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Full Length Research Article

VALIDATING MEASURES OF DRIVER BEHAVIOR'S TRAINING FACTORS FOR PRIME DECISION-MAKING

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ABSTRACT
This paper validates the Driver Behavior's Training Instrument (BDTI) for measuring training factors that influence prime decision-making in a driving domain. First, the training factors were developed to evaluate Computational Rabi's Driver Training (C-RDT) model for prime decision-making in driving. In order to validate the model, a three-phase validation method has been used in this paper. In the first phase, items were generated from the literature to measure driver behavior's training factors. In the 2nd phase, 4 academic experts and 3 experts from a driving institution were consulted for face and content validity. A Content Validity Index (CVI) of both the items-level and the scale-level CVIs was conducted from the ratings of the seven (7) experts. Finally, the items were subjected to a reliability test and an Exploratory Factor Analysis (EFA) with Varimax rotation in the 3rd phase. The findings presented in this study revealed 10 valid scales for measuring driver behavior's training factors namely; basic skills, basic practice, sensory ability, driving goal, driving intention, potential hazardous information, exposure to task complexity, perception about risk, driving knowledge, and involuntary/voluntary automaticity. The scales validated in this paper should assist other model developers; particularly driver behavior's training modelers to validate their factors for prime decision-making. In literature the measures of driver behavior and training factors that influence drivers' prime decision are limited. Hence, this paper considers the validation of driver behavior's training instrument that measures the training factors for prime decision-making important.

Keywords: DBTI, Development, Training factors, Prime Decision-Making, Driver Training, Driving

1. Introduction

Driving a car involves a constant process of perception, understanding, action choice, and action execution (Inagaki, 2011; Inagaki & Itoh, 2013). Error in situation recognition may occur while driving a car, and the error can sometimes result in an 'erroneous' behaviour of the driver (Inagaki, 2011). Human errors such as from driver's distraction, over speeding due to driver's fatigue, unnecessary overtaking etc. have been observed as major causative factors of road accidents (Mashadi & Majidi, 2014; Salmon et al., 2017).

Moreover, road accident is one of the causes of death of young persons in the globe (ages from 15 to 29 years) and the 8th leading cause of death (World Health Organization, 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).

In addition to fatality rate, less severe injuries occur that leads to disabilities. The Road traffic injuries place a huge strain on health care services in terms of financial resources, bed occupancy and demand placed on health professionals (Phanindra & Chaitanya, 2016). The total number of road traffic deaths worldwide and injuries is forecasted to rise by 65% between 2000 and 2020 without extra efforts and novel initiatives and in low-income and middle-income countries the deaths are expected to rise by as much as 80% (WHO, 2017).

Hence, driver training is essential to improve on the knowledge and the skills required to drive safely and efficiently. The knowledge and skills that the driver needs to have must be known for the training to be appropriate (Vegvesen, 2014). The objective of driver training for critical decision making is to provide the driver with experiences and instruction on cues, patterns, mental models, and actions that efficiently establish a collection of well-learned concepts that enable the driver 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). Having analysed this ability, it will provide a good perspective towards safety driving. Training is also essential in recognizing situations, in communicating situation assessment of the driver in the driving environment, and in acquiring the experience to conduct mental simulation of options through the act of human cognitive unconscious decision-making, or automaticity (Orasanu & Connolly, 1993; Klein, 2008). The driver training is modelled to predict the behaviour of the driver in making a prime decision.

Literature review has shown that there is Driver Behaviour Questionnaire as a predictor of road traffic crashes (af Wåhlberg et al., 2011). However, there is no driver behaviour training instrument that measures the training level of the driver in order to make prime decision particularly during demanding situations. Hence, this paper considers this as a challenge to develop the DBTI to overcome the challenge. The Instrument consist of 10 factors (constructs), namely basic skills, basic practice, sensory ability, driving goal, driving intention, potential hazardous information, exposure to task complexity, perception about risk, driving knowledge, and involuntary automaticity/voluntary automaticity with each factor having items that measure them. The total number of items in the factors measured is sixty-seven (67).

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The training instrument proposed in this paper is to measure training factors that influence prime decision-making as discussed in our previous studies, the Automaticity Recognition-Primed Decision training model (ARPDT), Situation Awareness (SA) model for decision making in driving and the hybrid model for Prime Decision Making in driving (Mustapha et al., 2016, 2017a, 2017b, 2018).

The instrument presented is also used to measure training factors of the C-RDT model that influence prime decision-making particularly in driving domain. That is the model validation. The instrument integrates related dynamic factors based on cognitive theories such as Situation Awareness and Naturalistic Decision Making to describe basic training required by a driver.

The organization of the remaining part of this paper is as follows. The method of developing the instrument for C-RDT model is described in section 2, followed by the findings of the instrument development and then the conclusion of the study.

