RDT model. The enhancement of this model was explained in detailed in Chapter Four (Section 4.2).

Research Objective #3:

The third objective is to computationalise the enhanced IDM in order to have a model with a reasoning ability to backtrack. To realise this objective, the obtained factors related to their corresponding theories (derived from a conceptual model) were expressed in formal specifications, which were later translated into a computational model. The informal specification follows the concepts of factors interactions as depicted in related corresponding theories and previous empirical studies, while the formal specification expression is based on first order differential equations. In particular, the study employed thirty-one (31) factors in the design of the enhanced computational model as presented in Chapter Four (Section 4.3).

Research Objective #4:

The fourth objective is to evaluate the enhanced computational IDM by verification and validation analyses. The verification analysis was achieved by using simulation, mathematical analysis and automated analysis methods. For mathematical analysis, four selected cases from equilibrium points were used to prove the convergence (stability) of the enhanced model as in Section 5.2.1. The advantage of implementing this approach is to show how the model stabilizes under certain conditions despite the presence of a small disturbance in the model. Six different empirical cases showing the effects of driving conditions were demonstrated in line with the literature, where four (4) cases were based on awareness component of the RDT model and two (2) cases were from the RPD training component of the RDT model. Each of these cases was formalized and analysed using Temporal Trace Language (TTL) as a basis for performing automated analysis. This evaluation confirmed the logical verification of the Computational-RDT model. These stages were achieved in Chapter Five (Sections 5.1, 5.2 & 5.3).

The second evaluation stage (validation) was achieved by external validation using human experiment that ensured the logical correctness of the RDT model by using twenty participants as presented in Chapter Six (Sections 6.1 & 6.2).

7.2 Implications of the Study

The implication of this study can be understood from three points of view, namely the theoretical, practical and domain perspectives. As it has been previously discussed, IDM has not been computationalised. Hence, the present study closes this gap by computationalising the enhanced ID (RDT) model. The Computational-RDT model that is simulated for its temporal dynamics is one of the theoretical contributions of the study. The Computational-RDT model is a complete theory on its own and can also serve as a tool for future theories in the driving domain. The Computational-RDT model helps to explain better in a logical manner the fundamental theories utilised to enhance the conceptual model (domain model) as stated in Sun (2008). The simulated results of the Computational-RDT model give support to known theories and concepts in naturalistic decision making literatures that will be of great interest to the researchers in the driving domain.

From the practical perspective (application wise), the Computational-RDT model realised in this study can serve as a guideline for software developers on the development of driving assistance systems for prime decision-making process. Also, the Computational-RDT model when combined with the support components can serve as the intelligent artefacts for the driver's assistance systems. Moreover, the Computational-RDT model realised in this study has reasoning ability; hence, it can backtrack why certain decision had been made. The implication is that using the

Computational-RDT model realised in this study can enable software developers to design a good system (artefact) that can enhance and provide robust driver's assistance systems that has good reasoning ability to backtrack, and alert the driver on why certain prime decisions had been taken. Hence, this serves as an important contribution of this study in the field of computing, otherwise known as computer science domain.

In relation to problem domain perspective, the RDT model affords the training factors missing in RPD part of the IDM. This is a known problem in previous research of RPD. Hence, future research on RPD that uses the RDT model obtained in this study will have an advantage of a comprehensive model integrated with more training factors that are relevant for prime decision-making.

7.3 Limitations of the Study

The study covers only the relevant factors necessary for prime decision-making process. Since the study was conducted in the driving domain, only a good car condition was considered in the configuration of the game simulator integration. Also, the use of off-the-shelf software (simulator) is one of the limitations of this study. Hence, the configuration of the model features in the simulator is constrained only to the available features to validate the model. However, within the simulated scenarios, both good and faulty cars conditions were explained and tested.

This study employed a method of varying parameters to observe the behaviour of the systems for exploring the predictions in the simulation environment in order to see changes that occured as shown in the simulation scenarios demonstrated in Chapter Five. Thus, there is a need to employ other techniques such as response analysis and response surface modelling for a precise and refined result for a generic model. The present study does not have support model that can be integrated with the RDT model. Concisely, the RDT model achieved in this study is generic and tested in a driving domain.

7.4 Suggestions for Future Work

In this section, the study make some suggestions for the potential future work based on the limitations of the study. In particular, this study suggests that a support model should be developed and integrated with the RDT model. This will endow the model with the ability to provide necessary assistance to user to take the best prime decision at the right time. The combination of the enhanced and support models can serve as a basic intelligent engine or as a tool to be used in cognitive/intelligent artefacts (driving assistance systems) that can render support to the driver when the driver fails to make prime decision in the demanding situations.

A proprietary software application (driving simulator) could be developed rather than off-the-shelf software that restricts the personalized mapping of all the factors. This allows seamless factors integration and adaptation to future enhancement of the model. Other evaluation methods (e.g., evaluating models against each other) should be explored for a better understanding of systems with dynamic variables and in facilitating the prediction regarding the behaviour of the systems. Furthermore, instead of theory driven approach, data can be collected to build a model (data driven approach) where genetic algorithm and other techniques can be used to optimise the selected factors to be used in building the model.

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APPENDICES

Appendix A

Sample Photos with the Expert

Appendix B

Experts' Evaluation Questionnaire in English and Malay

INSTRUCTION

The questionnaire is divided into two parts: Part **A** deals with the demographic questions of the Experts and part **B** consists of Items on Driver Behavior (DB) based on the training model factors.

SECTION A: Demographic characteristics of Experts

Please tick ☐✓ at the appropriate box.

1. Age Group

   <20 ☐ 20-29 ☐ 30-39 ☐ 40-49 ☐ 50-59 ☐ ≥60 ☐

2. Gender

   Male ☐ Female ☐

3. Educational Level

   Undergraduate ☐ Master ☐ PhD ☐ Others ☐

4. Driving experience

   <2 year ☐ 2-5 years ☐ 6-10 years ☐ >10 years ☐

5. Do you have a valid driving licence? Yes ☐ No ☐
6. Years of Service:____
7. Officer's Rank:____

SECTION B: Items on Driver Behavior (DB) based on the training model

Kindly indicate the importance of each of these items provided in training drivers. The rating scale is from **1-3**, with **1** indicating **Not Important, 2** indicating **Important** and **3** indicating **Very Important**. Please tick √ as appropriate**.**

S/N	Basic Skills Items	EXPERT VALIDATION			
		SCALE			REMARKS
		1	2	3	
1.	Maintaining lane positioning				
2.	Turning				
3.	Speed control				
4.	Braking				
5.	Use of turn signals				
6.	Use of mirrors				
7.	Controlling the steering wheel				
8.	Gear selection in operating manual /automatic car				

S/N	Basic Practice Items	EXPERT VALIDATION			
		SCALE			REMARKS
		1	2	3	
9.	Holding the steering wheel while driving?				
10.	Looking into the side mirrors while overtaking another car?				
11.	Driving between the lines?				
12.	Using the signal lights while turning?				
13.	Driving a car in reverse?				
14.	Turning in prohibited areas (e.g, no U-Turn)?				
15.	Stopping in prohibited areas (e.g. Roundabout, four-way intersection or crossroad)?				
16.	The use of seat belt while driving?				
17.	Driving within the speed limit?				

S/N	Sensory Ability Items	EXPERT VALIDATION			
		SCALE			REMARKS
		1	2	3	
18.	Seeing dark coloured cars when driving at night?				
19.	Seeing pedestrians on the road side when driving at night?				
20.	Seeing pedestrians on the road side when driving in a day time?				
21.	Reading street signs when driving at night?				
22.	Reading street signs when driving in a day time?				
23.	Seeing the road due to oncoming headlights when driving at night?				
24.	Seeing the road due to oncoming headlights when driving in a day time?				
25.	Seeing the road in rain when driving at night?				
26.	Seeing the road in rain when driving in a day time?				
	How often do you distracted by:				
27.	Eating/drinking while driving?				
28.	Read roadside advertisements?				
29.	Daydream?				

S/N	Driver's Goal Items	EXPERT VALIDATION			
		SCALE			REMARKS
		1	2	3	
30.	Safety goal (i.e. Making sure of your safety and safety of others).				
31.	Time goal (i.e. Making sure you reach your destination on time).				
32.	Avoiding traffic violation.				

S/N	Intention Items	EXPERT VALIDATION			
		SCALE			REMARKS
		1	2	3	
33.	Safety goal.				
34.	Time goal.				
35.	Avoiding traffic violation.				

S/N	Potential Hazardous Information Items	EXPERT VALIDATION			
		SCALE			REMARKS
		1	2	3	
36.	Car stopping at the Pedestrian Crossing?				
37.	Curves (or bend) on the road?				
38.	Other cars driving in front of you?				
39.	Pedestrian crossing the road in a wrong place?				

S/N	Exposure on Task Complexity Items	EXPERT VALIDATION			
		SCALE			REMARKS
		1	2	3	
40.	Accelerating when approaching a flickering green light?				
41.	Activating a direction indicator when negotiating a bend?				
42.	Braking by slowing down before negotiating roundabout				
43.	Emergency braking when another car pull into driver's path				
44.	Changing gear when reducing the car speed.				
45.	Check surrounding for unsafe situations.				
46.	Maintain lane in traffic.				
47.	Controlling the steering wheel.				

S/N	Risk Perception Items	EXPERT VALIDATION			
		SCALE			REMARKS
		1	2	3	
48.	Driving at night?				
49.	Bypassing slow car through the left hand side instead of the right hand side?				
50.	Pulling over the road way (getting on and off lower road shoulder)?				
51.	Driving in a city at a speed above the speed limit?				
52.	Bypassing when you are hidden by a truck and have no good vision of the car coming in front of you?				
53.	Losing control over the car while driving on a wet and slippery road?				
54.	Losing control over the car while driving on a dry road?				
55.	Backward driving (reverse) when there are blind sights?				
56.	Backward driving (reverse) when there are no blind sights?				
57.	Sudden braking?				
58.	Challenged-driving aimed at testing your driving abilities?				

S/N	Driving Knowledge	EXPERT VALIDATION			
		SCALE			REMARKS
		1	2	3	
59.	Road signs?				
60.	Use of maximum speed limits driving in a city?				
61.	Traffic rules and regulations?				
62.	Road markings?				

S/N	Involuntary/Voluntary Items	EXPERT VALIDATION			
		SCALE			REMARKS
		1	2	3	
63.	Sudden swerve to another direction without thinking (e.g. when another car swerved in front of my car while driving.)?				
64.	Begin panic stop before I realize I’m doing it (e.g. when pedestrian crossing the road in a wrong place in front of my car while driving.)?				
65.	Do change lane without meaning to do it?				
66.	Find it hard to stop myself from doing dangerous overtaking?				

Tinjauan Soal Selidik

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06010
DARUL AMAN, KEDAH

Peserta yang saya hormati,

Saya pelajar siswazah yang sedang mengendalikan kajian berhubung tingkah laku pemandu yang menggunakan simulator permainan pemanduan. Kajian ini menguji model faktor keberkesanan untuk melihat sekiranya senario simulasi yang dihasilkan berasaskan model faktor berpadanan dengan tingkah laku pemandu dalam domain situasi sebenar. Kajian juga bermatlamat untuk melihat sama ada latihan memandu memberikan kesan terhadap keupayaan pemandu dalam membuat keputusan penting dengan pantas.

Maklum balas yang anda berikan tidak akan digunakan untuk tujuan lain, melainkan untuk tujuan akademik.

Kami amat menghargai maklum balas yang anda berikan. Sekiranya anda memerlukan maklumat tambahan tentang kajian ini, anda boleh menghubung individu berikut:

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ARAHAN

Soal selidik ini terbahagi kepada dua bahagian. Bahagian **A** merangkumi aspek demografi dan bahagian **B** mengandungi item berkenaan Tingkah laku Pemandu (DB) berdasarkan faktor model latihan.

BAHAGIAN A: Ciri-ciri demografi Pakar

Sila tanda ✓ at pada kotak yang bersesuaian.

