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Driver Behavior Questionnaire-Based Study in Malaysia: A Structural Equation Modeling Analysis Approach

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ABSTRACT

Road safety is still one of the major concerns worldwide, with driving behavior being one of the important factors in the outcome of any road accident. This paper presents a study on driver behaviors and their classification as violations, errors, and lapses in relation to road safety in the Malaysian context, where special cultural and infrastructural challenges are different. This study used a quantitative approach by using the technique of Structural Equation Modeling and used data from 301 participants through an adapted Driver Behavior Questionnaire (DBQ). The confirmatory analyses of reliability and validity assured the DBQ was robust, hence all Cronbach's Alpha values were above 0.8 for the various constructs. EFA suggested that factor loadings are high (>0.6), meaning each item represents its construct. Good fit indices such as an RMSEA less than 0.071 and incremental fit measures greater than 0.90 showed the good fit between the theoretical framework and the observed data. The results indicate that safety interventions on both aggressive and passive driving styles are very vital in road safety improvement. The risk factors identified that were important include violations-like speeding and distraction while driving, errors related to misjudgment and lapses due to temporary inattention. Though the structural link between lapses and errors showed a statistically insignificant path, all other structural relationships established indicated cultural interventions on unsafe acts. Therefore, for improved predictive accuracy in the DBQ, the advanced technologies of telematics and dashboard cameras should be combined with self-reported data. The present study therefore provides worthwhile insights into the driver's behavioral attributes in Malaysia, with several actionable strategies that policymakers may consider in efforts toward the reduction of traffic accidents in light of the global road safety goals.

Keywords:
Road safety; driver behavior questionnaire; aggressive driving; passive driving

1. Introduction

Road safety is a global concern, with millions of lives affected annually due to traffic accidents. Traffic-related fatalities not only impose emotional and financial burdens but also affect public health and economic stability. Central to road safety challenges are driving behaviors, which significantly influence accident rates and traffic dynamics. The Driver Behavior Questionnaire (DBQ), a self-report instrument developed in the 1990s, has become a cornerston Aggression, driver stress, and accident

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risk e in studying these behaviors [1]. By categorizing behaviors into aggressive violations, ordinary violations, lapses, and errors, the DBQ facilitates comprehensive evaluations of driving patterns. This article examines the role of driving behaviors in shaping road safety, with a particular focus on Malaysia, where traffic conditions and cultural norms create unique challenges.

1.1 Driving Behaviors and Their Impact

Driving styles can be broadly classified as aggressive or passive, each with distinct implications for road safety. Aggressive drivers often exhibit risky behaviors such as speeding, tailgating, and frequent lane changes. Such behaviors, driven by impatience or animosity, significantly increase the risk of collisions and road rage incidents [2,3]. The consequences extend beyond physical harm, contributing to heightened stress among road users [4]. Conversely, passive drivers prioritize caution and adherence to rules, promoting smoother traffic flow. However, their reluctance to engage assertively can lead to inefficiencies, such as exploitation by aggressive drivers and increased delays [5,6]. In Malaysia, understanding the spectrum of aggressive and passive behaviors is critical. Cultural norms, road infrastructure, and enforcement policies influence these behaviors, making targeted interventions necessary.

1.2 Road Safety in Malaysia

Malaysia faces significant road safety challenges. In 2020 alone, the nation reported 348,393 road accidents, resulting in 4,634 fatalities and 153,263 injuries [7]. Motorcyclists, a vulnerable group, accounted for a disproportionate share of these statistics. Contributing factors include reckless driving, speeding, DUI, and fatigue [8]. These behaviors are exacerbated during peak travel seasons, such as Chinese New Year and Hari Raya Aidilfitri, when highways are congested. Efforts to improve road safety align with the United Nations' Sustainable Development Goals (SDGs), aiming to halve traffic fatalities and injuries globally by 2020 [9]. While Malaysia has made progress, comprehensive measures particularly in enforcing traffic laws and addressing high risk behaviors are needed.