2. METHOD

The Computational-Rabi's Driver Training (C-RDT) model (Mustapha et al., 2019) is an enhancement of the Integrated Decision-making Model (IDM) developed by Noyes et al., (2012), which includes improvement on RPD component of the IDM. The C-RDT includes 18 additional training factors obtained from cognitive theories that make a total of 24 training factors that facilitate driver's prime decision-making during emergencies. The designed model is realized by identifying factors for prime decision-making in driving domain and designing the conceptual model of the Rabi's Driver Training (RDT) model and formalizing it using differential equation. Hence, from the conceptual model in Fig. 1. It can be seen that the model is divided into two part the awareness and the training phase. The factors obtained from the awareness phase is based on situation awareness model (Endsley, 2016) and that of the training phase is based on Recognition prime decision model (Klein, 2008). The factors are called training factors because they are main for training in order to enhance prime decision-making particularly during emergency for example in driving domain such as panic stop in traffic and sudden swerving to another direction during driving to avoid accident.

The model was developed based on the methodology frame work adapted from (Drogoul et al., 2002). Hence, this methodology has been used in an agent-based modeling research in various domains such as in economics (Luna & Stefansson, 2012), social behavior (Conte & Paolucci, 2014), environment (Serrano et al., 2014), medicine (Wang et al., 2015) and energy consumption (Rai and Robinson, 2015). The methodology has five different stages including domain, design, operational, simulation and evaluation as shown in Fig. 2. The detail explanation of this methodology is given as follows.

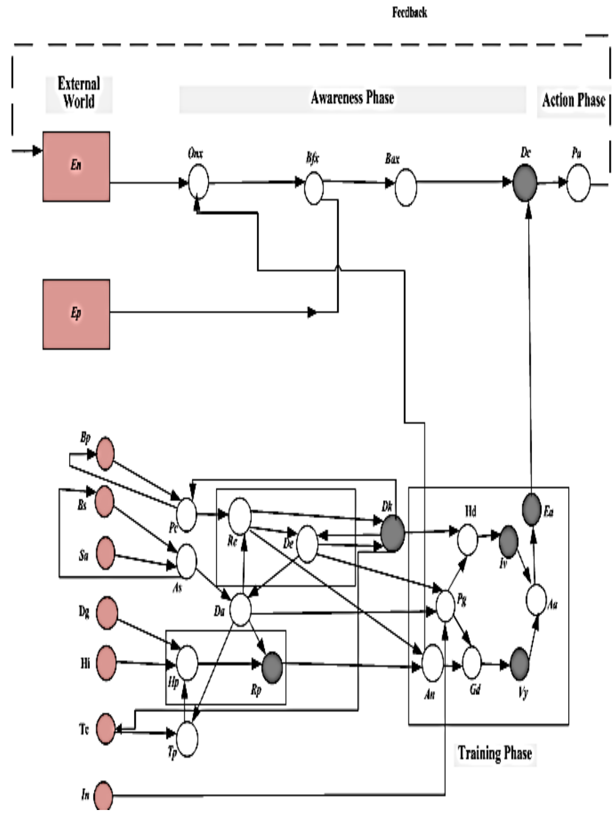

Fig.1: Generic RDT model for Prime Decision-Making

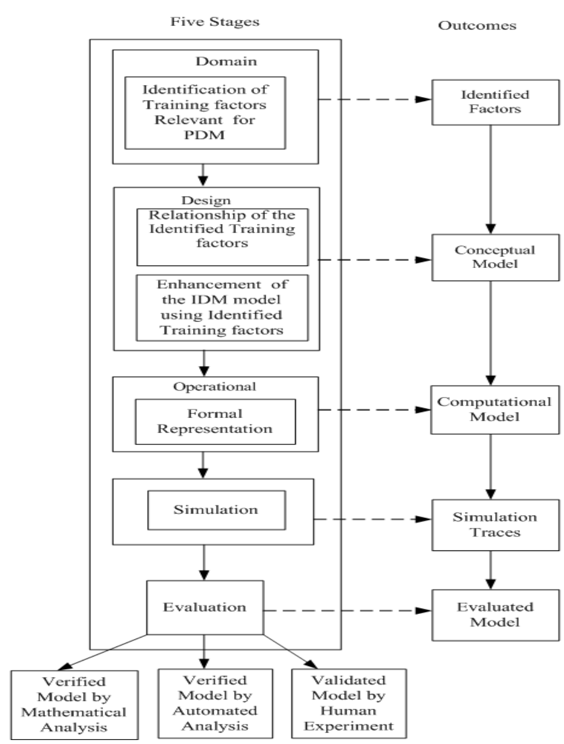

Fig.2: Methodology Framework from Drogoul et al. (2002)

2.1 Domain 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, internet and library resources were utilized to review the relevant literatures from experts in the respective domains, such as experts in the domains of cognitive and computational sciences.

