

A Hybrid Model for Prime Decision Making in Driving

Rabi Mustapha¹, Yuhanis Yusof² and Azizi Ab Aziz¹

¹*Cognitive Artefacts Group, Human-Centred Computing Research Lab*

²*Data Science Research Lab, School of Computing, College of Arts and Sciences,
Universiti Utara Malaysia, 06010 UUM Sintok, Kedah, Malaysia.*

rabichubu@yahoo.com

Abstract—Hybridization can be defined as a method of combining two or more complementary, single stranded models to form a combined model through base pairing. This study proposes a computational hybrid model that combines Recognition Primed Decision (RPD) training and Situation Awareness (SA) model. The model incorporates cognitive factors that will influence the automaticity of the driver to make an effective decision to evaluate the performance of action of the driver during a number of conditions. To illustrate the proposed model, simulation scenarios based on driver's training and awareness have been performed. It is learned that the simulation results are related to the existing concepts that can be found in literatures. Moreover, this model has been verified using an automated verification tool by checking its traces with the existing results from the literature.

Index Terms—Agent Based Model; Automaticity Recognition Primed Decision Model; Computational Model; Situation Awareness Model.

I. INTRODUCTION

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 has the ability to take advantage of different techniques, methods or models combined [1]. The objective of driver training is to remove the barrier between knowledge and the skills required to drive safely and efficiently when commencing training. The knowledge and skills that the driver needs to have must be known, for the training to be appropriate [2]. Also, 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 efficiently establish a collection of well-learned concepts that enable the operator to perform mainly at the skill-based level of processing, while providing adequate knowledge-based foundation to perform well in new situations [3]. Having analyzed this ability, it will provide a good perspective towards driving assistance systems. Based on the review of previous studies [4],[5] on computational recognition prime decision (RPD) and situation awareness (SA) model for driving, it is learned that it has yet to be reported on a model that includes training as one of its component. This type of model is important since training is needed in recognizing situations, in communicating situation assessment, and in acquiring the experience to conduct mental simulation of options through the act of human cognitive unconscious decision making, or automaticity [6],[7]. To address this issue, this paper proposes an agent based model that integrates RPD training and SA

model that includes dynamic factors based on cognitive and psychology theories to describe basic training required by a driver. It explores the effect of environment, expectation, basic practice, basic skills, sensory ability, driver's goal, potential hazardous information and exposure on task complexity on the driver's automaticity to make effective decision which influences the driver's performance of action.

The organization of the remaining part of this paper is as follows. The underlying concepts of automaticity RPD training and SA models are discussed in Section II. The computational hybrid model of automaticity RPD and SA is described in Section III. The employed scenarios and simulation results are described in Section IV and followed by the automated verification in Section V. Finally, Section VI concludes this paper.

II. UNDERLYING CONCEPTS OF AUTOMATICITY RPD TRAINING AND SA MODELS

Recognition Primed Decision (RPD) is defined as “the decision makers draw upon their experience to identify a situation as representative of or similar to a particular class of problem” [8]. 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. Also known for fast decision making, RPD utilizes intuition to be applied to situations quickly in order to arrive at decisions [9]. Hence intuition in a way can said to automatic where by individual can act autonomously known as automaticity. One of the theoretical concepts in automaticity is overlearning information or operations to the point where they can be used or recall with little mental effort is known as automaticity. This concept denotes limited conscious awareness, attention, and control of one's actions, intentions, or psychological processes [10]. Essentially, it requires a learned or conditioned response to stimuli; learning and conditioning, in turn, require rehearsal [11].

Automaticity is developed due to experience and high level of learning (training). At that point, the automatic processing part tends to be fast, autonomous, effortless and unavailable to conscious awareness. This process can be said to be an agent process due to it reflex nature which is said to be autonomous. For example, when behavior is repeated severally it becomes a habit. Therefore, habit is better conceptualized as a form of automaticity which, once formed, need not be defined by repeated performance called habitual or involuntary automaticity [12].

The idea of situation awareness has been recognized as a

significant contributor to the quality of decision-making in computational modeling and in complex, dynamic changing environments. The concept of situation awareness has been discussed in our paper [13]

III. AN AGENT BASED HYBRID MODEL

This section describes the details of the model in mathematical specifications. Varieties of interactions occur between the driver and a dynamic situation in a real-world driving environment. This model is presented in Figure 1. In

this figure it can be seen that the model consist of several interrelated nodes. After the structural relationships in the model have been determined, the models can be formalized. In the formalization, all the nodes are designed in a way to have value ranging from 0 (poor) to 1 (good).