8. Kelompok Umur

   <20 ☐ tahun 20-29 ☐ tahun 30-39 ☐ tahun 40-49 ☐ tahun 50-59 ☐ tahun

   ≥60 ☐ tahun

9. Jantina

   Lelaki ☐ Perempuan ☐

10. Tahap Pendidikan

    Ijazah Sarjana muda ☐ Ijazah Sarjana ☐ Ijazah PhD ☐ Lain-lain ☐

11. Pengalaman memandu

    <2 tahun ☐ 2-5 tahun ☐ 6-10 tahun ☐ >10 tahun ☐

12. Adakah anda memiliki lesen memandu yang sah? Ya ☐ Tidak ☐
13. Jumlah tahun dalam Perkhidmatan:

    ____

14. Jawatan Pegawai:

    ____

BAHAGIAN B: Item berhubung Tingkah laku Pemandu (DB) berdasarkan model latihan

Sila nyatakan kepentingan setiap item yang diberikan semasa anda melatih pemandu. Skala penilaian adalah antara **1-3**, dengan **1** memperlihatkan **Tidak Penting, 2** menunjukkan **Penting,** manakala **3** menunjukkan **Sangat Penting**. Sila tanda √ pada ruang yang bersesuaian.

N/S	Item Berhubung Kemahiran Asas	PENGESAHAN PAKAR			
		SKALA			CATATAN
		1	2	3	
1.	Mengekalkan kedudukan laluan				
2.	Pusingan				
3.	Kawalan kelajuan				
4.	Membrek				
5.	Menggunakan isyarat pusingan				
6.	Menggunakan cermin				
7.	Mengawal stereng				
8.	Menentukan gear semasa mengendalikan kereta manual /kereta automatik				

N/S	Item Berhubung Kemahiran Asas	PENGESAHAN PAKAR			
		SKALA			CATATAN
		1	2	3	
9.	Memegang stereng ketika memandu?				
10.	Melihat cermin sisi ketika memotong kenderaan lain?				
11.	Memandu antara garisan?				
12.	Menggunakan lampu isyarat ketika membuat pusingan?				
13.	Mengundurkan kenderaan?				
14.	Membuat pusingan di kawasan terlarang (cth. Dilarang berpusing balik)?				
15.	Berhenti di kawasan terlarang (cth. Bulatan, persimpangan empat laluan atau lintasan)?				
16.	Menggunakan tali pinggang keledar ketika memandu?				
17.	Memandu di bawah had kelajuan?				

N/S	Item Berhubung Keupayaan Deria	PENGESAHAN PAKAR			
		SKALA			REMARKS
		1	2	3	
18.	Melihat kenderaan berwarna gelap ketika memandu pada waktu malam?				
19.	Melihat pejalan kaki di tepi jalan ketika memandu pada waktu malam?				
20.	Melihat pejalan kaki di tepi jalan ketika memandu pada waktu siang?				
21.	Membaca papan tanda ketika memandu pada waktu malam?				
22.	Membaca papan tanda ketika memandu pada waktu siang?				
23.	Melihat jalan apabila disuluh lampu kenderaan dari arah hadapan ketika memandu pada waktu malam?				
24.	Melihat jalan apabila disuluh lampu kenderaan dari arah hadapan ketika memandu pada waktu siang?				
25.	Melihat jalan ketika hujan apabila memandu pada waktu malam?				
26.	Melihat jalan ketika hujan apabila memandu pada waktu siang?				
	Berapa kerapkah anda dialih perhatian oleh perbuatan:				
27.	Makan/minum ketika memandu?				
28.	Membaca iklan-iklan di tepi jalan?				
29.	Berkhayal?				

N/S	Item Berhubung Matlamat Pemandu	PENGESAHAN PAKAR			
		SKALA			CATATAN
		1	2	3	
30.	Matlamat keselamatan (cth. Memastikan keselamatan anda dan keselamatan orang lain).				
31.	Matlamat masa (cth. Memastikan anda tiba ke destinasi anda tepat pada waktunya).				
32.	Mengelak daripada melanggar peraturan lalu lintas.				

N/S	Item Berhubung Hasrat	PENGESAHAN PAKAR			
		SKALA			CATATAN
		1	2	3	
33.	Matlamat keselamatan.				
34.	Matlamat masa.				
35.	Mengelak daripada melanggar peraturan lalu lintas.				

N/S	Item Berhubung Maklumat Potensi Berbahaya	PENGESAHAN PAKAR			
		SKALA			CATATAN
		1	2	3	
36.	Kenderaan berhenti di Lintasan Pejalan kaki?				
37.	Lengkung (atau liku) di atas jalan?				
38.	Kenderaan lain yang dipandu di hadapan anda?				
39.	Pejalan kaki melintas jalan di tempat yang salah?				

N/S	Item Berhubung Pendedahan Terhadap Kesukaran Tugas	PENGESAHAN PAKAR			
		SKALA			CATATAN
		1	2	3	
40.	Memecut ketika mendekati lampu hijau yang berkelip-kelip?				
41.	Menyalakan isyarat laluan apabila berhadapan dengan selekoh jalan?				
42.	Membrek secara perlahan sebelum memasuki bulatan				
43.	Membrek secara mengejut apabila kenderaan lain memasuki laluan anda				
44.	Mengubah gear apabila ingin memperlahankan kenderaan.				
45.	Memeriksa sekeliling apabila berada dalam keadaan yang tidak selamat.				
46.	Mengekalkan laluan di jalan raya.				
47.	Mengawal stereng.				

N/S	Item Berhubung Persepsi Risiko	PENGESAHAN PAKAR			
		SKALA			CATATAN
		1	2	3	
48.	Memintas kenderaan yang perlahan di sebelah kiri dan bukannya di sebelah kanan?				
49.	Berhenti di bahu jalan (menuruni dan menaiki bahu jalan yang rendah)?				
50.	Memandu dalam bandar melepasi had kelajuan?				
51.	Memintas dari belakang trak yang menghalang pandangan anda dengan tidak melihat kenderaan yang datang dari arah hadapan anda?				
52.	Hilang kawalan ke atas kenderaan ketika memandu di atas jalan yang basah dan licin?				
53.	Hilang kawalan ke atas kenderaan ketika memandu di atas				

	jalan yang kering?				
54.	Mengundurkan kenderaan apabila terdapat penglihatan tak peka?				
55.	Mengundurkan kenderaan apabila tiada penglihatan tak peka?				
56.	Membrek secara mengejut?				
57.	Cabaran memandu bertujuan menguji kemampuan memandu anda?				
58.	Memintas kenderaan yang perlahan di sebelah kiri dan bukannya di sebelah kanan?				

N/S	**Pengetahuan Pemanduan**	**PENGESAHAN PAKAR**			
		SKALA			**CATATAN**
		1	**2**	**3**	
59.	Papan tanda?				
60.	Memandu melepasi had laju dalam bandar?				
61.	Peraturan dan kawalan lalu lintas?				
62.	Tanda jalan?				

N/S	**Item Berhubung Tindakan Secara Tidak Sedar/ Tindakan Secara Sedar**	**PENGESAHAN PAKAR**			
		SKALA			**CATATAN**
		1	**2**	**3**	
63.	Membelok secara mendadak ke arah lain tanpa berfikir (cth. Apabila kenderaan lain membelok di hadapan anda ketika memandu.)?				
64.	Panik sebelum menyedari anda melakukannya (cth. Apabila pejalan kaki melintas jalan di tempat yang salah di hadapan kenderaan anda ketika anda sedang memandu.)?				
65.	Mengubah laluan tanpa berniat untuk berbuat demikian?				
66.	Sukar mengawal diri daripada memintas kenderaan lain secara berbahaya?				

Komen Umum:

____

____

____

Nama Pengawai Tandatangan Tarikh

Appendix C

Hybrid Model Matlab Simulation Codes

```
clc
    %Intializing all parameters to normalise the equations
    maxLimY = 1;
    minLimX = 0;
    numStep = 500;
    X = 0;
    Bp=zeros(1,numStep);% Basic Practice
    Bpbasic=zeros(1,numStep);% Basic Practice Basic
    Bs=zeros(1,numStep);% basic Skills
    Sa=zeros(1,numStep);% Sensory Ability
    Dg=zeros(1,numStep);% Driver's Goal
    Hi=zeros(1,numStep);% Potential Hazardous Information
    Tc=zeros(1,numStep);% Exposure on Task Complexity
    Tcbasic=zeros(1,numStep);% Exposure on Task Complexity Basic
    Pc=zeros(1,numStep);% Practice
    Re=zeros(1,numStep);% Rehearsed Experience
    De=zeros(1,numStep);% Driver's Experience
    As=zeros(1,numStep);% Acquired Skills
    Da=zeros(1,numStep);% Driving ability
    Pg=zeros(1,numStep);% Priming
    Hp=zeros(1,numStep);% Perception about Hazard
    Rp=zeros(1,numStep);% Perception about Risk
    An=zeros(1,numStep);% Attention
    Hd=zeros(1,numStep);% Habitual-Directed Action
    Gd=zeros(1,numStep);% Goal-Directed Action
    Vy=zeros(1,numStep);% Voluntary
    Iv=zeros(1,numStep);% Involuntary
    Dk=zeros(1,numStep);% Driving Knowledge
    Tp=zeros(1,numStep);% Task Perception
    In=zeros(1,numStep);% Intention
    Onr=zeros(1,numStep);% Observation for Road
    Onf=zeros(1,numStep);% Observation for Traffic
    Onb=zeros(1,numStep);% Observation for Obstacles
    Onc=zeros(1,numStep);% Observation for Car Condition
    Onv=zeros(1,numStep);% Observation for Visibility
    Bfr=zeros(1,numStep);% Belief Formation for Road
    Bff=zeros(1,numStep);% Belief Formation for Traffic
    Bfb=zeros(1,numStep);% Belief Formation for Obstacles
    Bfc=zeros(1,numStep);% Belief Formation for Car Condition
    Bfv=zeros(1,numStep);% Belief Formation for Visibility
    Bas=zeros(1,numStep);% Belief Activation for Safe
    Bar=zeros(1,numStep);% Belief Activation for Risky
    Ea=zeros(1,numStep);% Experienced Automaticity
    Dc=zeros(1,numStep);% Decision
    Aa=zeros(1,numStep);% Acquired Automaticity
    Anr=zeros(1,numStep);% Attention for Road
    Anf=zeros(1,numStep);% Attention for Traffic
    Anb=zeros(1,numStep);% Attention for Obstacles
    Anc=zeros(1,numStep);% Attention for Car Condition
    Anv=zeros(1,numStep);% Attention for Visibility
    Pa=zeros(1,numStep);% Performance of Action
```

```
AlphaRe=0.8;
AlphaPm=0.8;
AlphaVy=0.8;
AlphaIn=0.8;
AlphaOnr=zeros(1,numStep);
AlphaOnf=zeros(1,numStep);
AlphaOnb=zeros(1,numStep);
AlphaOnc=zeros(1,numStep);
AlphaOnv=zeros(1,numStep);
GammaDc=zeros(1,numStep);
Beta=1;
BetaAs=0.8;
BetaIv=0.8;
BetaVy=0.8;
BetaEa=0.8;
BetaBp=0.8;
BetaBs=0.8;
BetaTc=0.8;
BetaPa=0.8;
GammaRe=0.8;
GammaDk=0.8;
GammaRp=0.8;
PhiRe=0.8;
XiAn=0.8;
XiPg=0.8;
OmegaPc=0.8;
Delta_t=0.3;
EtaTp=0.8;
LambdaDe=0.01;
LambdaDk=0.01;
LambdaRp=0.01;
lambdaDc=0.001;
wAs1=0.5; %Weight of Acquired Skills one
wAs2=0.5; %Weight of Acquired Skills two
wDa1=0.5; %Weight of Driving ability one
wDa2=0.5; %Weight of Driving ability two
wHd1=0.5; %Weight of Habitual-Directed Action one
wHd2=0.5; %Weight of Habitual-Directed Action two
wGd1=0.5; %Weight of Goal-Directed Action one
wGd2=0.5; %Weight of Goal-Directed Action two
wHp1=0.5; %Weight of Hazard Perception one
wHp2=0.5; %Weight of Hazard Perception two
wRp1=0.5; %Weight of Risk Perception one
wRp2=0.5; %Weight of Risk Perception two
wAa1=0.5; %Weight of Acquired Automaticity one
wAa2=0.5; %Weight of Acquired Automaticity two
wDk1=0.5; %Weight of Driving Knowledge one
wDk2=0.5; %Weight of Driving Knowledge two
wBasr=1; %Weight of the Road with respect to Belief Activation
for Safe
wBasf=1; %Weight of the Traffic with respect to Belief
Activation for Safe
wBasb=0.5;%Weight of the Obstacles with respect to Belief
Activation for Safe
wBasc=1; %Weight of the Car Condition with respect to Belief
Activation for Safe
```

```
     wBasv=1; %Weight of the Visibility with respect to Belief
Activation for Safe
     wBarr=1; %Weight of the Road with respect to Belief Activation
for Risky
     wBarb=5; %Weight of the Obstacles with respect to Belief
Activation for Risky
     wBarc=1; %Weight of the Car Condition with respect to Belief
Activation for Risky
     wBarf=1; %Weight of the Traffic with respect to Belief
Activation for Risky
     wBarv=1; %Weight of the Visibility with respect to Belief
Activation for Risky
     Epr=1;% Expectations for Road
     Epf=1;% Expections for Traffic
     Epb=1;% Expections for Obstacles
     Epc=1;% Expections for Car Condition
     Epv=1;% Expections for Visibility
     decision_threshold=0.5;
     z=numStep/4;
  % initializing external factors

  % Scenario 1 = "1"
  % Scenario 2 = "2"
  % Scenario 3 = "3"

  Scenario = 1;
 for t=1:numStep
   switch (Scenario)
    case 1
          % Initializing training inputs
     if (t<z)
         Bpbasic(t)=1;
         Bs(t)=1;
         Sa(t)=1;
         Dg(t)=0;
         Hi(t)=1;
         Tcbasic(t)=1;
         In(t)=1;
     elseif (t<2*z)
         Bpbasic(t)=1;
         Bs(t)=1;
         Sa(t)=1;
         Dg(t)=1;
         Hi(t)=0;
         Tcbasic(t)=1;
         In(t)=1;
     else
         Bpbasic(t)=1;
         Bs(t)=1;
         Sa(t)=1;
         Dg(t)=1;
         Hi(t)=1;
         Tcbasic(t)=1;
         In(t)=1;
     end  % end if of case 1
```

```
    case 2
     if (t<z)
         Bpbasic(t)=1;
         Bs(t)=1;
         Sa(t)=1;
         Dg(t)=0;
         Hi(t)=0;
         Tcbasic(t)=1;
         In(t)=1;
     else
         Bpbasic(t)=1;
         Bs(t)=1;
         Sa(t)=1;
         Dg(t)=0;
         Hi(t)=1;
         Tcbasic(t)=1;
         In(t)=0;
     end  %end if of case 2
    case 3
     if (t<z)
         Bpbasic(t)=1;
         Bs(t)=1;
         Sa(t)=1;
         Dg(t)=0;
         Hi(t)=1;
         Tcbasic(t)=0;
         In(t)=1;
     end % end if of case 3
   end   %end switch
 end  %end for

% Initializing temporal Factors
 Dk(1)=0.1;
 Rp(1)=0.1;
 Iv(1)=0.1;
 Vy(1)=0.1;
 Ea(1)=0.1;

 % Initializing Awareness inputs
 for t=numStop+1:numStep
    switch (Scenario)
    case 1
          % Initializing training inputs
        AlphaOnr(t)=1;
        AlphaOnf(t)=1;
        AlphaOnb(t)=0;
        AlphaOnc(t)=1;
        AlphaOnv(t)=1;
     case 2
     if (t<z*3)
        AlphaOnr(t)=0;
        AlphaOnf(t)=1;
        AlphaOnb(t)=0;
        AlphaOnc(t)=1;
        AlphaOnv(t)=1;
```

```
      else
         AlphaOnr(t)=1;
         AlphaOnf(t)=0;
         AlphaOnb(t)=0;
         AlphaOnc(t)=1;
         AlphaOnv(t)=1;
      end % endif of case 2
    case 3
      if (t<z*2)
         AlphaOnr(t)=0;
         AlphaOnf(t)=0;
         AlphaOnb(t)=0;
         AlphaOnc(t)=1;
         AlphaOnv(t)=1;
      elseif (t<z*3)
         AlphaOnr(t)=1;
         AlphaOnf(t)=1;
         AlphaOnb(t)=1;
         AlphaOnc(t)=1;
         AlphaOnv(t)=1;
      else
         AlphaOnr(t)=1;
         AlphaOnf(t)=1;
         AlphaOnb(t)=0;
         AlphaOnc(t)=0;
         AlphaOnv(t)=1;
      end % end if of case 3
    end   %end switch

  end % end for

  % Initializing temporal Factors
Dc(numStop+1)=0.1;

  % initialize Internal Factors at time, t=376

      t=numStop+1;
      Onr(t)=AlphaOnr(t) * constAn;
      Onf(t)=AlphaOnf(t) * constAn;
      Onb(t)=AlphaOnb(t) * constAn;
      Onc(t)=AlphaOnc(t) * constAn;
      Onv(t)=AlphaOnv(t) * constAn;
      Bfr(t)=Onr(t) * Epr;
      Bff(t)=Onf(t) * Epf;
      Bfb(t)=Onb(t) * Epb;
      Bfc(t)=Onc(t) * Epc;
      Bfv(t)=Onv(t) * Epv;
      Bas(t)=1 /( 1 + exp ( -Beta*((wBasr*Bfr(t)  + wBasf*Bff(t)+
wBasv*Bfv(t))* (1-wBasc*(1-Bfc(t)))* (1-wBasb*Bfb(t))) ));
      Bar(t)=1 /( 1 + exp (-Beta*(1-((wBarr*Bfr(t)+wBarf*Bff(t)+
wBarv*Bfv(t))*(1-wBarc*(1-Bfc(t)))*(1-wBarb*Bfb(t))))));
      GammaDc(t) = X;
for t=numStop+2:numStep
```

```
        % Instantaneous Factors
    GammaDc(t) = Ea(t-1);
    % Observation of Road
    Onr(t)=AlphaOnr(t) * constAn;

    % Observation of Traffic
    Onf(t)=AlphaOnf(t) * constAn;
    % Observation of Obstacles
    Onb(t)=AlphaOnb(t) * constAn;
    % Observation of Car Condition
    Onc(t)=AlphaOnc(t) * constAn;
    % Observation of Visibility
    Onv(t)=AlphaOnv(t) * constAn;
    % Belief Formation for Road
    Bfr(t)=Onr(t) * Epr;
    % Belief Formation for Traffic
    Bff(t)=Onf(t) * Epf;
    % Belief Formation for Obstacles
    Bfb(t)=Onb(t) * Epb;
    % Belief Formation for Car Condition
    Bfc(t)=Onc(t) * Epc;
    % Belief Formation for Visibility
    Bfv(t)= Onv(t) * Epv;
    % Belief Activation for Safe
    Bas(t)=1 /( 1 + exp ( -Beta*((wBasr*Bfr(t)  + wBasf*Bff(t)+
wBasv*Bfv(t))* (1-wBasc*(1-Bfc(t)))* (1-wBasb*Bfb(t)))));
    % Belief Activation for Risky
    Bar(t)=1 /( 1 + exp (-Beta*(1-((wBarr*Bfr(t)+wBarf*Bff(t)+
wBarv*Bfv(t))*(1-wBarc*(1-Bfc(t)))*(1-wBarb*Bfb(t))))));

                %Temporal Factors
    % Decision

    if((Bas(t)-Bar(t))>=0)
      Dc(t)= Dc(t-1)+GammaDc(t)*(((Bas(t)-Bar(t))-(Dc(t-1)))*(1-
Dc(t-1)))*(Delta_t);
    else
     Dc(t)= Dc(t-1)+ GammaDc(t)*(((Bas(t)-Bar(t))-(Dc(t-1)))*(Dc(t-
1)))*(Delta_t);
    end
    GammaDc(t) = GammaDc(t) - lambdaDc;
    Ea(t)=GammaDc(t);
    if (Dc(t)>=decision_threshold)
      Pa(t)=1;
    else
      Pa(t)=0;
    end
end
```

```
%//////////////////////////////////////////////////////////////////////
% Excute the model at t=1 to numStep
hold on
t=1:numStep;
subplot(2,2,1);
y = plot(t, Dk,'b:',t, Rp,'r--' );
xlabel('time steps');ylabel('levels');
xlim([0 numStep]);ylim([minLimX maxLimY]);
hold off;
legend(y,'Driv.Know.','Risk Perceptn') ;

%//////////////////////////////////////////////////////////////////////
subplot(2,2,2);
y = plot(t, Ea,'k--',t, Dc,'r--');
xlabel('time steps');ylabel('levels');
xlim([0 numStep]);ylim([minLimX maxLimY]);
hold off;
legend(y,'Exp. Automaticity','Conf.to Decide');
%//////////////////////////////////////////////////////////////////////

subplot(2,1,2);
y = plot(t, Pa,'r-');
xlabel('time steps');ylabel('levels');
xlim([0 numStep]);ylim([minLimX maxLimY]);
hold off;
legend(y,'Perf. of Action') ;
```

Appendix D

Sample of Participants' Selection Questionnaire in English & Malay

Participants Selection Questionnaire

INSTRUCTION:

Please tick ✓ at the appropriate box.

1. Age Group

   <30 ☐ 30-39 ☐ 40-49 ☐ ≥50 ☐

2. Gender

   Male ☐ Female ☐

3. Educational Level

   Undergraduate ☐ Master ☐ PhD ☐ Others ☐

4. Driving experience

   Inexperience Driver <1 year ☐ Average Driver 1-5 years ☐ Experience Driver ≥6 years ☐

5. Annual Mileage

   <5,000km per year ☐ ≥5,000km per year ☐

6. Do you have a valid driving licence?

   Yes ☐ No ☐

7. Have you ever used a desktop driving simulator?

   Yes ☐ No ☐

8. Do you play any type of video games?

   Yes ☐ No ☐ If Yes, answer # 9 and # 10. If No, skip to 11.

9) If Yes, how often? For example, one hour a month or a week? ________________________
10) At what age did you start playing video games? __________________________________
11) If you do use a computer, how many hours per week?______________________________

ARAHAN:

Sila tandakan ☑ pada kotak yang bersesuaian.

1. Kelompok Umur

<30 ☐ 30-39 ☐ 40-49 ☐ ≥50 ☐

2. Gender

Lelaki ☐ Perempuan ☐

3. Tahap Pendidikan

Ijazah Sarjana Muda ☐ Ijazah Sarjana ☐ Ijazah PhD ☐ Lain-lain ☐

4. Pengalaman memandu

Pemandu Kurang Berpengalaman <1 tahun ☐ Pemandu Sederhana 1-5 tahun ☐ Pemandu Berpengalaman ≥6 tahun ☐

5. Perbatuan Tahunan

<5,000km setahun ☐ ≥5,000km setahun ☐

6. Adakah anda memiliki lessen memandu yang sah?

Ya ☐ Tidak ☐

7. Pernahkah anda menggunakan simulasi pemanduan atas meja (DTP)?

Ya ☐ Tidak ☐

8. Adakah anda bermain sebarang jenis permainan video?

Ya ☐ Tidak ☐ Jika jawapan anda Ya, sila jawab soalan 9 dan soalan 10. Sekiranya jawapan anda Tidak, sila jawab soalan 11 sahaja.

9. Jika jawapan anda Ya, berapa kerapkah anda bermain permainan video? Contohnya, satu jam sebulan atau satu jam seminggu?
____

10. Pada usia berapakah anda mula bermain permainan video?
____

11.Sekiranya anda menggunakan komputer, berapa jamkah anda luangkan untuk menggunakan komputer setiapminggu?____

Appendix E

Sample of Participant Consent Form English Vs Malay

Please read this consent document carefully before you decide to participate in this study experiment.

Purpose of the research study experiment: The purpose of this study is to validate the proposed model by investigating if the model factors are effective in terms of making prime decision, to see if the simulation scenarios based on the model factors matches the behaviour of the driver in real life domain.

What you will be asked to do in the study experiment: A protocol guide will be provided to the participants on how to use the game simulator. Then, a training session for the experimental group will commence using city driving test. Thereafter, both groups will play the free driving test for the three scenarios. Finally, both group fill up a questionnaire for each scenarios played.