2.2 Design Stage

At this stage, the eighteen (18) training factors of the C-RDT model including Basic Practice, Practice, Basic Skills, Acquired skills, Sensory Ability, Driver Abilities, Rehearsed Experience, Attention, Priming, Habitual-direction action, Goal-directed action, Involuntary automaticity, Voluntary automaticity, Acquired automaticity, Experienced automaticity, Potential hazardous information, Perception about task and Perception about Risk were obtained by expanding some of the IDM factors (Noyes et al, 2012). Then identified other factors from SA model and other related literatures are all combined together to enhance the RPD component of the IDM model see (Mustapha et al., 2019). 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. 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 activities in the design model followed the process used by Bosse et al. (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 Fig. 3. 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.

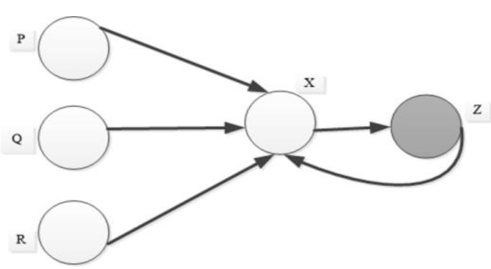

Fig.3: Example of Design Model

From Fig. 3, 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 (external) and instantaneous factors. It is indicated with gray color.

2.3 Operational Stage

At this stage, the conceptual model obtained from the design model is formalized. From Fig. 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 (2016) and Naturalistic Decision Making (Klein, 2008). The equations are generated from the relationship of the factors (P,Q, R and X) and for this purpose, it can be assumed that if equations 1 and 2 are non-zero or not equal to one, then the concepts conditions stated in Table 1, can be formalized (Computerized) to gain equations 2 and 3. Assuming Z is the combination of the four factors as can be seen in Fig. 3.

Table 1: Example of Different Condition of X

Conditions	Values of Factors	Value of Z	Description
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.
2	*P* = Low Q = High *R* = Low *X* = High	*Z* = Moderate	
3	*P* = Low Q = Low *R* = Low *X* =Low	*Z* = Low	

Table 1 is describing the implementation concepts of the equations in a simulation environment that is MATLAB environment. The table is generated based on figure 3, where it is stated that P, Q, and R are external factors, X is the instantaneous and Z is the temporal factor. Factors in this study is analogous to variables in social science research. The external factors are independent variables (I. V's) that determines the outcome of the whole process, they are independent factors that contribute to other factors; in case of this relationship in figure 3, it contributes to X.

X being the instantaneous factor is known as the mediator; it is dependent factor that are time-bounded with fast response time. This is contrary to the temporal factor (Z) also known as the dependent variable (D. V) that is time-bounded with much delay in the execution process.

More so, in table three, conditions were given and for each condition the relationship between the external and the instantaneous factors were measured based on logical values (0-1). 0 means low and 1 means high. This is to determine the value of the temporal factor (Z) and *Z* will be high if and only if *P*, *Q*, *R* and *X* are high or any of the three are high and vice versa.

$$Z = f\,[P, Q, R, X] \qquad (1)$$

Where

$0 \leq P \leq 1, 0 \leq Q \leq 1, 0 \leq R \leq 1, 0 \leq X \leq 1$

and $0 \leq Z \leq 1$

$$X(t) = \omega x1.P(t) + \omega x2.Q(t) + \omega x3.R(t) + \omega x4.Z(t)X(t) = \omega_{x1}.P(t) + \omega_{x2}.Q(t) + \omega_{x3}.R(t) + \omega_{x4}.Z(t) \qquad (2)$$

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

Where,

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

$$Z(t + \Delta t) = Z(t) + \gamma_z \cdot (X(t) - Z(t)).Z(t).(1 - Z(t)).\Delta t \qquad (3)$$

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Equation 3, were obtained based on the concepts of the differential equation (DE). The change process in these equations is "measured in a time interval between *t* and *t*+Δ*t*. Moreover, the rate of change for all temporal specifications is determined by flexibility rates" of γ_Z, which is the change rate parameters. And $(1 - Z(t))$ are regulating function in the equation that regulate the equations. It can be depicted that *Z* will be high if at least three variables from this equation are high.
Table 1 describes the implemented concepts in a simulation environment. The procedure for the simulation is explained next.