The proposed model consists of several external, instantaneous and temporal factors that are interrelated to each other. The external factors determine the outcome of the whole processes and the relationship is explained in details using the Equations (1)-(19).

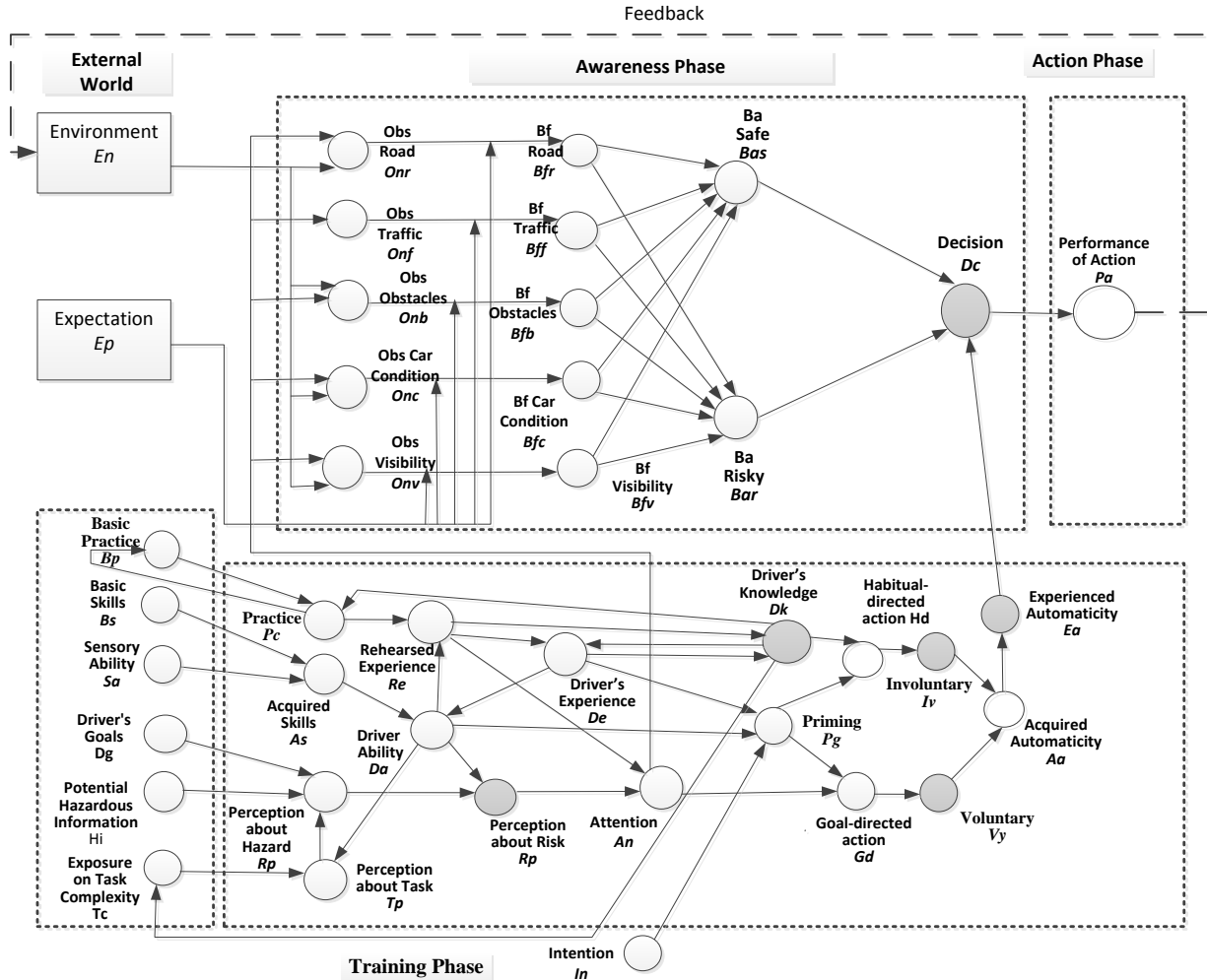


Figure 1: Hybrid Training Model for Driver

The proposed model integrates two models; the automaticity RPD training model and situation awareness model that make it to be hybrid. It also said to be agent based as a result of automaticity which is developed due to experience and training. At that point, the process tends to be automatic. This process can be said to be an agent process due to its reflex nature which is said to be autonomous. The simulation environment for the proposed model is also an agent based that enable the simulation of various scenarios.