Required time for the experimental Group: 45 minutes.

Date & Time for the experiment: ____

Venue: Human Centred Computing Research Lab, School of Computing, Universiti Utara Malaysia.

Risks: No risk is associated with this experiment.

Benefits / Compensation: There is a free meal to compensate the participants but no other direct benefit to you for participation.

Confidentiality: Your identity will be kept confidential to the extent provided by law. The participants' profiles will be created for playing the game simulator. When the study is completed and the data have been analysed, the profile lists of the participants will be destroyed. Your profile name will not be used in any report.

Voluntary participation: Your participation in this study is voluntary. There is no penalty for not participating.

Right to withdraw from the study: You have the right to withdraw from the study at any time without consequence.

Permission to snap and use Photos: The researcher will take photos of the participants while engaged during the experiment. Do you permit the researcher to snap and put your photo in her thesis?

Yes ☐ No ☐

Whom to contact if you have questions about the study experiment: Rabi Mustapha (School of Computing, UUM) telephone (0169810644), and email (rabichubu@yahoo.com); **Supervisor:** Assoc. Prof. Dr.Yuhanis binti Yusof (School of Computing, UUM) telephone (013-392-1224) and email (yuhanis@uum.edu.my).

____

Participant Signature Date

I have read the procedure described above.
I voluntarily agree to participate in the experiment.

Borang Persetujuan Peserta

Sila baca dokumen persetujuan ini dengan teliti sebelum anda membuat sebarang keputusan untuk mengambil bahagian dalam eksperimen kajian ini.

Tujuan eksperimen kajian penyelidikan: Kajian ini bermatlamat untuk mengesahkan model yang diusulkan dengan meneliti sama ada faktor model berkesan dari segi membuat keputusan penting, dan untuk melihat sama ada senario simulasi yang dihasilkan berdasarkan model faktor berpadanan dengan tingkah laku pemandu dalam domain situasi sebenar.

Apakah tugas anda dalam eskperimen kajian ini? Satu panduan protokol yang membimbing para peserta untuk menggunakan simulator permainan akan disediakan. Sesi latihan untuk kumpulan eksperimen kemudiannya akan dimulakan dengan menggunakan ujian pemanduan di bandar. Selepas itu, kedua-dua kumpulan akan bermain dengan ujian pemanduan yang percuma untuk ketiga-tiga senario. Akhir sekali, kedua-dua kumpulan akan melengkapkan soal selidik untuk setiap senario yang telah dimainkan.

Masa yang diperlukan untuk kumpulan eksperimen: 45 minit.

Tarik & Masa eksperimen: ____

Tempat: Makmal Penyelidikan Pengkomputeran Berpusatkan Manusia, Pusat Pengajian Pengkomputeran, Universiti Utara Malaysia.

Risiko: Tiada sebarang risiko dikaitkan dengan eksperimen ini.

Faedah / Ganjaran: Makanan percuma disediakan kepada para peserta tetapi tiada sebarang ganjaran lain yang diberikan atas penyertaan anda.

Kerahsiaan: Identiti anda dirahsiakan seperti yang termaktub dalam undang-undang. Profil peserta akan dicipta untuk membolehkan peserta menggunakan simulator permainan. Apabila kajian sudah disempurnakan dan data dianalisis, senarai profil peserta akan dimusnahkan. Nama profil anda tidak akan digunakan dalam sebarang laporan.

Penyertaan secara Sukarela: Penyertaan anda dalam kajian ini secara suka rela. Tiada sebarang penalti dikenakan sekiranya anda tidak mengambil bahagian.

Hak untuk menarik diri daripada kajian: Anda berhak untuk menarik diri daripada kajian ini bila-bila yang anda mahu tanpa sebarang akibat.

Keizinan untuk mengambil gambar dan menggunakan gambar: Penyelidik akan mengambil gambar peserta yang sedang menjalani eksperimen. Adakah anda mengizinkan penyelidik untuk mengambil gambar dan memuatkan gambar anda dalam tesis penyelidik?

Ya ☐ Tidak ☐

Individu yang boleh anda hubungi sekiranya anda mempunyai sebarang pertanyaan berhubung eksperimen kajian: Rabi Mustapha (Pusat Pengajian Pengkomputeran, UUM) no telefon (0169810644), dan e-mel (rabichubu@yahoo.com); **Penyelia:** Prof. Mady Dr.Yuhanis binti Yusof (Pusat Pengajian Pengkomputeran, UUM) no telefon (013-392-1224) dan e-mel (yuhanis@uum.edu.my).

Peserta	Tandatangan	Tarikh

Saya telah membaca prosedur yang dijelaskan di atas. Saya secara suka rela bersetuju untuk mengambil bahagian dalam eksperimen tersebut.

Appendix F

Paricipants Demogarphic Information

Table Showing Participants' Age Ranges

Age Range	Frequency	Percent	Valid Percent	Cumulative Percent
20-29	6	30.0	30.0	30.0
30-39	12	60.0	60.0	90.0
40-49	2	10.0	10.0	100.0
Total	20	100.0	100.0	

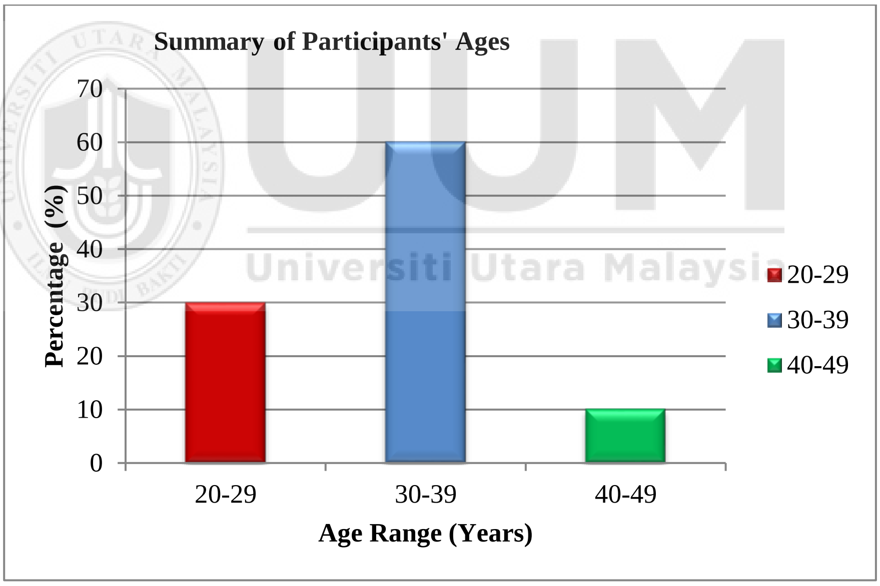


Table Showing Participants' Gender

Gender	Frequency	Percent	Valid Percent	Cumulative Percent
Male	18	90.0	90.0	90.0
Female	2	10.0	10.0	100.0
Total	20	100.0	100.0	

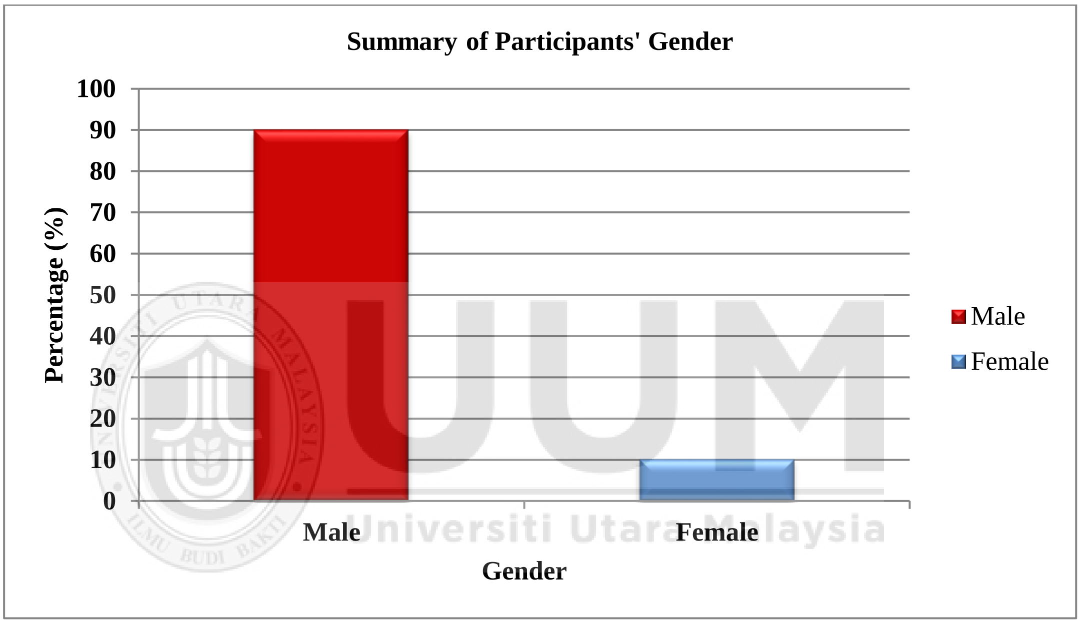


Table Showing Participants' Educational Level

	Frequency	Percent	Valid Percent	Cumulative Percent
Under Graduate	3	15.0	15.0	15.0
Master	15	75.0	75.0	90.0
PhD	2	10.0	10.0	100.0
Total	20	100.0	100.0	

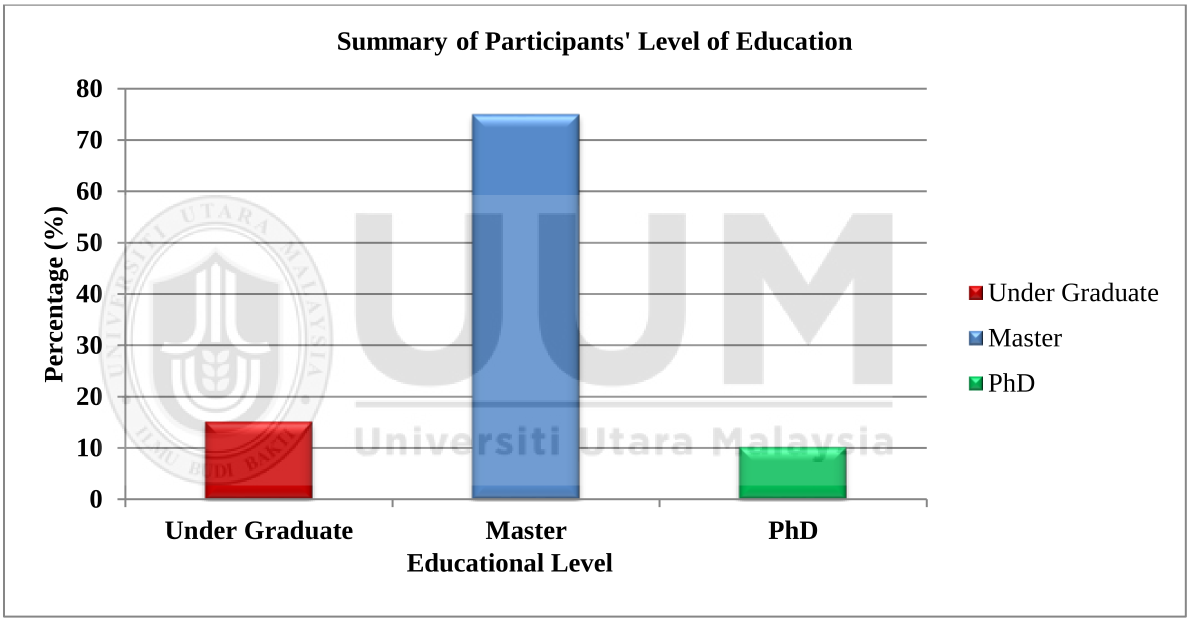


Table Showing Participants' Years of Driving Experience

Years of Driving Experience	Frequency	Percent	Valid Percent	Cumulative Percent
6-10 Years	13	65.0	65.0	65.0
>10 Years	7	35.0	35.0	100.0
Total	20	100.0	100.0	