2.4 Simulation Stage

The simulation is implemented in a numerical simulation environment and then verified by selected testing procedures. 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 model development to prove it correctness.
To achieve the simulation result, 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.
For example, the simulation traces for equations 2 and 3 using the combinations of factors values in Table 2 can be demonstrated using only the high and low values as depicted in Fig. 4 and Fig. 5. 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 2: Sample 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

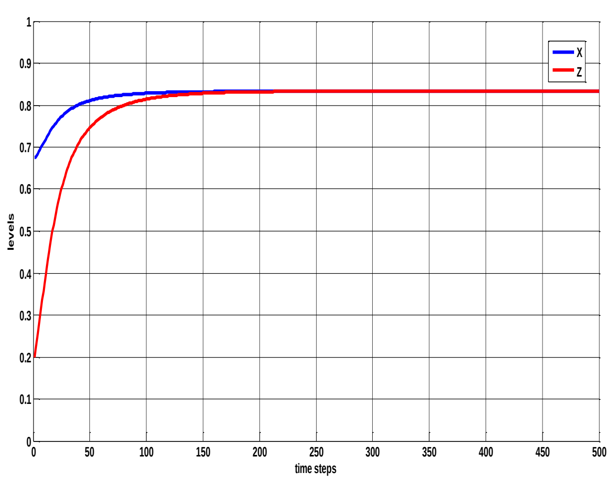

Fig.4: Simulation Traces showing a High Condition for X and Z.

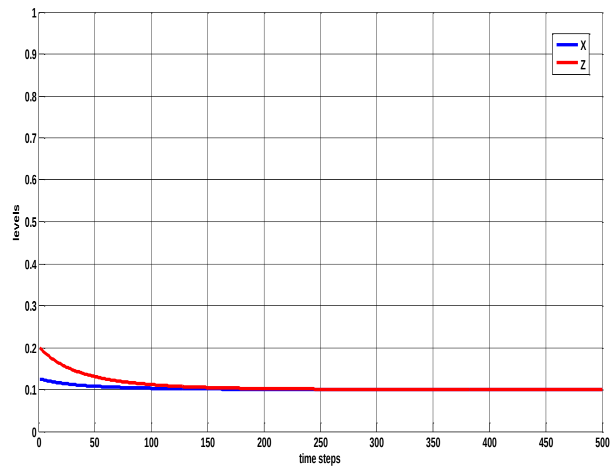

Fig.5: Simulation Traces for Low Condition in X and Z.

From Fig. 4 it can be seen that the combinations of *P, Q*, R and Z provide a simulation traces that shows a scenario stabilizes at high values as shown in Table 2.

The low condition of *X* and *Z* is depicted in Fig. 5 that shows the simulation traces as a result of combinations of low values of *P, Q*, and *R* (as presented in Table 2).

2.5 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 Fig. 6.

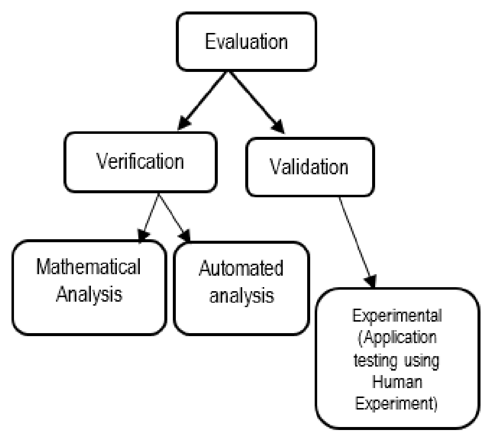

Fig.6: Evaluation Stage Activities

In order to validate the model, a three-phase validation method has been used thus; first phase, items were generated from previous studies to measure driver behavior's training factors. In the second phase, 4 academic experts and 3 experts from a driving institution were consulted for face and content validity. In the first phase, studies on prime decision-making model for drivers were reviewed. Subsequently, eight (8) items were generated for measuring basic skills, 12 items were generated for sensory ability from Lajunen and Summala, (1995), Cox et al. (2012) and Patrick (2016). Also, 10 items related to visual ability were generated from Vision and Night

Driving scale (Kimlin, 2016). For perception about risk, 11 items were generated from Rosenbloom et al. (2008). Also, four items for measuring involuntary/Voluntary automaticity were pulled from Verplanken & Orbell (2003) and Panek et al. (2015). Other items that measure training factors were also generated such as basic practice (Tajvar et al., 2015), driving goal (Dogan et al., 2011), driving intention (Moskowitz, 2001), potential hazardous information (Konishi, 2004; Takahashi, 2007; Crundall, 2012; Huestegge & Böckler, 2016), exposure on task complexity (Grill, 2012) and driving knowledge (OKafor et al., 2013; Phanindra & Chaitanya, 2016).