The uniqueness of this study is one; it introduces some new concepts (factors) as itemized from literature based on cognitive and psychological theories which are presented in form of symbols, having arrows to show the casual relationships between the concepts (factors). Two; it introduced computational model defined as the mathematical or logical representation of concepts as defined casually in the conceptual model in Figure 1. The computational model

is translated into high level language for easy simulation. The simulation is necessary to see if the simulation scenarios based on the model factors matches the behavior of the agent in the real-life domain. Hence, the computational model can be used to reason out and track back errors easily.

The validity of the proposed model will be achieved using human experiment. Experimental study will be conducted using game simulator to test the effectiveness of the model factors particular to see the effect of training on prime decision making of the driver.

A. Equations

1) Instantaneous Relationships:

Basic practice (Bp) of the driver increased with practice (Pc). That is practice has contributed positively is influenced by basic practice (Bp) and driver's knowledge (Dk).

$$Bp(t) = \beta_{bp} \cdot Bp_{basic}(t) + (1 - \beta_{bp}) \cdot Pc(t) \quad (1)$$

$$Pc(t) = \omega_{pc} \cdot Bp(t) + (1 - \omega_{pc}) \cdot Dk(t) \quad (2)$$

Rehearsed Experience (Re) of the driver is influenced by driver's practice (Pc) and ability (Da) by saying "with continuous practice any knowledge or skill is retained in short term memory and later transfer to long term memory otherwise it will decay". Next, the driver's experience (De) is influenced by rehearsed experience (Re) and driver's knowledge (Dk). The concept of acquired skills (As) is computed by combining driver's basic skills, goals (Dg) and knowledge.

$$Re(t) = \gamma_{re} \cdot Pc(t) + (1 - \gamma_{re}) \cdot Da(t) \quad (3)$$

$$De(t) = \lambda_{de} \cdot Re(t) + (1 - \lambda_{de}) \cdot Dk(t) \quad (4)$$

$$As(t) = \beta_{as} \cdot [w_{as1} \cdot Bs(t) + w_{as2} \cdot Dg(t)] + (1 - \beta_{as}) \cdot Dk(t) \quad (5)$$

In the case of driver's ability (Da), this concept is influenced by the skills acquired and experiences of the driver (De) during the training session. The combination of driver's experience, ability and intention (In) generates priming levels. Perception about hazard (Hp) is determined by combining concepts in driver's sensory ability (Sa), potential hazardous information (Hi) and perception about task (Tp).

$$Da(t) = w_{da1} \cdot De(t) + w_{da2} \cdot As(t) \quad (6)$$

$$Pg(t) = [\xi_{pg} \cdot Da(t) + (1 - \xi_{pg}) \cdot De(t)] \cdot In(t) \quad (7)$$

$$Hp(t) = [w_{hp1} \cdot Sa(t) + w_{hp2} \cdot Tp(t)] \cdot Hi(t) \quad (8)$$

Attention (An) is generated combining a proportional ratio of rehearsed experience (Re) and perception about the risk (Rp). Next, the proportional contribution between exposure on task complexity (Tc) and driver ability (Da) provides a computational concept of perception about task.

$$An(t) = [\xi_{an} \cdot Rp(t) + (1 - \xi_{an}) \cdot Re(t)] \quad (9)$$

$$Tp(t) = [\eta_{tp} \cdot Da(t) + (1 - \eta_{tp}) \cdot Tc(t)] \quad (10)$$

Another important concept is the exposure on task complexity (Tc). This concept is positively correlated with the knowledge of the driver. Habitual-directed action (Hd) is influenced by driver's knowledge (Dk) and priming (Pg). Using the same computational concept as in habitual directed action, priming (Pg) and attention (An) generates goal-directed action (Gd). Similarly, it also the case of acquired automaticity (Aa) as it is influenced by weightage contribution of involuntary (Iv) and voluntary (Vy).