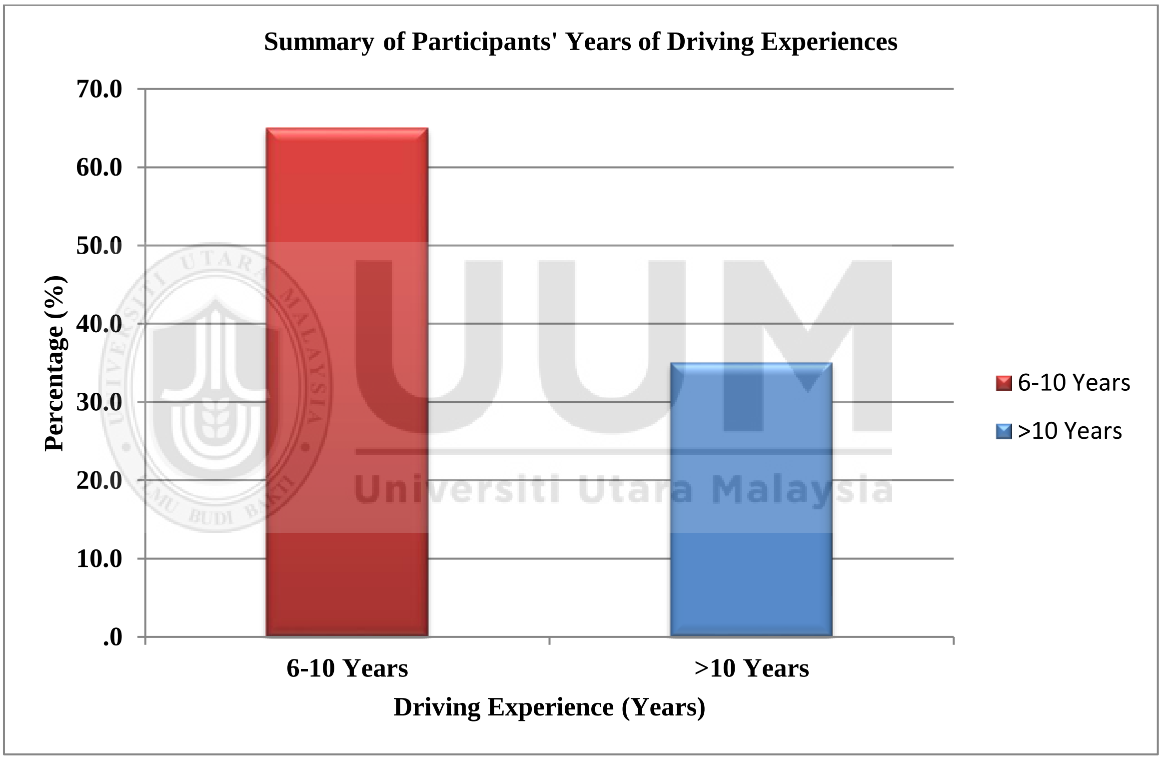
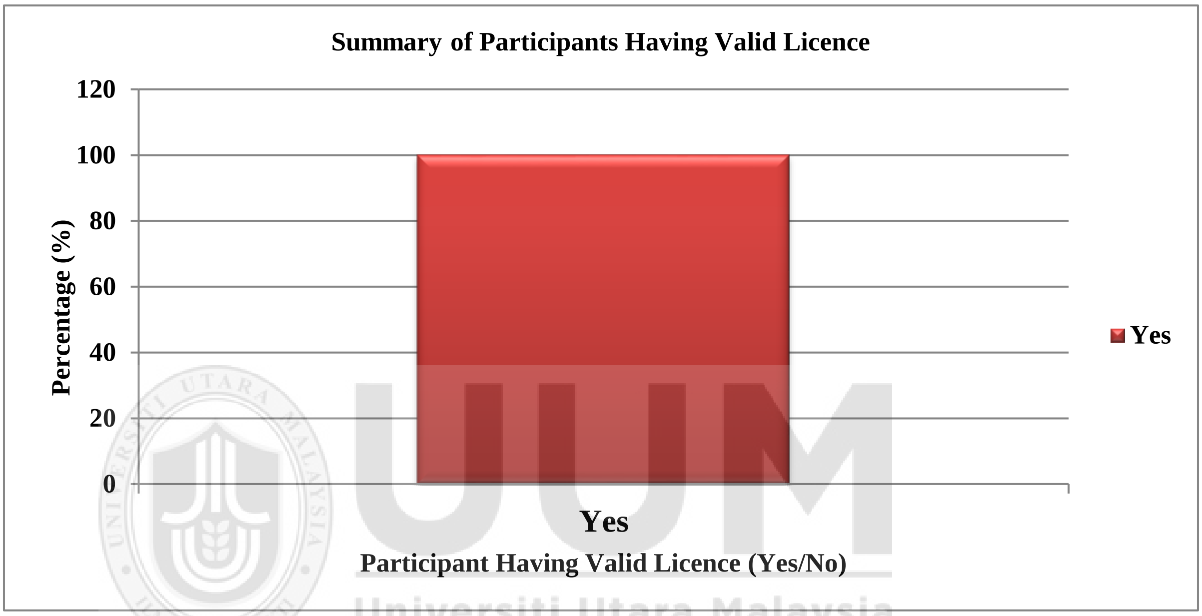


Table Showing Participants' with Valid Licence

Valid Licence	Frequency	Percent	Valid Percent	Cumulative Percent
Yes	20	100.0	100.0	100.0



Appendix G

Participants' Experiment User Guide

EXPERIMENTAL GROUP USER GUIDE

1. CREATE A PROFILE

Step 1: Click on "Profile"

Step 2: Click on "Create"

Step 3: Enter a name for your Profile

Step 4: Click on "New"

Step 5: Click on "SELECT"

2. START THE TRAINING

Step 1: Click on **"Career"**

Step 2: Click on right arrow to select **"City test".**

Step 3: Click on "Start" to play. Wait for the simulator to complete loading. Thereafter, the game is ready for play.

Step 4: Press **"B"** on the keyboard to put on the "seat belt".

Step 5: Press **"E"** on the keyboard to on/off the "car engine".

Step 6: Press **"Spacebar"** on the keyboard to remove the car from parking gear.

Step 7: Press and hold down the "**Down Arrow**" and Pressing **"W"** on the keyboard to move to the next gear**.**

Note: Still hold down the "**Down Arrow**" and press **W** again for selecting gear 2, 3, 4 and 5. Also, you can press **"S"** to move to the previous gear.

Step 8: Press **"Up-arrow"** on the keyboard to start moving **"Accelerating".**

Note: You can use **left** and **right arrow** to turn the car left or right respectively, you can also use **"Down-arrow"** to break or stop.

Step 9: Press **">"**on the keyboard to **turn right signal**, or Press **"<"**on the keyboard to **turn left signal**.

Step 10: Once you violated 5 traffic rules, a prompt will appear with instruction that you may **try again** or **quit**.

Step 11: Click on **"Start again"** to repeat the training.

Step 12: Continue the training for at least 30 minutes.

Note: While driving, an instruction will be given to you at the right hand side of the screen for action to be taken, warning and violation of traffic rules information.

Step 13: press **"Esc"** to go to the **Menu** or **Exit**

3. **START FREE DRIVING**

Step 1: Click on **“Free Driving”**

Step 2: Wait for scenario settings

Step 3: Click on **“Start”** to play. Wait for the simulator to complete loading. Thereafter, the game is ready for play.

Step 4: Press **“B”** on the keyboard to put on the “seat belt”.

Step 5: Press **“E”** on the keyboard to start the “car engine”.

Step 6: Press **“Spacebar”** on the keyboard to remove the car free from parking gear.

Step 7: Press and hold down the “**Down Arrow**” and Pressing **“W”** on the keyboard to move to the next gear**.**

Note: Still hold down the “**Down Arrow**” and press **W** again for selecting gear 2, 3, 4 and 5. Also, you can press **“S”** to move to the previous gear.

Step 8: Press **“Up-arrow”** on the keyboard to start moving **“Accelerating”.**

Note: You can use **left** and **right arrow** to turn the car left or right respectively, you can also use **“Down-arrow”** to break or stop.

Step 9: Press **“>”**on the keyboard to **turn right signal**, or Press **“<”**on the keyboard to **turn left signal**.

Step 10: Press **“K”** to turn on the **High Beam light**, **“L”** for **Parking/Lower Beam/Head light**, **“G”** for **Hazard light**.

Step 11: press **“Esc”** to go to the **Menu** or **Exit.**

Note: Press **“1”** on the keyboard for neutral gear. **“0”** for Reverse, **“X”** to Reduce the car gear.

CONTROL GROUP USER GUIDE

1. **CREATE A PROFILE**

Step 1: Click on “Profile”

Step 2: Click on “Create”

Step 3: Enter a name for your Profile

Step 4: Click on “New”

Step 5: Click on “SELECT”

2. **START FREE DRIVING**

Step 1: Click on **“Free Driving”**

Step 2: Wait for scenario settings

Step 3: Click on **“Start”** to start playing the game. Wait for the simulator to complete loading. Thereafter, the game is ready for play.

Step 4: Press **“B”** on the keyboard to put on the seat belt.

Step 5: Press **“E”** on the keyboard to start the car engine.

Step 6: Press **“Spacebar”** on the keyboard to set the car free from parking gear.

Step 7: Press **“W”** on the keyboard to set for **gear 1.**

Note: You can press **“W”** again for gear 2, 3, 4 and 5. Also, you can press **“S”** to reduce the gear backward from 5 to 1.

Step 8: Pres **“Up-arrow”** on the keyboard to start moving

Note: You can use left and right arrow to turn the car left or right respectively, you can also use down-arrow to stop.

Step 9: Press **“>”**on the keyboard to turn right signal, or Press **“<”**on the keyboard to turn left signal

Step 10: Press **“K”** to **on** the High Beam light, **“L”** for Parking/**Lower Beam/Head light**, **“G”** for **Hazard light**.

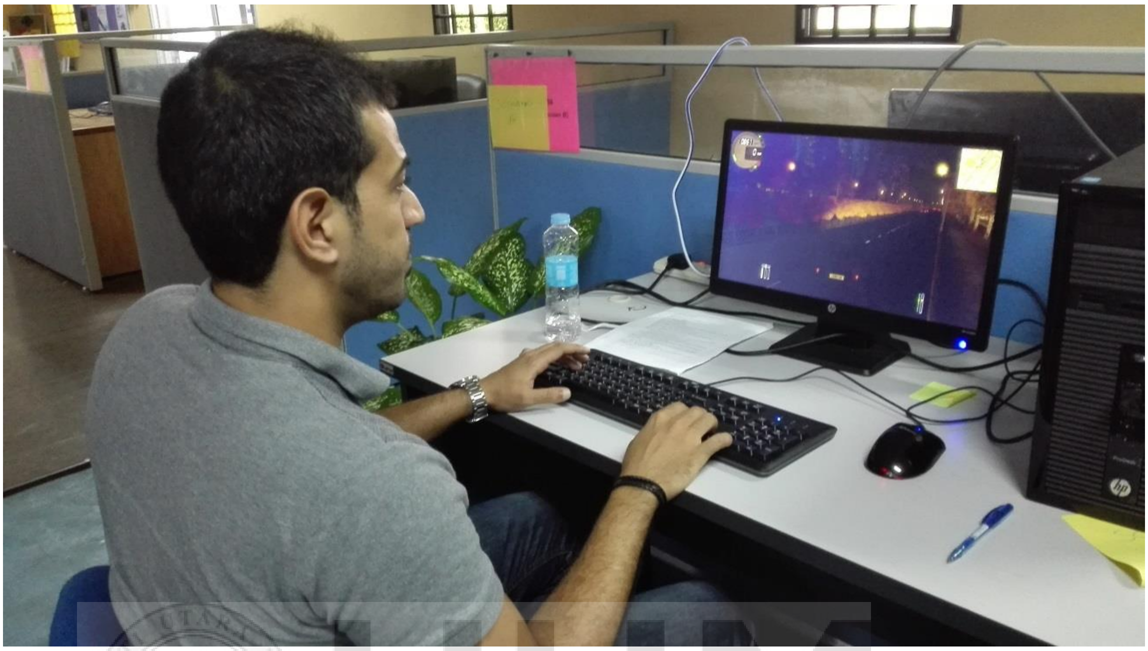
Step 11: press **“Esc”** to go to the **Menu** or **Exit**