In phase 2, the generated items were given to, four (4) academic experts and three (3) experts from a driving institution making a total of 7 experts recruited for the face and content validities. According to Polit et al. (2007), calculating CVI from the ratings of 7 experts is appropriate because more than 10 experts are considered unnecessary. The experts were requested to make inputs and corrections with regard to ambiguities, format, wording, simplicity and clarity of the items (Yaghmaei, 2003). Also, the experts were required to rate the items based on their relevance with the constructs they were proposed to measure. The experts were provided a 4-point scale using the following labels namely; 1 = “not relevant”, 2 = “somewhat relevant”, 3 = “quite relevant” and 4 = “highly relevant”. Lastly, the experts were provided two types of comment boxes to provide additional comments on the items and on the overall scale.

Finally, in the third phase, the internal consistency of the scale and convergent validity was assessed. As such, a survey was conducted among a convenient sample of 200 experienced drivers. A total number of 151 usable responses were obtained and analyzed using SPSS. The respondents were requested to rate the importance of each items for the driver behavior’s training factors. The study following the approach employed by Son et al. (2016), Karstoft et al. (2017) and Sung et al. (2017) adapted the use of an eleven-point-likert scale for the best validity of the scale. The rating of the scale is from (0-10), with (0-5) indicating Low and (6-10) indicating High, was used to record the ratings of the respondents. In each case, low means poor/bad decision while high means good/correct decision.

3. Findings

3.1 Content Validity Index (CVI) for Items and Scales

The validity of the items and the scales for driver behavior’s training factors were examined by calculating the CVI of both the items-level and the scale-level CVIs from the ratings of seven (7) experts (Polit et al, 2007). The item-level CVI evince the validity of the items while the scale-level CVI signifies the validity of the scale. The item-level CVI is calculated by converting both 1= “not relevant” and 2 = “somewhat relevant” ratings to 0 and 3 “quite relevant” and 4 “highly relevant” to 1. Thus, every 1 and 2 ratings from the experts are counted as 0 and every 3 and 4 ratings are counted as 1. The total number of items rated relevant is divided by the total number of raters (7 in the case of this research). According to Polit et al. (2007) an acceptable Item-Level CVI for raters more than six is 0.83. The results of the Item-Level CVI calculations were used for deleting items that were rated not relevant. Appendix A shows the results of the Item-Level CVI. The results showed that majority of the items scored 0.85 and above. The items that scored lower than 0.85 were deleted from the scales. Following this procedure, no item was deleted, which is an indication that the items are relevant for measuring the variables they are measuring.

Additionally, for the calculation of Scale-Level CVI, Polit et al. (2007) suggested using the average of the Item-Level CVI for calculating Scale-Level CVI. Thus, Scale-Level CVI is calculated by the mean of every item rated relevant divided by the total number of items. An acceptable Scale-Level CVI according to Polit et al. (2007) is 0.90. The results presented in Appendix A show that all the scales have Scale-Level CVIs more than 0.90, indicating a content validity of the overall scales. Furthermore, to examine the face validity, the 7 experts were requested to comment and make suggestions on how to improve the clarity of the items by suggesting better synonyms to certain technical words, so as to eradicate ambiguous wordings. This prompted some re-wording and paraphrasing of the wordings in the scales, which helped improve the clarity of the scales.

3.2 Exploratory Factor Analysis (EFA)

EFA was conducted in this study to validate the items in the proposed scales. This procedure allowed the data to statistically load on factors that were related in any initial or priori assumptions that guided the development of the scale (Field, 2013; Raji et al., 2018). According to Pallant (2013), there are two prerequisite issues that are considered important when conducting a factor analysis. First is the sample size, which needs to be more than 150 before considering a factor analysis, therefore, a sample size of 151 is considered adequate for factor analysis. Second is the inter-correlation between the items before considering a factor analysis. Regarding the inter-correlation between items, Pallant (2013) added that this is to ensure using Bartlett’s test of sphericity and the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy. Hair et al. (2013) stated that the KMO value of 0.90 is marvelous, 0.80 is meritorious, 0.70 is middling, 0.60 is mediocre; 0.50 is acceptable but miserable; and below 0.50 is unacceptable. In order to be safe, he suggest that KMO values must exceed 0.50 to be considered fit for factor analysis, otherwise, the researcher would either need to collect more data and/or include more variables (Hair et al., 2013). In addition, the result of Bartlett’s test of sphericity must be significant ($p < 0.05$) before proceeding with factor analysis. In determining the adequacy of sample size, the KMO and Bartlett tests were first applied. The result presented in Table 3 indicates the KMO value for involuntary / voluntary automaticity is 0.598 which is acceptable but miserable; for sensory ability is 0.676 indicating mediocre; for exposure on task complexity is 0.750 indicating middling; basic skills is 0.810, basic practice is 0.812, perception about risk is 0.867, and driving knowledge is 0.823. The last four mentioned values indicated level of sample adequacy (Hair et al., 2013), and thus factor analysis was deemed to be appropriate for this data. Furthermore, Table 3 presented the output of Bartlett’s test and the KMO values for each of the factors. The results confirm the existence of some relationship between the items measuring each of the ten driver behavior’s training factors namely; basic skills, basic practice, sensory ability, driving goal, driving intention, potential hazardous information, exposure to task complexity, perception about risk, and involuntary/ voluntary automaticity.