$$Tc(t) = \beta_{tc} \cdot Tc_{basic}(t) + (1 - \beta_{tc}) \cdot Dk(t) \quad (11)$$

$$Hd(t) = w_{hd1} \cdot Pg(t) + w_{hd2} \cdot Dk(t) \quad (12)$$

$$Gd(t) = w_{gd1} \cdot An(t) + w_{gd2} \cdot Pg(t) \quad (13)$$

$$Aa(t) = w_{aa1} \cdot Iv(t) + w_{aa2} \cdot Vy(t) \quad (14)$$

Note that equations (1) to (14) are derived based on the relationship that show the interrelated connectivity of the nodes in the proposed conceptual model in Figure 1. β_{bp} , ω_{pc} , γ_{re} , λ_{de} , β_{as} , ξ_{pg} , ξ_{an} , η_{tp} , β_{tc} are known as proportional parameters. Moreover, w_{as1} , w_{as2} , w_{da1} , w_{da2} , w_{hp1} , w_{hp2} , w_{hd1} , w_{hd2} , w_{gd1} , w_{gd2} , w_{aa1} and w_{aa2} are weight parameters with $\sum w = 1$.

2) Temporal Relationship:

Driver's knowledge (Dk) primarily contributed to the accumulation of rehearsed experience (Re) and driver's experience (De). Perception of the driver about risk (Rp) is influenced by perception of the driver about the hazard (Hp) and driver's ability to handle vehicle (Da), while the involuntary decision (Iv) is contributed through habitual-directed action (Hd). The positive change in goal-directed action (Gd) improves voluntary (Vy) level. Experienced automaticity is influenced by acquired the automaticity of the driver.

$$Dk(t + \Delta t) = Dk(t) + \gamma_{dk} \cdot \left[\left(Pos \left((\omega_{dk1} \cdot Re(t) + \omega_{dk2} \cdot De(t)) - Dk(t) \right) \right) \cdot (1 - Dk(t)) - Pos \left(-(\omega_{dk1} \cdot Re(t) + \omega_{dk2} \cdot De(t)) - Dk(t) - \lambda_{dk} \cdot Dk(t) \right) \right] \cdot \Delta t \quad (15)$$

$$Rp(t + \Delta t) = Rp(t) + \gamma_{rp} \cdot \left[\left(Pos \left((\omega_{rp1} \cdot Hp(t) + \omega_{rp2} \cdot Da(t)) - Rp(t) \right) \right) \cdot (1 - Rp(t)) - Pos \left(-(\omega_{rp1} \cdot Hp(t) + \omega_{rp2} \cdot Da(t)) - Rp(t) - \lambda_{rp} \cdot Rp(t) \right) \right] \cdot \Delta t \quad (16)$$

$$Iv(t + \Delta t) = Iv(t) + \beta_{iv} \cdot \left[\left(Pos \left((Hp(t) - Iv(t)) \right) \right) \cdot (1 - Iv(t)) - Pos \left(-(Hd(t) - Iv(t)) \right) \cdot Iv(t) \right] \cdot \Delta t \quad (17)$$

$$Vy(t + \Delta t) = Vy(t) + \beta_{vy} \cdot \left[\left(Pos \left((Gd(t) - Vy(t)) \right) \right) \cdot (1 - Vy(t)) - Pos \left(-(Gd(t) - Vy(t)) \right) \cdot Vy(t) \right] \cdot \Delta t \quad (18)$$

$$Ea(t + \Delta t) = Ea(t) + \beta_{ea} \cdot \left[\left(Pos \left((Aa(t) - Ea(t)) \right) \right) \cdot (1 - Ea(t)) - Pos \left(-(Aa(t) - Ea(t)) \right) \cdot Ea(t) \right] \cdot \Delta t \quad (19)$$

Note that the equations [15] – [19] are deriving based on the concepts of differential equation. The change process in these equations is measured in a time interval between t and t+Δt. Moreover, the rate of change for all temporal specifications is determined by flexibility rates γ_{dk} , γ_{rp} , β_{iv} , β_{vy} and β_{ea} which are change rate parameters. The derivation of all the equations in this paper follows the same concepts used in our paper [13] and other papers [14], [15]. A simulator was developed using all defined formulas for experiment purposes; precisely to explore interesting patterns and traces that explains the behavior of driver agent model

related automaticity.