1.3 Key Risk Factors for Road Traffic Accidents

Several key factors significantly contribute to road traffic accidents, with speeding, drunk driving, and fatigue being among the most critical. Speeding, a prevalent issue, reduces drivers' reaction times and escalates the severity of crashes. In the United States, speeding was responsible for 29% of all traffic fatalities in 2021 [10]. Similarly, high-speed driving is a common cause of accidents in Malaysia, where it endangers not only drivers but also other road users such as pedestrians and cyclists. Effective measures to mitigate speeding include stricter enforcement of speed limits and public awareness campaigns highlighting the risks associated with excessive speed. DUI significantly impair judgment and reaction times. Malaysia's legal blood alcohol concentration (BAC) limit of 0.08 is more lenient than in many countries, contributing to DUI-related accidents [11].

Fatigue also plays a critical role in road safety, particularly for long-distance travelers and shift workers. Drowsy driving leads to impaired cognitive and motor functions, often resulting in microsleep episodes that significantly elevate crash risks. Between 2011 and 2021, fatigue was a contributing factor in 1,305 fatalities in Malaysia [12]. Addressing fatigue requires multifaceted strategies, including raising public awareness about the dangers of drowsy driving, encouraging rest breaks for long-haul drivers, and implementing workplace policies that ensure drivers are well-rested before embarking on extended trips. These risk factors highlight the multifaceted nature of road traffic accidents and the necessity of combining strict enforcement, education, and innovative approaches to mitigate them. Leveraging tools like the Driver Behavior Questionnaire (DBQ) can further enhance the understanding of risky behaviors, enabling policymakers to implement targeted interventions for improving road safety.

1.4 The Driver Behavior Questionnaire (DBQ)

The DBQ was developed to measure self-reported driving behaviors and categorize them into four constructs: aggressive violations, ordinary violations, lapses, and errors [1]. These constructs provide a framework for understanding both deliberate and inadvertent behaviors that contribute to traffic incidents. Over time, the DBQ has been adapted for various cultural contexts, demonstrating its versatility. In Lebanon, for example, Salameh and Abou-Abbas modified the DBQ to reflect local behaviors, achieving high internal consistency (Cronbach's $\alpha = 0.892$) [13]. Similarly, Taiwo *et al.,* [14] validated the DBQ for Nigerian truck drivers, emphasizing its relevance in occupational research. These adaptations highlight the need to tailor the DBQ to specific traffic environments.

While the DBQ is a valuable tool, its reliance on self-reported data poses challenges. Social desirability bias often leads participants to underreport aggressive behaviors or exaggerate passive ones, affecting data reliability [15]. Studies have also noted discrepancies between self-reported behaviors and actual driving patterns [16]. To address these issues, integrating objective measures such as telematics or dashboard cameras with self-reported data has been suggested. Such a hybrid approach could improve the validity of DBQ findings, particularly in diverse contexts like Malaysia. Cultural and contextual factors play a significant role in shaping driving behaviors. For instance, in India, the DBQ was adapted to address occupational fatigue among professional drivers [17]. In Iran, the questionnaire was modified to include context-specific behaviors using principal component analysis (PCA) [18]. In Malaysia, adapting the DBQ might involve incorporating items related to motorcycle lane compliance, pedestrian crossing behavior, and rural traffic conditions.

Traditional DBQ constructs are increasingly challenged by modern driving risks, such as smartphone use and vehicle automation. In Malaysia, where smartphone penetration is high, distractions like texting while driving are prevalent. Expanding the DBQ to include such behaviors ensures its relevance in addressing contemporary road safety challenges [19]. While the DBQ is effective for assessing current behaviors, its predictive validity remains underexplored. Studies linking DBQ constructs to crash involvement often lack longitudinal data [20]. Conducting longitudinal studies in Malaysia could enhance the DBQ's utility by correlating responses with real-world outcomes over time.

Advanced technologies offer promising avenues for enhancing the DBQ's reliability. Telematics, dashboard cameras, and mobile apps can provide real-time data to validate self-reported behaviors [21]. In Malaysia, such technologies could reveal regional differences in driving patterns, aiding policymakers in designing targeted interventions. The DBQ remains a versatile tool for analyzing driving behaviors, offering valuable insights into road safety challenges worldwide. In Malaysia, adapting the DBQ to reflect the nation's unique traffic environment and cultural practices is essential. Addressing the limitations of self-reported data, incorporating cultural adaptations, and expanding the DBQ to include emerging risks will ensure its continued relevance. By integrating advanced technologies and focusing on predictive methodologies, Malaysia can leverage the DBQ to design effective road safety interventions, contributing to global efforts to reduce traffic fatalities and injuries.