Table 3**:** KMO and Bartlett's Test

Factors	Kaiser-Meyer-Olkin Measure of Sampling Adequacy	Approx. Chi-Square	Bartlett's Test of Sphericity	
			df	Sig.
Basic Skills	.810	488.945	15	.000
Basic Practice	.812	954.690	28	.000
Sensory Ability	.676	630.296	28	.000
Driver's Goal	.676	630.296	28	.000
Driver's Intention	.694	693.411	36	.000
Potential Hazardous Information	.602	344.058	6	.000
Exposure on Task Complexity	.750	993.279	28	.000
Risk Perception	.867	738.232	28	.000
Driving Knowledge	.823	427.867	6	.000
Involuntary/Voluntary Automaticity	.598	193.393	6	.000

After confirming the necessary criteria for conducting factor analysis, a Principal Component Analysis (PCA) with Viramix rotation was performed on the training factors that influence Prime Decision-Making. Applying the latent root criterion, only the factors that accounted for the variance of at least a single variable were considered for retention (Hair et al., 2013). From the 67 items that measured Prime Decision-Making, 56 items have a factor loading above 0.50 as presented in Appendix B. The result reveals that in some of the factors some items were deleted for example in basic skills 2 items, basic practice 1 item, sensory ability 5 items and perception about risk 3 items due to low loading below 0.50.

Subsequently, the internal consistency of the items measuring the driver behavior's training factors was examined. Appendix B shows that the Cronbach's Alpha value for the pilot test was 0.754 – 0.996. According to Hair et al. (2013) the threshold for acceptable Cronbach's Alpha value is 0.70. Based on the result presented in Appendix B, the least Cronbach's Alpha value is 0.754 for basic practice which is above the suggested threshold. Therefore, no amendment is required in the questionnaire and the 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.

4. **Conclusion**

In this study, ten (10) training factors are used with each having items to measure prime decision-making of a driver particularly during emergency. For example in a driving domain such as; panic stop in a traffic and sudden swerving to another direction to avoid an accident.

The scale also explores the importance of those factors in providing useful and reliable information to drivers and improving the prime decision-making skills of the driver which is an important tool in preventing the number of accidents on the road. The main purpose of these scales is to measure the driver behavior's training instruments as in C-RDT model that determines the prime decision-making of the driver.

In a nutshell, this study validates 10 scales measuring driver behavior's training factors with acceptable values of reliability and validity. Though, because these scales are still undergoing development, further validation, most especially by assessing their psychometric properties through Confirmatory Factor Analysis (CFA) using Structural Equation Modeling (SEM) is on-going. The implications of validating these scales is that it should assist model developers particularly driver behavior training modelers that focus on the training factors influencing prime decision-making.

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Appendix A**:** Items and Scales Level CVIs for Measuring Training Factors that influence Prime Decision-Making