IV. SIMULATION RESULTS

This section illustrates the mechanism of the proposed model whereby three scenarios were simulated using fictional driver’s conditions as shown in Table 1. The simulations conditions are based on the input values of 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*) where 0 means poor and 1 means good for those inputs. We also have the input values based on of the five input factors conditions (*road, traffic, obstacles, car condition and visibility*) of the awareness model where 1 means good and 0 means bad for all the awareness input factor conditions except obstacle. In this simulation, we used the following settings: ($0 \leq t \leq 500$) with $t_{max} = 500$ (to represent a set of training activities of the driver up to eight months). In each time step, it denotes the time range for the training, where 1 time step represents 5 hours of training.

The parameters are as follows; $\Delta t = 0.1$, $\lambda = 0.01$. All proportional and flexibility rates equal to 0.8.

Table 1
The hybrid Training Model Conditions

Scenarios	Training conditions				Description
#1	1110111	1111011	1111111	11011	More training and less awareness.
#2	1110011	1110110	01011	10011	Equal proportion of training and awareness.
#3	1110101	00011	11111	11001	Less training and more awareness.

These settings were obtained from a number of experiments to determine the most appropriate parameter values for the model. The simulation results for three scenarios are shown in Figure 2, Figure 3 and Figure 4 respectively.

A. Scenario #1: Long-Term Training

In scenario 1, Figure 2(a) depicts that the driver’s level of perception about risk is increased with the 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 is eventually increased again due to good driving condition and skillfulness of the driver. Figure 2(b) provides an insight of driver’s experienced automaticity level through the exposure in a long-term training which leads to high confidence level to make decision. Figure 2(c) relates that long-term training leads to high performance of action by the driver.

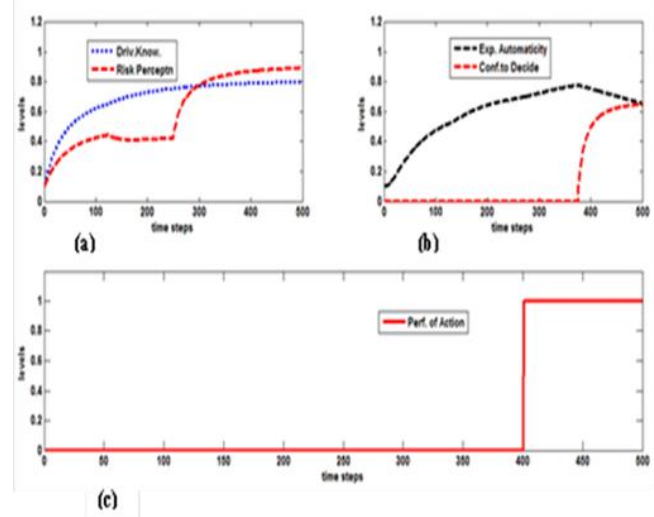


Figure 2: Simulation Conditions Result (for scenario 1)

B. Scenario #2: Medium-Term Training

In scenario 2, Figure 3(a) visualized that the driver’s level of perception about risk increased with proportional increased in driver’s knowledge but the driver’s level of perception about risk decreased a bit to certain level due to the effect of driver’s low level of potential hazardous information in the traffic environment and eventually increased and became stable due to skillfulness of the driver and other good driving conditions.

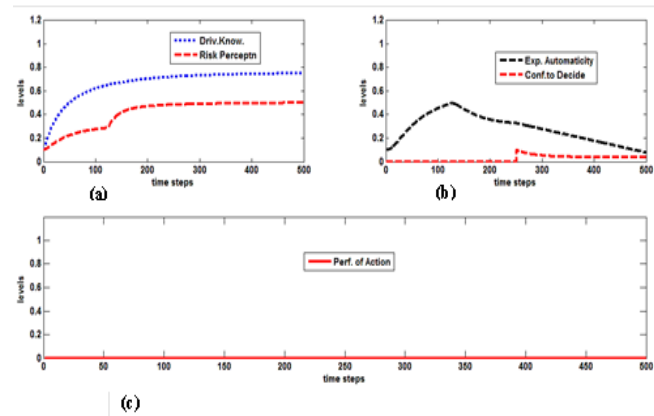


Figure 3: Simulation Conditions Result (for scenario 3)

Another result (decreasing automaticity), as a result of short period of training which lead to low confidence level to make decision has been visualized in Figure 3(b). Figure 3(c) provides a visual representation of driver’s low performance as a result of short period of training.

C. Scenario #3: Short-Term Training

In scenario 3, Figure 4(a) indicated that the driver’s level of perception about risk increased with proportional increase in driver’s knowledge to certain level and eventually decreased drastically due to very short period of training.