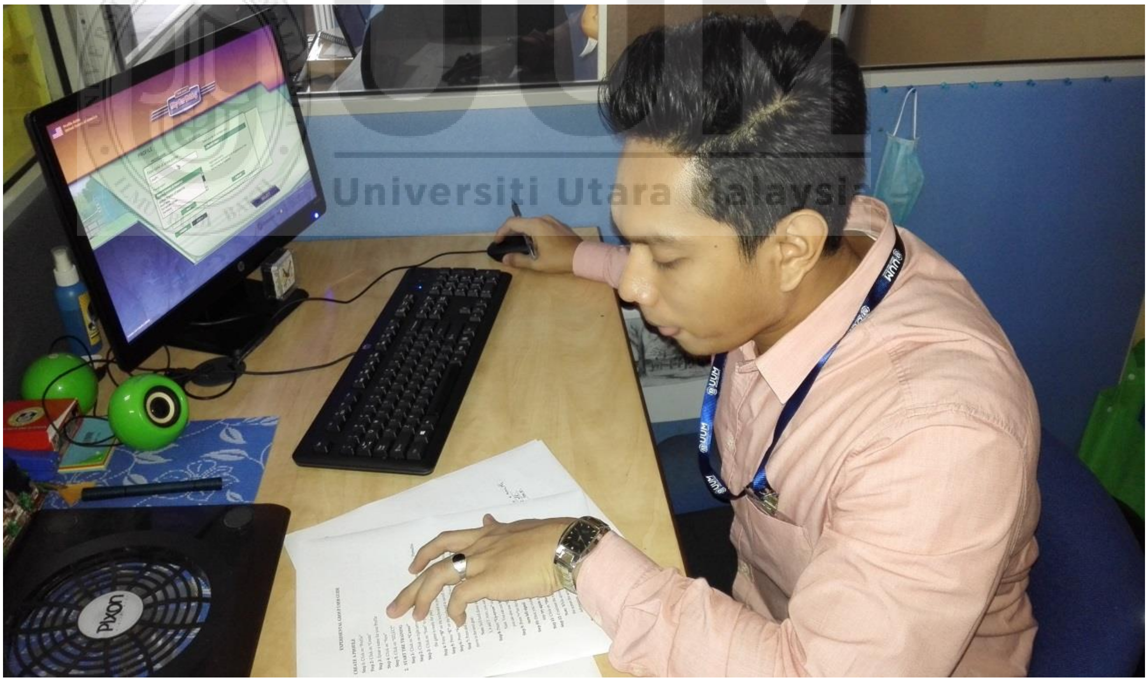
Note: Press **“1**” on the keyboard for neutral gear. **“0”** for Reverse gear, **“X”** to Reduce the car gear.

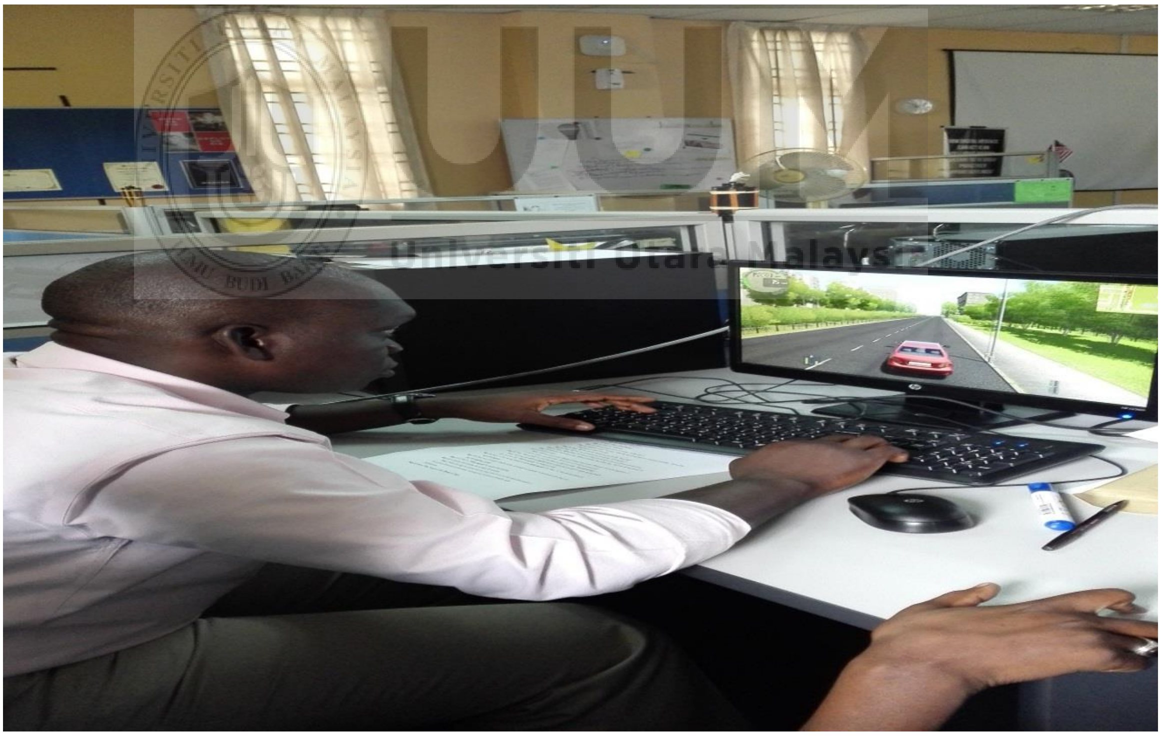
Appendix H

Sample Photos of some participants during the experiments

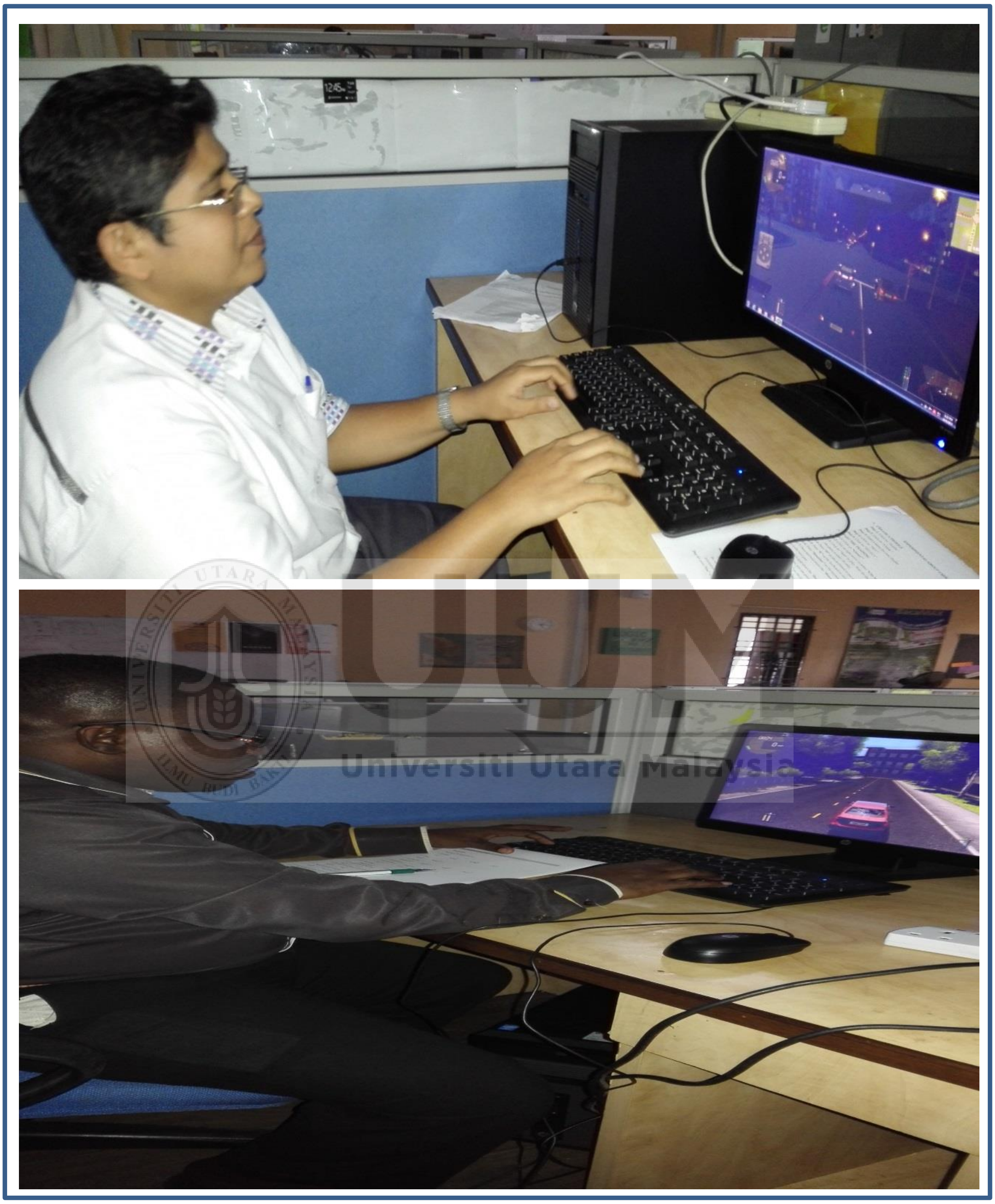
Experimental Group Participants







Control Group Participants



Appendix I

Sample of Post-test Experiment Questionnaire in English Vs Malay

Questionnaire

UNIVERSITI UTARA MALAYSIA
COLLEGE OF ARTS AND SCIENCES
06010
DARUL AMAN, KEDAH
MALAYSIA

Dear participants,
I am a post graduate student conducting a study on driver's behaviour using a driving game simulator. The study is to test the model factors effectiveness to see if the simulation scenarios based on the model factors matches the behaviour of the driver in real life domain. To also see if training have effect on the automaticity of the driver to make prime decision.
Please be assured that your response will not be used for any other purposes other than academic.

Thank you so much in anticipation of your responses. If you require additional information about this study, kindly contact any of the following:

Researcher:
Rabi Mustapha,
School of Computing,
College of Arts and Sciences,
Universiti Utara Malaysia,
Sintok, Kedah, Malaysia.
Email: rabichubu@yahoo.com

Main Supervisor:
Assoc.Prof. Dr.Yuhanis Yusof
School of Computing,
UUM, Sintok, Kedah, Malaysia.

Co-Supervisor:
Dr. Azizi Ab Aziz
School of Computing,
UUM, Sintok, Kedah, Malaysia.

INSTRUCTION

The questionnaire is divided into two sections: Section **A** deals with the demographic questions and Section **B** consists of Items on Driver Behavior (DB) based on the training model.

SECTION A: Demographic characteristics of the study participants

Please tick ☐✓ at the appropriate box.

Age Group

<20 ☐ 20-29 ☐ 30-39 ☐ 40-49 ☐ 50-59 ☐ ≥60 ☐

Gender

Male ☐ Female ☐

Educational Level

Undergraduate ☐ Master ☐ PhD ☐ Others ☐

Driving experience

<2 year ☐ 2-5 years ☐ 6-10 years ☐ >10 years ☐

Do you have a valid driving licence? Yes ☐ No ☐

SECTION B: Items on Driver Behavior (DB) based on the training model

The respondents are expected to answer the questions in this section using their driving experience with the game simulator. Kindly indicate your rating level when training with the game simulator in each of the items. The rating scale is from **0-10**, with **(0-5)** indicating **Low** and **(6-10)** indicating **High**. Please tick ☐√ as appropriate.