	Experts							
Items	1	2	3	4	5	6	7	Item-Level CVI
Basic Skills								
Maintaining lane positioning	4	4	1	3	4	4	3	6/7=0.85
Turning	4	4	4	3	4	4	3	7/7=1.00
Speed control	4	4	4	3	4	4	3	7/7=1.00
Braking	4	4	4	3	4	4	3	7/7=1.00
Use of turn signals	4	4	4	3	4	4	3	7/7=1.00
Use of mirrors	4	4	4	3	4	4	3	7/7=1.00
Controlling the steering wheel	4	4	4	3	4	4	3	7/7=1.00
Gear selection in operating manual /automatic car	4	4	4	3	4	3	3	7/7=1.00
Scale-Level CVI	1	1	0.87	1	1	1	1	S-CVI/Ave = 6.87/7= 0.98
Basic Practice								
Holding the steering wheel while driving?	4	4	4	3	4	4	2	6/7=0.85
Looking into the side mirrors while overtaking another car?	4	4	4	3	3	4	4	7/7=1.00
Driving between the lines?	4	4	4	3	4	4	2	6/7=0.85
Using the signal lights while turning?	4	4	4	3	4	4	2	6/7=0.85
Driving a car in reverse?	4	4	4	3	4	4	3	7/7=1.00
Turning in prohibited areas (e.g., no U-Turn)?	4	4	4	3	4	4	3	7/7=1.00
Stopping in prohibited areas (e.g. Roundabout, four-way intersection or crossroad)?	4	4	4	3	4	4	3	7/7=1.00
The use of seat belt while driving?	4	4	4	3	4	4	2	6/7=0.85
Driving within the speed limit?	4	4	4	3	4	4	1	6/7=0.85
Scale-Level CVI	1	1	1	1	1	1	0.4	S-CVI/Ave = 6.4/7= 0.91
Sensory Ability								
Seeing dark coloured cars when driving at night?	4	4	4	3	4	4	1	6/7=0.85
Seeing pedestrians on the road side when driving at night?	4	4	4	3	4	4	3	7/7=1.00
Seeing pedestrians on the road side when driving in a day time?	4	4	4	3	4	4	1	6/7=0.85
Reading street signs when driving at night?	4	4	4	3	4	4	4	7/7=1.00
Reading street signs when driving in a day time?	4	4	4	3	4	4	3	7/7=1.00
Seeing the road due to oncoming headlights when driving at night?	4	4	4	3	4	4	3	7/7=1.00
Seeing the road due to oncoming headlights when driving in a day time?	4	4	4	3	4	4	2	6/7=0.85
Seeing the road in rain when driving at night?	4	4	4	3	4	4	2	6/7=0.85
Seeing the road in rain when driving in a day time?	4	4	4	4	4	3	4	7/7=1.00
How often are you distracted by:								
Eating/drinking while driving?	4	4	3	4	4	4	3	7/7=1.00
Read roadside advertisements?	4	3	3	4	4	4	1	6/7=0.85
Daydream?	3	3	3	4	4	3	2	6/7=0.85
Scale-Level CVI	1	1	1	1	1	1	0.5	S-CVI/Ave = 6.5/7= 0.92

Driver's Goal								
Safety goal (i.e. Making sure of your safety and safety of others).	4	4	4	3	4	4	3	7/7=1.00
Time goal (i.e. Making sure you reach your destination on time).	4	4	4	3	4	4	3	7/7=1.00
Avoiding traffic violation.	4	4	4	3	4	4	3	7/7=1.00
Scale-Level CVI	1	1	1	1	1	1	1	S-CVI/Ave = 7/7 = 1.00
Driver's Intention								
Safety goal.	4	2	4	3	4	4	4	6/7=0.85
Time goal.	4	3	4	3	4	4	3	7/7=1.00
Avoiding traffic violation.	4	4	4	3	4	4	4	7/7=1.00
Scale-Level CVI	1	0.85	1	1	1	1	1	S-CVI/Ave = 6.85/7= 0.97
Potential Hazardous Information								
Car stopping at the Pedestrian Crossing?	4	4	4	3	4	4	2	6/7=0.85
Curves (or bend) on the road?	4	4	4	3	4	4	3	7/7=1.00
Other cars driving in front of you?	4	4	4	3	4	4	4	7/7=1.00
Pedestrian crossing the road in a wrong place?	4	4	4	4	4	4	3	7/7=1.00
Scale-Level CVI	1	1	1	1	1	1	0.85	S-CVI/Ave = 6.85/7= 0.97
Exposure on Task Complexity								
Accelerating when approaching a flickering green light?	1	4	4	3	4	4	3	6/7=0.85
Activating a direction indicator when negotiating a bend?	4	4	4	3	4	4	3	7/7=1.00
Braking by slowing down before negotiating roundabout	4	4	4	3	4	4	3	7/7=1.00
Emergency braking when another car pull into driver's path	4	4	4	3	4	4	3	7/7=1.00
Changing gear when reducing the car speed.	4	4	4	3	4	4	3	7/7=1.00
Check surrounding for unsafe situations.	4	4	4	3	4	4	3	7/7=1.00
Maintain lane in traffic.	4	4	4	3	4	4	3	7/7=1.00
Controlling the steering wheel.	4	4	4	3	4	3	3	7/7=1.00
Scale-Level CVI	0.85	1	1	1	1	1	1	S-CVI/Ave = 6.85/7= 0.97
Risk Perception								
Driving at night?	4	4	4	3	4	4	3	7/7=1.00
Bypassing slow car through the left hand side instead of the right hand side?	4	4	4	3	4	4	3	7/7=1.00
Pulling over the road way (getting on and off lower road shoulder)?	4	4	4	3	4	4	3	7/7=1.00
Driving in a city at a speed above the speed limit?	4	4	4	3	4	4	1	6/7=0.85
Bypassing when you are hidden by a truck and have no good vision of the car coming in front of you?	4	4	4	3	4	4	3	7/7=1.00
Losing control over the car while driving on a wet and slippery road?	4	4	4	3	4	4	2	6/7=0.85
Losing control over the car while driving on a dry road?	4	4	4	3	4	4	3	7/7=1.00
Backward driving (reverse) when there are blind sights?	4	4	4	3	4	3	3	7/7=1.00
Backward driving (reverse) when there are no blind sights?	4	4	4	3	4	4	4	7/7=1.00
Sudden braking?	4	4	4	3	4	4	1	6/7=0.85
Challenged-driving aimed at testing your driving abilities?	4	4	4	3	4	3	3	7/7=1.00
Scale-Level CVI	1	1	1	1	1	1	0.72	S-CVI/Ave = 6.72/7= 0.96
Driving Knowledge								
Road signs?	4	4	4	3	4	4	2	6/7=0.85
Use of maximum speed limits driving in a city?	4	4	4	3	4	4	3	7/7=1.00
Traffic rules and regulations?	4	4	4	3	4	4	4	7/7=1.00
Road markings?	4	4	4	4	4	4	3	7/7=1.00
Scale-Level CVI	1	1	1	1	1	1	0.85	S-CVI/Ave = 6.85/7= 0.97
Involuntary/Voluntary Automaticity								