2. Methodology

This study employs a quantitative research approach, utilizing Structural Equation Modeling (SEM) as the primary analytical technique. SEM is a powerful statistical tool designed to measure and investigate linear causal relationships between variables while concurrently accounting for measurement error and assessing model fitness. SEM was chosen over other methods, such as regression analysis, due to its ability to handle latent variables and analyze them simultaneously, providing a comprehensive understanding of complex relationships.

2.1 Questionnaires Development

Driving behaviors play a crucial role in determining road safety outcomes. These behaviors are often categorized into violations, errors, and lapses, each representing a distinct aspect of driver behavior. Below is an in-depth categorization based on referenced studies in Table 1. Violations represent deliberate deviations from traffic rules, often reflecting aggressive or risk-prone behaviors. These actions are intentional and typically involve a conscious decision by the driver.

Table 1
Driver behavior questionnaire (DBQ)

Violations	Errors	Lapses
V1: Driving close to the car in front to signal impatience [22].	E1: Failing to check rear-view mirrors before lane changes [22].	L1: Entering the wrong lane at roundabouts or junctions [22].
V2: Disregarding speed limits on highways [22].	E2: Underestimating the speed of oncoming vehicles during overtaking [23].	L2: Misreading traffic signs and exiting on the wrong road [22].
V4: Impatience with a slow driver, overtaking on the left [22].	E3: Attempting to overtake without noticing a signaling vehicle [24].	L3: Forgetting where the car is parked [23].
V5: Using the car horn to express annoyance [22].	E4: Passing a car without checking mirrors, causing conflict with another vehicle [25].	L4: Accidentally operating the wrong vehicle control [24].
V6: Driving dangerously close to the car in front [23].	E5: Focusing on main-road traffic while turning left and almost hitting a car in front [26].	L5: Driving to the wrong destination due to distraction [24].
V7: Entering an intersection after the traffic light has turned red [24].	E6: Applying sudden brakes or incorrect steering during skids [6].	L6: Forgetting the current gear while driving [25].
V8: Getting angry at another driver and expressing it [24].	E7: Choosing the wrong lane at a roundabout or junction [27].	L7: Realizing no memory of the road recently traveled [27].
V9: Staying in a closing lane until the last minute before merging [24].	E8: Failing to notice pedestrians when turning into a side street [28].	L8: Hitting unseen objects while reversing [28].
V10: Distracted driving, e.g., texting or changing music [25].		
V11: Obeying speed limits in residential areas [26].		
V12: Improper overtaking while turning [26].		
V14: Chasing another driver out of anger [27].		
V15: Engaging in unofficial street races [28].		

Errors are unintentional behaviors that arise from a lack of skill, misjudgment, or failure to recognize traffic conditions. These actions are often due to inattention or miscalculation. Lapses are momentary lapses in attention or memory, often reflecting cognitive limitations rather than deliberate actions. These lapses may not always result in direct safety consequences but can disrupt traffic flow.

2.2 Pre-Test Procedure

Prior to conducting the full study, a Pre-Test Procedure was carried out to gather preliminary feedback and refine the research instrument. Using Cronbach's Alpha to analyse the questionnaires' consistency across the four sections Demographic, Violations, Errors, and Lapses and ensure the instrument's relevance to the research goals. The pre-test procedure was conducted with a small sample of 20 drivers. This step aimed to ensure that the questionnaire was free from technical issues and ambiguities. Based on the feedback received, the survey instrument underwent additional refinements to eliminate any residual issues, ensuring it was fully optimized for the primary data-gathering phase. There is a range that is acceptable in Cronbach's Alpha, demonstrating the reliability of the survey. Hence, a reliability score of 0.6 to 0.7 indicates an acceptable degree of dependability, while a score of 0.8 or above indicates extremely good reliability, according to a general rule of thumb. The value of Cronbach's Alpha and its internal consistency are displayed in Table 2. Generally, the questionnaire is acceptable if the score is more than 0.7.