S/N	**How do you rate yourself in the ability to do these:**	**SCALE** **Low** ←→ **High**										
1.	Maintaining lane positioning	0	1	2	3	4	5	6	7	8	9	10
2.	Turning the car	0	1	2	3	4	5	6	7	8	9	10
3.	Speed control	0	1	2	3	4	5	6	7	8	9	10
4.	Braking	0	1	2	3	4	5	6	7	8	9	10
5.	Use of turn signals	0	1	2	3	4	5	6	7	8	9	10
6.	Use of mirrors	0	1	2	3	4	5	6	7	8	9	10
7.	Controlling the steering wheel	0	1	2	3	4	5	6	7	8	9	10
8.	Gear selection in operating manual /automatic car	0	1	2	3	4	5	6	7	8	9	10

S/N	How do you rate yourself on the following:	SCALE Low ⟷ High										
9.	Holding the steering wheel while driving?	0	1	2	3	4	5	6	7	8	9	10
10.	Looking into the side mirrors while overtaking another car?	0	1	2	3	4	5	6	7	8	9	10
11.	Driving between the lines?	0	1	2	3	4	5	6	7	8	9	10
12.	Using the signal lights while turning?	0	1	2	3	4	5	6	7	8	9	10
13.	Driving a car in reverse?	0	1	2	3	4	5	6	7	8	9	10
14.	Turning in prohibited areas (e.g, no U-Turn)?	0	1	2	3	4	5	6	7	8	9	10
15.	Stopping in prohibited areas (e.g. Roundabout, four-way intersection or crossroad)?	0	1	2	3	4	5	6	7	8	9	10
16.	The use of seat belt while driving?	0	1	2	3	4	5	6	7	8	9	10
17.	Driving within the speed limit?	0	1	2	3	4	5	6	7	8	9	10

S/N	How do you rate your vision:	SCALE Low ⟷ High										
18.	Seeing dark coloured cars when driving at night?	0	1	2	3	4	5	6	7	8	9	10
19.	Seeing pedestrians on the road side when driving at night?	0	1	2	3	4	5	6	7	8	9	10
20.	Seeing pedestrians on the road side when driving in a day time?	0	1	2	3	4	5	6	7	8	9	10
21.	Reading street signs when driving at night?	0	1	2	3	4	5	6	7	8	9	10
22.	Reading street signs when driving in a day time?	0	1	2	3	4	5	6	7	8	9	10
23.	Seeing the road due to oncoming headlights when driving at night?	0	1	2	3	4	5	6	7	8	9	10
24.	Seeing the road due to oncoming headlights when driving in a day time?	0	1	2	3	4	5	6	7	8	9	10
25.	Seeing the road in rain when driving at night?	0	1	2	3	4	5	6	7	8	9	10
26.	Seeing the road in rain when driving in a day time?	0	1	2	3	4	5	6	7	8	9	10
	How often do you distracted by:											
27.	Eating/drinking while driving?	0	1	2	3	4	5	6	7	8	9	10
28.	Read roadside advertisements?	0	1	2	3	4	5	6	7	8	9	10
29.	Daydream?	0	1	2	3	4	5	6	7	8	9	10

S/N	Prioritize your goals based on the following items and rate accordingly:	SCALE Low ⟷ High										
30.	Safety goal (i.e. Making sure of your safety and safety of others).	0	1	2	3	4	5	6	7	8	9	10
31.	Time goal (i.e. Making sure you reach your destination on time).	0	1	2	3	4	5	6	7	8	9	10
32.	Avoiding traffic violation.	0	1	2	3	4	5	6	7	8	9	10

S/N	Rate your intention to achieving these goals:	SCALE Low ⟷ High										
33.	Safety goal.	0	1	2	3	4	5	6	7	8	9	10
34.	Time goal.	0	1	2	3	4	5	6	7	8	9	10
35.	Avoiding traffic violation.	0	1	2	3	4	5	6	7	8	9	10
S/N	**How do you rate your information level on the following items:**	**SCALE Low ⟷ High**										
36.	Car stopping at the Pedestrian Crossing?	0	1	2	3	4	5	6	7	8	9	10
37.	Curves (or bend) on the road?	0	1	2	3	4	5	6	7	8	9	10
38.	Other cars driving in front of you?	0	1	2	3	4	5	6	7	8	9	10
39.	Pedestrian crossing the road in a wrong place?	0	1	2	3	4	5	6	7	8	9	10

S/N	How do you rate your exposure on the following complex tasks:	SCALE Low ⟷ High										
40.	Accelerating when approaching a flickering green light?	0	1	2	3	4	5	6	7	8	9	10
41.	Activating a direction indicator when negotiating a bend?	0	1	2	3	4	5	6	7	8	9	10
42.	Braking by slowing down before negotiating roundabout	0	1	2	3	4	5	6	7	8	9	10
43.	Emergency braking when another car pull into driver's path	0	1	2	3	4	5	6	7	8	9	10
44.	Changing gear when reducing the car speed.	0	1	2	3	4	5	6	7	8	9	10
45.	Check surrounding for unsafe situations.	0	1	2	3	4	5	6	7	8	9	10
46.	Maintain lane in traffic.	0	1	2	3	4	5	6	7	8	9	10
47.	Controlling the steering wheel.	0	1	2	3	4	5	6	7	8	9	10

S/N	How do you rate your degree of risk associated with:	SCALE Low ⟷ High										
48.	Driving at night?	0	1	2	3	4	5	6	7	8	9	10
49.	Bypassing slow car through the left hand side instead of the right hand side?	0	1	2	3	4	5	6	7	8	9	10
50.	Pulling over the road way (getting on and off lower road shoulder)?	0	1	2	3	4	5	6	7	8	9	10
51.	Driving in a city at a speed above the speed limit?	0	1	2	3	4	5	6	7	8	9	10
52.	Bypassing when you are hidden by a truck and have no good vision of the car coming in front of you?	0	1	2	3	4	5	6	7	8	9	10
53.	Losing control over the car while driving on a wet and slippery road?	0	1	2	3	4	5	6	7	8	9	10
54.	Losing control over the car while driving on a dry road?	0	1	2	3	4	5	6	7	8	9	10
55.	Backward driving (reverse) when there are blind sights?	0	1	2	3	4	5	6	7	8	9	10
56.	Backward driving (reverse) when there are no blind sights?	0	1	2	3	4	5	6	7	8	9	10
57.	Sudden braking by another car in front of you?	0	1	2	3	4	5	6	7	8	9	10
58.	Challenged-driving aimed at testing your driving abilities?	0	1	2	3	4	5	6	7	8	9	10

S/N	How do you rate your level of understanding of the following items:	SCALE Low ⟷ High										
59.	Road signs?	0	1	2	3	4	5	6	7	8	9	10
60.	Use of maximum speed limits driving in a city?	0	1	2	3	4	5	6	7	8	9	10
61.	Traffic rules and regulations?	0	1	2	3	4	5	6	7	8	9	10
62.	Road markings?	0	1	2	3	4	5	6	7	8	9	10

S/N	How can you rate yourself performing these actions Involuntarily(I.e. unconsciously):	SCALE Low ⟷ High										
63.	Sudden swerve to another direction without thinking (e.g. when another car swerved in front of my car while driving.)?	0	1	2	3	4	5	6	7	8	9	10
64.	Begin panic stop before I realize I'm doing it (e.g. when pedestrian crossing the road in a wrong place in front of my car while driving.)?	0	1	2	3	4	5	6	7	8	9	10
65.	Do change lane without meaning to do it?	0	1	2	3	4	5	6	7	8	9	10
66.	Find it hard to stop myself from doing dangerous overtaking?	0	1	2	3	4	5	6	7	8	9	10

ARAHAN

Soal selidik ini terbahagi kepada dua bahagian. Bahagian **A** merangkumi aspek demografi dan bahagian **B** mengandungi item berkenaan Tingkah laku Pemandu (DB) berdasarkan model latihan.

BAHAGIAN: Ciri-ciri demografi peserta kajian.

Sila tanda ☑ pada kotak yang bersesuaian.

1) Kelompok Umur

<20 ☐ tahun 20-29 ☐ tahun 30-39 ☐ tahun 40-49 ☐ tahun 50-59 ☐ tahun

≥60 ☐ tahun

2) Jantina

Lelaki ☐ Perempuan ☐

3) Tahap Pendidikan

Ijazah Sarjana muda ☐ Ijazah Sarjana ☐ Ijazah PhD ☐ Lain-lain ☐

4) Pengalaman memandu

<2 tahun ☐ 2-5 tahun ☐ 6-10 tahun ☐ >10 tahun ☐

5) Adakah anda memiliki lesen memandu yang sah? Ya ☐ Tidak ☐

BAHAGIAN B: Item berhubung Tingkah laku Pemandu (DB) berdasarkan model latihan

Para responden diharapkan dapat menjawab soalan dalam bahagian ini berpandukan pengalaman memandu mereka dengan menggunakan simulator permainan. Sila nyatakan tahap penilaian anda apabila berlatih menggunakan simulator permainan untuk setiap item. Skala penilaian adalah antara 0-10, dengan **0** menunjukkan **Rendah** dan **10** menunjukkan **Tinggi**. Sila tanda pada ruang yang bersesuaian.

S/N	**Bagaimanakah anda menilai kemampuan anda untuk melakukan perkara-perkara berikut:**	**SKALA** **Rendah** ⟷ **Tinggi**										
1.	Mengekalkan kedudukan laluan	0	1	2	3	4	5	6	7	8	9	10
2.	Pusingan	0	1	2	3	4	5	6	7	8	9	10
3.	Kawalan kelajuan	0	1	2	3	4	5	6	7	8	9	10
4.	Membrek	0	1	2	3	4	5	6	7	8	9	10
5.	Menggunakan isyarat pusingan	0	1	2	3	4	5	6	7	8	9	10
6.	Menggunakan cermin	0	1	2	3	4	5	6	7	8	9	10
7.	Mengawal stereng	0	1	2	3	4	5	6	7	8	9	10
8.	Mengentukan gear semasa mengendalikan kereta manual /kereta automatik	0	1	2	3	4	5	6	7	8	9	10

S/N	Bagaimanakah anda menilai diri anda berhubung perkara berikut:	SKALA Rendah ⟷ Tinggi										
9.	Memegang stereng ketika memandu?	0	1	2	3	4	5	6	7	8	9	10
10.	Melihat cermin tepi ketika memotong kenderaan lain?	0	1	2	3	4	5	6	7	8	9	10
11.	Memandu antara garisan?	0	1	2	3	4	5	6	7	8	9	10
12.	Menggunakan lampu isyarat ketika membuat pusingan?	0	1	2	3	4	5	6	7	8	9	10
13.	Mengundurkan kenderaan?	0	1	2	3	4	5	6	7	8	9	10
14.	Membuat pusingan di kawasan terlarang (cth. Dilarang berpusing balik)?	0	1	2	3	4	5	6	7	8	9	10
15.	Berhenti di kawasan terlarang (cth. Bulatan, persimpangan empat laluan atau lintasan)?	0	1	2	3	4	5	6	7	8	9	10
16.	Menggunakan tali pinggang keledar ketika memandu?	0	1	2	3	4	5	6	7	8	9	10
17.	Memandu di bawah had kelajuan?	0	1	2	3	4	5	6	7	8	9	10

S/N	Bagaimanakah anda menilai penglihatan anda:	SKALA Rendah ⟷ Tinggi										
18.	Melihat kenderaan berwarna gelap ketika memandu pada waktu malam?	0	1	2	3	4	5	6	7	8	9	10
19	Melihat kenderaan berwarna gelap ketika memandu pada waktu siang?	0	1	2	3	4	5	6	7	8	9	10
20.	Melihat pejalan kaki di tepi jalan ketika memandu pada waktu malam?	0	1	2	3	4	5	6	7	8	9	10
21.	Melihat pejalan kaki di tepi jalan ketika memandu pada waktu siang?	0	1	2	3	4	5	6	7	8	9	10
22.	Membaca papan tanda ketika memandu pada waktu malam?	0	1	2	3	4	5	6	7	8	9	10
23.	Membaca papan tanda ketika memandu pada waktu siang?	0	1	2	3	4	5	6	7	8	9	10
24.	Melihat jalan apabila disuluh lampu kenderaan dari arah hadapan ketika memandu pada waktu malam?	0	1	2	3	4	5	6	7	8	9	10
25.	Menentukan jarak untuk keluar ketika memandu?	0	1	2	3	4	5	6	7	8	9	10
26.	Menentukan jarak antara anda dengan kenderaan lain yang bergerak ketika memandu?	0	1	2	3	4	5	6	7	8	9	10
27.	Melihat jalan ketika hujan apabila memandu pada waktu malam?	0	1	2	3	4	5	6	7	8	9	10
	Berapa kerapkah anda dialih perhatian oleh perbuatan:	0	1	2	3	4	5	6	7	8	9	10
28.	Makan/minum ketika memandu?	0	1	2	3	4	5	6	7	8	9	10
29.	Membaca iklan-iklan di tepi jalan?	0	1	2	3	4	5	6	7	8	9	10
30.	Memerhati secara berterusan sekiranya ada kejadian kemalangan di tepi jalan?	0	1	2	3	4	5	6	7	8	9	10
31.	Berbual dengan penumpang, sekiranya ada penumpang?	0	1	2	3	4	5	6	7	8	9	10
32.	Berkhayal?	0	1	2	3	4	5	6	7	8	9	10