Sudden swerve to another direction without thinking (e.g. when another car swerved in front of my car while driving.)?	4	4	1	3	4	4	4	6/7=0.85
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.)?	4	4	4	3	4	4	3	7/7=1.00
Do change lane without meaning to do it?	4	4	4	3	4	4	4	7/7=1.00
Find it hard to stop myself from doing dangerous overtaking?	4	4	4	4	4	4	3	7/7=1.00
Scale-Level CVI	1	1	0.85	1	1	1	1	S-CVI/Ave = 6.85/7= 0.97

Appendix B**:** Factor Loadings for Measuring Training Factors that influence Prime Decision-Making

Factors	Items	Loadings	Cronbach's Alpha
Basic Skills	Gear selection in operating manual /automatic car	.916	0.874
	Turning	.890	
	Controlling the steering wheel	.865	
	Use of turn signals	.835	
	Maintaining lane positioning	.827	
	Speed control	.789	
Basic Practice	The use of seat belt while driving	.936	0.754
	Holding the steering wheel while driving	.932	
	Driving between the lines	.931	
	Driving within the speed limit	.916	
	Using the signal lights while turning	.903	
	Stopping in prohibited areas (e.g. Roundabout, four-way intersection or crossroad)	-.820	
	Turning in prohibited areas (e.g., no U-Turn)	-.803	
	Looking into the side mirrors while overtaking another car	.600	
Sensory Ability	Seeing the road due to oncoming headlights when driving at night	.880	0.911
	Seeing dark coloured cars when driving at night	.846	
	Seeing pedestrians on the road side when driving in a day time	.840	
	Reading street signs when driving in a day time	.819	
	Seeing dark coloured cars when driving in a day time	.772	
	Seeing the road in rain when driving at night	.711	
	Read roadside advertisements	.605	
	Seeing the road due to oncoming headlights when driving in a day time	.563	
Driver's Goal	Time goal (i.e. Making sure you reach your destination on time).	.998	0.996
	Avoiding traffic violation.	.998	
	Safety goal (i.e. Making sure of your safety and safety of others).	.993	
Driver's Intention	Time goal.	.998	0.996
	Avoiding traffic violation.	.998	
	Safety goal.	.993	
Potential Hazardous Information	Other cars driving in front of you	.969	0.869
	Curves (or bend) on the road	.913	
	Pedestrian crossing the road in a wrong place	.774	
	Car stopping at the Pedestrian Crossing	.736	
Exposure on Task Complexity	Controlling the steering wheel.	.953	0.937
	Changing gear when reducing the car speed.	.903	
	Activating a direction indicator when negotiating a bend	.881	
	Braking by slowing down before negotiating roundabout	.875	
	Maintain lane in traffic.	.828	
	Check surrounding for unsafe situations.	.814	
	Emergency braking when another car pulls into driver's path	.809	
	Accelerating when approaching a flickering green light	.665	
Perception about Risk	Driving in a city at a speed above the speed limit	.933	0.860

	Sudden braking	.905	
	Driving at night	.877	
	Bypassing slow car through the left-hand side instead of the right-hand side	.870	
	Bypassing when you are hidden by a truck and have no good vision of the car coming in front of you	.849	
	Pulling over the road way (getting on and off lower road shoulder)	.818	
	Backward driving (reverse) when there are blind sights	.776	
	Losing control over the car while driving on a wet and slippery road	.761	
Driver's Knowledge	Traffic rules and regulations	.953	0.950
	Road signs	.940	
	Use of maximum speed limits driving in a city	.939	
	Road markings	.908	
Involuntary/Voluntary Automaticity	Sudden swerve to another direction without thinking (e.g. when another car swerved in front of my car while driving.)	.923	0.797
	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.)	.847	
	Find it hard to stop myself from doing dangerous overtaking	.685	
	Do change lane without meaning to do it	.677	