Table 2
Value of Cronbach's Alpha and the internal consistency

Cronbach's Alpha	Internal consistency
$\alpha \geq 0.9$	Excellent
$0.9 > \alpha \geq 0.8$	Good
$0.8 > \alpha \geq 0.7$	Acceptable
$0.7 > \alpha \geq 0.6$	Questionable
$0.6 > \alpha \geq 0.5$	Poor
$0.5 > \alpha$	Unacceptable

2.3 Data Cleaning

Following data collection, a rigorous data cleaning process was undertaken to ensure the datasets' quality and reliability for analysis. Data cleaning is a critical preparatory step that involves identifying and addressing errors or inconsistencies in the dataset. This process is essential for eliminating ambiguity and imprecision in areas such as question wording, instrument length, and content completeness. By resolving these issues, the study ensured that the data were suitable for further analysis, machine learning applications, or visualization.

2.4 Sample Size

After all necessary tests have been completed and validated, the questionnaire was administered as an online survey. The inquiry then used the convenience sampling method. Moreover, this study utilized social media sites like Facebook, WhatsApp, and Telegram to disseminate the questionnaires. Note that 318 people completed the online survey and returned the questionnaire, and 17 respondents were rejected for providing false information, leaving 301 respondents (a 90% response rate) for empirical analysis. The calculation below indicates that the minimum data required is 273 people based on Eq. (1). The population of Malaysia is 34,308,525 people.

$$S = Z^2 \times P \times \frac{1-P}{M^2} \; ; \; S = 1.65^2 \times 0.50 \times \frac{1-0.50}{0.05^2} ; S = 272.25 ; S \approx 273 \quad (1)$$

where S is sample size, Z is z-score (confident level; 90% = 1.65), P is population proportion (50% = 0.50) and M is margin error (5% = 0.05).

2.5 Demographic Data

The analyzed data provides a detailed demographic and behavioral profile of the surveyed population in terms of driving habits and vehicle ownership in Table 3. The gender distribution within the sample is nearly equal, with 49.5% males and 50.5% females. The majority of respondents belong to the 18–39 age group, accounting for 65.1% of the total, indicating a predominantly younger demographic. This suggests that the findings may primarily reflect the behaviors and preferences of younger individuals. Education levels among the respondents are notably high, with a significant proportion holding advanced qualifications. Over half of the respondents (56.1%) possess a Bachelor’s degree, while an additional 21.9% have attained a Diploma. Advanced degrees such as Master’s and PhDs are held by 10.6% and 2.7% of respondents, respectively. This indicates a highly educated population, which could influence their driving habits and preferences due to greater access to resources and opportunities.

Table 3
Socio demographic data

Demographic item	Number	Percentage (%)	Demographic item	Number	percentage (%)
Gender			Vehicle ownership		
Male	149	49.5	Personal	204	67.8
Female	152	50.5	Family	97	32.2
Age			Vehicle type		
18-24 years old	88	29.2	Compact car	107	35.5
25-39 years old	108	35.9	Sedan	123	40.9
40-59 years old	48	15.9	Multi-Purpose Vehicle (MPV)	47	15.6
60 years old and above	57	18.9	Sport Utility Vehicle (SUV)	24	8
Highest education level			Years of driving experience		
Secondary school	7	2.3	Less than 5 years	59	19.6
Certificate	19	6.3	6-10 years	89	29.6
Diploma	66	21.9	11-15 years	42	14
Bachelor’s degree	169	56.1	16-20 years	24	8
Master	32	10.6	21 years and above	87	28.9
PhD	8	2.7	Frequency of driving		
Employment			Everyday	115	38.2
Full-time working	143	47.5	Almost Everyday	103	34.2
Part-time working	29	9.6	Occasionally	63	20.9
Pensioner	45	15	Rarely	20	6.6
Others	84	27.9	Main reason of driving		
Own a driving license			Only to commute for work	158	52.5
Yes	293	97.3	Only for recreation	75	24.9
No	8	2.7	Others	68	22.6