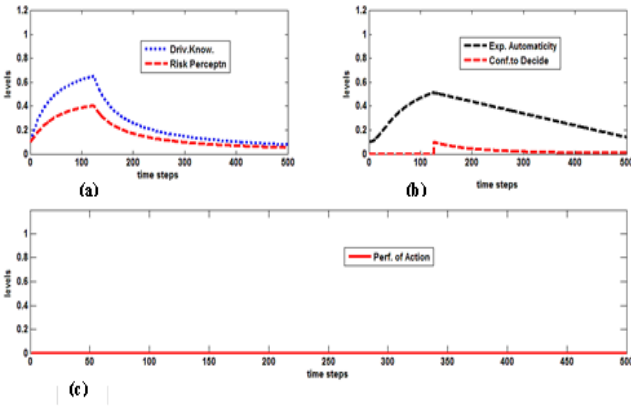


Figure 4: Simulation Conditions Result (for scenario 3)

Result in Figure 4(b) indicated that driver experienced automaticity level decreased with very short period of training which leads to very low confidence level to make decision. Result in Figure 4(c) indicated that very short period of training leads to lower performance of action by the driver.

V. AUTOMATED VERIFICATION

In order to verify whether the model produces results that adhered to the literatures, a set of 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 [16]. This relationship can be presented as holds (state $(\gamma, t), p$) or state $(\gamma, t) = p$, which means that state property p is true in the state of trace γ at time point t . 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, by using quantifiers over time and traces and first-order logical connectives such as $\neg, \wedge, \vee, \Rightarrow, \forall$ and \exists .

A. VP1: The Automaticity Level of the Driver Decreased With Decreased In Practice and Experience

If the driver has low practice time and experience levels, it reduces the automaticity level [10].

$VP1 \equiv \forall \gamma: \text{TRACE}, \forall t1, t2: \text{TIME}, \forall R1, R2, P1, P2, D1, D2: \text{REAL}$

$[\text{state}(\gamma, t1) = \text{has_value}(\text{practice_level}, R1) \& \text{state}(\gamma, t2) = \text{has_value}(\text{practice_level}, R2) \& \text{state}(\gamma, t1) = \text{has_value}(\text{experience_level}, P1) \& \text{state}(\gamma, t2) = \text{has_value}(\text{experience_level}, P2) \& \text{state}(\gamma, t1) = \text{has_value}(\text{automaticity}, D1) \& \text{state}(\gamma, t2) = \text{has_value}(\text{automaticity}, D2) \& t1 < t2 \& R2 > R1 \& P2 > P1] \Rightarrow D1 \geq D2$

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

For all time points $t1$ and $t2$ between t_b and t_e 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 $x2 \geq x1$

$VP4 \equiv \forall \gamma: \text{TRACE}, \forall t1, t2: \text{TIME}, \forall X1, X2: \text{REAL}$

$[\text{state}(\gamma, t1) = \text{has_value}(v, X1) \& \text{state}(\gamma, t2) = \text{has_value}(v, X2) \& t_b \leq t1 \leq t_e \& t_b \leq t2 \leq t_e \Rightarrow x2 \geq x1$

C. VP3: Higher Attention Increases Voluntary Action

Individual's attention is related to the improved voluntary action [11, 12].

$VP2 \equiv \forall \gamma: \text{TRACE}, \forall t1, t2: \text{TIME}, \forall F1, F2, H1, H2, d: \text{REAL}$

$[\text{state}(\gamma, t1) = \text{attention}(F1) \& \text{state}(\gamma, t1) = \text{voluntary}(H1) \& \text{state}(\gamma, t2) = \text{attention}(F2) \& \text{state}(\gamma, t2) = \text{voluntary}(H2) \& t2 \geq t1 + d \& F1 > 0.6 \& F1 < F2] \Rightarrow H2 > H1$

VI. CONCLUSION

This paper proposed a computational hybrid training model to train drivers in order to enhance their decision making. The model was formalized and simulated based on scenarios to evaluate the applicability of the model in real life. It has pointed out that the simulation results are related to the existing concepts that can be found in literatures. It has also shown that, for the given scenarios that the external factors have effect particularly on the automaticity of the driver to make effective decision which influences the driver's performance of action. Lastly, the verification of the model has also been presented.

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