S/N	Susun matlamat anda mengikut keutamaan berhubung item berikut dan berikan penilaian dengan wajar:	SKALA Rendah ⟷ Tinggi										
33.	Matlamat keselamatan (cth. Memastikan keselamatan anda dan keselamatan orang lain).	0	1	2	3	4	5	6	7	8	9	10
34.	Matlamat masa (cth. Memastikan anda tiba ke destinasi anda tepat pada waktunya).	0	1	2	3	4	5	6	7	8	9	10
35.	Mengelak daripada melanggar peraturan lalu lintas.	0	1	2	3	4	5	6	7	8	9	10
S/N	**Nilai hasrat anda untuk mencapai matlamat yang dinilai di atas:**	**SKALA Rendah ⟷ Tinggi**										
36.	Matlamat keselamatan.	0	1	2	3	4	5	6	7	8	9	10
37.	Matlamat masa.	0	1	2	3	4	5	6	7	8	9	10
38.	Mengelak daripada melanggar peraturan lalu lintas.	0	1	2	3	4	5	6	7	8	9	10

S/N	Bagaimanakah anda menilai tahap maklumat berhubung item berikut:	SKALA Rendah ⟷ Tinggi										
39.	Kenderaan berhenti di Lintasan Pejalan kaki?	0	1	2	3	4	5	6	7	8	9	10
40.	Lengkung (atau liku) di atas jalan?	0	1	2	3	4	5	6	7	8	9	10
41.	Kenderaan lain yang dipandu di hadapan anda?	0	1	2	3	4	5	6	7	8	9	10
42.	Pejalan kaki melintas jalan di tempat yang salah?	0	1	2	3	4	5	6	7	8	9	10

S/N	Bagaimanakah anda menilai tahap pendedahan anda terhadap tugas sukar berikut:	SKALA Rendah ⟷ Tinggi										
43.	Memecut ketika mendekati lampu hijau yang berkelip-kelip?	0	1	2	3	4	5	6	7	8	9	10
44.	Menyalakan isyarat laluan apabila berhadapan dengan selekoh jalan?	0	1	2	3	4	5	6	7	8	9	10
45.	Membrek secara perlahan sebelum memasuki bulatan	0	1	2	3	4	5	6	7	8	9	10
46.	Membrek secara mengejut apabila kenderaan lain memasuki laluan anda	0	1	2	3	4	5	6	7	8	9	10
47.	Mengubah gear apabila ingin memperlahankan kenderaan.	0	1	2	3	4	5	6	7	8	9	10
48.	Memeriksa sekeliling apabila berada dalam keadaan yang tidak selamat.	0	1	2	3	4	5	6	7	8	9	10
49.	Mengekalkan laluan di jalan raya.	0	1	2	3	4	5	6	7	8	9	10
50.	Mengawal stereng.	0	1	2	3	4	5	6	7	8	9	10

S/N	Bagaimanakah anda menilai tahap risiko anda berhubung perkara berikut:	SKALA Rendah ⟷ Tinggi										
51.	Memandu pada waktu malam?	0	1	2	3	4	5	6	7	8	9	10
52.	Memintas kenderaan yang perlahan di sebelah kiri dan bukannya di sebelah kanan?	0	1	2	3	4	5	6	7	8	9	10
53.	Berhenti di bahu jalan (menuruni dan menaiki bahu jalan yang rendah)?	0	1	2	3	4	5	6	7	8	9	10
54.	Memandu dalam bandar melepasi had kelajuan?	0	1	2	3	4	5	6	7	8	9	10
55.	Memintas dari belakang trak yang menghalang pandangan anda dengan tidak melihat kenderaan	0	1	2	3	4	5	6	7	8	9	10

	yang datang dari arah hadapan anda?											
56.	Hilang kawalan ke atas kenderaan ketika memandu di atas jalan yang basah dan licin?	0	1	2	3	4	5	6	7	8	9	10
57.	Hilang kawalan ke atas kenderaan ketika memandu di atas jalan yang kering?	0	1	2	3	4	5	6	7	8	9	10
58.	Mengundurkan kenderaan apabila terdapat penglihatan tak peka?	0	1	2	3	4	5	6	7	8	9	10
59.	Mengundurkan kenderaan apabila tiada penglihatan tak peka?	0	1	2	3	4	5	6	7	8	9	10
60.	Membrek secara mengejut?	0	1	2	3	4	5	6	7	8	9	10
61.	Cabaran memandu bertujuan menguji kemampuan memandu anda?	0	1	2	3	4	5	6	7	8	9	10

S/N	**Bagaimanakah anda menilai tahap kefahaman anda berhubung perkara berikut:**	**SKALA** Rendah ⟵⟶ Tinggi										
62.	Papan tanda?	0	1	2	3	4	5	6	7	8	9	10
63.	Memandu melepasi had laju dalam bandar?	0	1	2	3	4	5	6	7	8	9	10
64.	Peraturan dan kawalan lalu lintas?	0	1	2	3	4	5	6	7	8	9	10
65.	Tanda jalan?	0	1	2	3	4	5	6	7	8	9	10

S/N	**Bagaimanakah anda menilai diri anda apabila anda melakukan tindakan di luar kawalan (iaitu secara tak sedar) seperti berikut:**	**SKALA** Rendah ⟵⟶ Tinggi										
66.	Membelok secara mendadak ke arah lain tanpa berfikir (cth. Apabila kenderaan lain membelok di hadapan anda ketika memandu.)?	0	1	2	3	4	5	6	7	8	9	10
67.	Panik sebelum menyedari anda melakukannya (cth. Apabila pejalan kaki melintas jalan di tempat yang salah di hadapan kenderaan anda ketika anda sedang memandu.)?	0	1	2	3	4	5	6	7	8	9	10
68.	Mengubah laluan tanpa berniat untuk berbuat demikian?	0	1	2	3	4	5	6	7	8	9	10
69.	Sukar mengawal diri daripada memintas kenderaan lain secara berbahaya?	0	1	2	3	4	5	6	7	8	9	10

Appendix J

Illustration of Decision Made by the Participants

Dangerous swerving

Hitting the Pedestrian

Hitting the Pedestrian

Appendix K

Summary of City Car Driving Simulator Features

Features	Explanation
Multilingual	Supported languages such as English, German, French, Italian, Spanish, Portuguese, Turkish, Czech, Chinese and Japanese. This enhances the usability of the simulator.
Right-handed and left-handed driving modes	Allows drivers drive to drive using both right-hand and left-handed driving modes. This feature makes this car simulator a versatile tool, regardless of the country which the user resides in.
Various times of day and weather conditions	Allows driver feel all the difficulties of driving in harsh weather conditions, such as time of day: day time, morning, evening, and night time. Summer weather: Clear (dry road), humid (cloudy, wet road), foggy and rainy. Winter weather: Clear, clear ice (slippery road), foggy and snow as well as in conditions of poor visibility at night or in the fog.
Sudden dangerous situations	Help driver feel realistic driving situations. There's generation of such sudden events as: a traffic car drives on the opposite lane or cutting the lane just in front of the player's car, pedestrians crossing the road in wrong places, broken traffic lights, etc.
Random routes in free driving mode	Make the driving more diverse and interesting. Routes can be defined as without any limitations (set only a destination, and let the navigator pave the best route to it), and be represented as a small mission with a limited penalty scores for traffic rules violations (user can choose what types of violations will be considered - all types of violations or only some types).
Virtual cities	Old district - narrow streets, a lot of unsupervised crossings; Modern district - wide streets, many multi-lane roads, a lot of signalled and unsupervised crossings; Superhighway; Country road; Cart road; Southern district - wide streets with tramways, a lot of signalled and unsupervised crosswalks, narrow tangled courtyard with many parked cars; Mountainous area - narrow roads with considerable height drops. These provide driver with huge driving area including roads, crossings and junctions of various types and complexity that helps get confidence on the road in any situation. Each virtual city has its own large and indivisible virtual space. It gives driver opportunity to drive

	from one district of the city to other without extra loading screens.
Multi-level car parks	Multi-level car parks with lots of parked cars, impeding the movement, teach driving safely in the modern realities of large cities with dense building and close parking.
Interactive detailed city map	will help driver not to get lost in a big virtual world. There're also navigator tips while drive along the route.
Different player cars	allow driver feel the difference in driving of various vehicle types. All cars have full set of controls, including the sound and light equipment.
Various driving missions	Missions are grouped by difficulty help driver train the driving skills in various road situations. They help learn traffic rules effectively and raise driving skills. By finishing exercises and getting achievements you gradually unlock new city districts and player cars. Categories of driving missions by difficulty: driving school student; beginner driver; experienced driver; professional driver defensive (extreme) driving exercises. This prepares you for the unexpected and extreme situations.
Accurate rules of road control system	help driver examine the road situation.
Advanced physics	engine provides with high realism of driving. Maximum speed corresponds to real car prototypes. And a mathematical model of a car engine simulates: friction force, inertia, realistic work of the starter and many other parameters.
Both manual and automatic transmission	Covers drivers of all type of vehicles. Transmission operates realistic and has all the relevant modes.
Smart traffic AI	not always follows the rules as in life settings. Traffic cars are physical; they're able to collide with player's car or with each other. Traffic density and its "aggression" can be adjusted in the game settings.
Pedestrians	look like alive and behave accordingly, sometimes crossing the road in the wrong places. The virtual city has lots of supervised and unsupervised crosswalks used by pedestrians. Pedestrian density also can be adjusted in the game settings.
High-quality graphics	Cars have shadows, highlights, reflections. Road becomes wet and greasy after rain.
Damage	All cars get visible damage, when collide.
Sound effects	are realistic and improve immersing in the driving process. There are such effects as the sound of the slipping wheels, etc.
Easy-to-use controls	are intuitive, and the wide range of supported devices allows driver use a keyboard, mouse,

	racing wheel, gamepad, joystick or multiple controllers simultaneously. And controlling of the driver's sight with the mouse allows you track the dead zones even while not having of more advanced peripherals.
Support for the newest and the most advanced racing wheels	allows driver get maximum realism while driving. Supported: the force feedback, 900 degrees rotation angle, clutch pedal and all the other features of the most advanced and multifunction racing wheels.
Mirror adjustment	allows driver to set the optimum viewing angle as well as enhances the realism.
Third-party mods support	allows driver moding of the game and add almost any new car. There're also other mods available at the simulator forum, such as: tuning of the physics, road signs, license plates, etc.
Virtual world	Each virtual city has its own large and indivisible virtual space. It gives driver opportunity to drive from one district of the city to other without extra loading screens. The city can be selected in the menu before the driving start. Interactive detailed city map will help driver not to get lost in a big virtual world.

Appendix L System requirements to run the application

Minimum system configuration:

OS: Windows 7 SP1 / 8 / 8.1 / 10 (64 Bit);

CPU: Intel Pentium Dual Core 3.2 GHz / AMD Athlon II X4 3.1 GHz;

RAM: 4 Gb;

Video: AMD Radeon R7 240 / NVidia GeForce GT 740;

DirectX: version 11;

HDD: 10 Gb of free space;

Sound: any sound card compatible with DirectX 9.0;

Controllers: keyboard, mouse;

Internet: constant Internet connection (for license validation).

Recommended system requirements for the Oculus Rift are determined by the equipment manufacturer.

Recommended system configuration:

OS: Windows 7 SP1 / 8 / 8.1 / 10 (64 Bit);

CPU: Intel Core i3 3.2 GHz / AMD FX 4xxx 3.6 GHz;

RAM: 8 Gb;

Video: AMD Radeon R7 250X / NVidia GeForce GTX 750;

DirectX: version 11;

HDD: 10 Gb of free space;

Sound: any sound card compatible with DirectX 9.0;

Controllers: keyboard, mouse, racing wheel;

Internet: constant Internet connection (for license validation).