Regarding employment, 47.5% of respondents are engaged in full-time work, while smaller segments of the population include pensioners (15%) and part-time workers (9.6%). This distribution points to a population that is predominantly active in the workforce, which likely contributes to the high frequency of driving for work-related purposes. Additionally, an overwhelming 97.3% of respondents hold a valid driving license, demonstrating that access to driving is nearly universal within this group. Vehicle ownership is widespread among the surveyed population, with 67.8% reporting ownership of personal vehicles. Among these, sedans (40.9%) and compact cars (35.5%) emerge as the most popular vehicle types. This preference reflects a trend toward efficient and versatile vehicles, suitable for urban commuting and daily use. The diversity in driving experience is also notable, with 29.6% of respondents having 6–10 years of driving experience and 28.9% reporting more than 21 years of experience.

Driving habits indicate frequent use of personal vehicles, with 72.4% of respondents driving daily or almost daily. The primary purpose of driving is work-related, accounting for 52.5% of all trips, while recreational driving constitutes 24.9% of usage. This reflects a population that is highly reliant on personal vehicles for commuting and daily activities, underscoring the central role of automobiles in their mobility patterns. In conclusion, the data reveals a highly mobile, educated, and employed population with widespread access to driving and vehicle ownership. The frequent use of personal vehicles, primarily for work commutes, highlights the dependence of this demographic on private transportation. These findings provide valuable insights into the driving behaviors and preferences of the surveyed group, which can inform transportation planning and policy development.

2.6 Analysis Data

Data analysis is critical to any study, as it involves summarizing and interpreting the collected information to uncover trends, correlations, and patterns. This phase combines logical reasoning with analytical techniques to make sense of the data gathered during the research. This study employed the Statistical Package for Social Sciences (SPSS) for data analysis after the collection phase. The analysis process commenced with SPSS Statistics to investigate the relationships among the variables: Violation, Error, and Lapses. Correlation analysis, a statistical method to determine the degree of association between two variables, was utilized for this purpose. Subsequently, Structural Equation Modeling (SEM) was conducted using SPSS Amos to explore the relationships among all variables in the study.

3. Results

3.1 Measurement Model Analysis

Reliability analysis was conducted in this study to evaluate the internal consistency of a survey tool developed to measure various constructs. Accordingly, 300 participants were involved in the dataset as sample respondents. A total of 31 items were included in the analysis and spread over various constructs. The item can be classified into three categories: Violations, Errors and Lapses. These terms are used to characterize many kinds of departures from predetermined standards or expectations in various disciplines, law, ethics, psychology and quality control. Furthermore, the cornerstone of this assessment was Cronbach’s Alpha, a widely employed measure of internal consistency. The results revealed all the factors’ reliability above 0.8.

Turning to individual constructs, the analysis scrutinized several key dimensions. “Violations,” comprising 15 items, displayed reasonable internal consistency, as indicated by an alpha coefficient of 0.800. The construct “Error,” comprising eight items, exhibited a notably strong internal consistency, as evidenced by Cronbach’s Alpha of 0.928. Lastly, the “Lapses” construct, comprising eight items, demonstrated a favorable internal consistency, yielding a Cronbach’s Alpha of 0.898.
To examine how close the connection a group of test items is to each other, a reliability test has been conducted using Cronbach’s Alpha formula to analyze the item. The result of Cronbach’s Alpha

coefficient for all the variables is provided in Table 4, in which Violations (0.800), Error (0.928) and Lapses (0.898). It can be concluded that all Cronbach's Alpha values are accepted.

Table 4
Cronbach's Alpha and factor loading coefficient for item reliability

Construct	Scale item	Cronbach's Alpha	CR	AVE	Factor loadings
Violations	V1	0.800	0.774	0.536	0.598
	V5				0.784
	V7				0.797
Error	E1	0.928	0.928	0.647	0.798
	E3				0.773
	E4				0.862
	E5				0.814
	E6				0.763
	E7				0.820
	E8				0.796
Lapses	L3	0.898	0.898	0.597	0.730
	L4				0.751
	L5				0.873
	L6				0.793
	L7				0.716
	L8				0.755

The EFA results provide valuable insight into the latent structure of the scales used in this study. EFA provided factor loadings for each item, allowing assessment of their significant contribution to the identified constructs. Moreover, validity criteria (> 0.60) were applied to determine the appropriateness of linking each item to its corresponding construct. The Violations construct, which was significant, also demonstrated impressive validity with factor loading over 0.6 for all items. As a result of their strong association with the latent factor, the items comprising the Error construct displayed increased factor loadings. Corresponding to Lapses suggested that all the eight elements inside the construct have factor loadings above 0.6, highlighting their significant contribution to the construct's development. The validity requirements and factor loadings taken together highlight that various constructs within the data were successfully identified and supported. These results support the measurement items' dependability and add to the validity of the scales used. Importantly, these findings are consistent with the construct predictions that form the basis of the study.

In this case study, the correlation matrix, which displays the study's findings, has special significance in understanding the driver's behavior, whether the driver is an aggressive or passive person. The Composite Reliability (CR) values exceeding 0.6 across all dimensions provide comforting insights in the Malaysian setting, where acceptance and perception of driver behavior are key factors. Our trust in the assessment scales' applicability for collecting attitudes and perceptions towards driver behavior increases by indicating that they display internal consistency. Note that all construct item has an acceptable value which is above 0.6. Average Variance Extracted (AVE) values exceeding the suggested cutoff point of 0.5 demonstrate that the variance within the indicators of each construct is in line with the latent component. This result indicates that the assessment items successfully tap into the fundamental aspects of driver behavior.

The factor loadings for various structures exhibit interesting, unique characteristics. Items that have a greater significance than the threshold in the Violation construct indicate the variables affecting Malaysian drivers' behavior. Meanwhile, the Error construct, which has elements that exhibit strong linkages, similarly emphasizes the effect of the driver's negligence. The Lapses construct, essential to comprehending Malaysian drivers' accidental failure behavior, has strong factor loadings. Driving is one of many contexts in which violations, errors, and lapses can occur (see Table 5). It is connected by the fact that they frequently occur in human behavior, can potentially affect safety, and can be prevented or addressed using various techniques. Furthermore, they all have the potential to impact safety and adherence to laws and conventions, making them significant factors to consider in a variety of areas, such as transportation, workplace safety, and healthcare. Validating the proposed structural linkages within the study framework depends on the evaluation of model fit. The alignment between the theoretical model and the observed data was assessed in this work using the goodness-of-fit indices, providing insight into the reliability of the suggested associations (see Table 6).

Table 5
The driving experience measurement model validation results

	Violations	Errors	Lapses
Violations	0.732		
Errors	0.794	0.804	
Lapses	0.587	0.77	0.772

Table 6
The fitness indexes for the driving experience measurement model

Name of category	Name of index	Level of acceptance	Full measurement
Absolute Fit	Chi-square	*p*-value > 0.05	242.721
	Root Mean Square of Error Approximation (RMSEA)	RMSEA < 0.08	0.071
	Goodness of Fit Index (GFI)	GFI > 0.90	0.907
Incremental Fit	Comparative Fit Index (CFI)	CFI > 0.90	0.952
	Normed Fit Index (NFI)	NFI > 0.90	0.922
	Tucker-Lewis Index (TLI)	TLI > 0.90	0.943
Parsimonious Fit	Chi-square/df	Chi-square/df < 5.0	2.427

Absolute Fit: Chi-square test statistics, frequently used to assess absolute fit, produce a p-value higher than 0.05. Although this suggests that the model and the observed data may differ, it is vital to remember that chi-square is sensitive to sample size. Beyond the chi-square, the RMSEA is 0.071, far lower than the advised cutoff point of 0.08. The GFI of 0.907, just a little below the preferred cutoff of 0.90, further supports the conclusion that the model and the data are reasonably well-fit. Incremental Fit: Incremental fit is rated using CFI, NFI, and Tucker-Lewis Index (TLI). Due to its value of 0.907, the CFI was unquestionably approved. Positive results are also proven by the NFI (0.922), and TLI (0.943), indicating a significant congruence between the theoretical model and the actual data.

Parsimonious Fit: A crucial factor is the evaluation of sparse fit using the Chisq/df ratio. The ratio in this case is 2.427, suggesting that the degrees of freedom for the Chi-square statistic are almost twice as large. The observed ratio suggests a good degree of parsimony even though the standard requirement is less than 3.0. However, more analysis is necessary. The model displays a diverse pattern of fit indices across many categories considering these findings. The optimistic RMSEA score, and the mild chi-square p-value suggest that the model and the data are meaningfully aligned. In addition, this alignment is strengthened by the incremental fit indices, notably the CFI and TLI. Although close to the target threshold, the GFI, and NFI readings call for critical thought and possible model improvement.

In conclusion, the assessment of model fit provides useful information on the consistency between the theoretical ideas and the collected data. Although the model demonstrates good alignment across several indices, a thorough grasp of the constraints and underlying assumptions is required due to the fit assessment's complex nature. Therefore, these findings help academics improve the model and deepen our understanding of the intricate interrelationships demonstrated by the study.

3.2 Structural Model Analysis

The phrase SEM refers to a group of techniques used by researchers in experimental and observational studies in a range of sectors. This includes business, science, and other disciplines. It is frequently employed in behavioral and social sciences. The structural model created using SPSS Amos is displayed in Figure 1. According to the structural model, three elements of violations, lapses, and errors have been tested. There are five incidents came under breaches, in which six items fell under lapses, and seven items fell under mistake. Therefore, to acquire a satisfactory result, eighteen items were evaluated in this study. The Lapse is dependent, whereas the Violation and Error are independent, according to the structural model. The final structural model (Figure 1) illustrates the relationship between all factors. Table 7 shows the summary of hypothesis test.

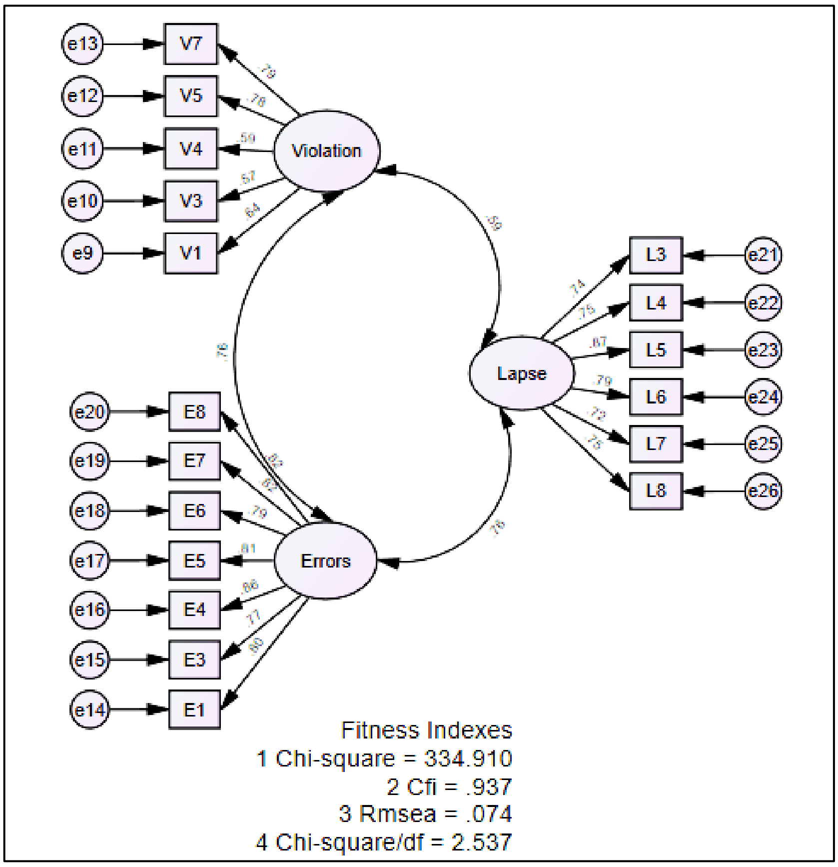

Fig. 1. The Regression path coefficient among constructs in the driving experience structural model

Table 7
Summary of hypothesis test

Hypothesis			Estimate	T-value	P-value	Support
Lapse	→	Violation	-0.079	0.121	0.515	Rejected
Lapse	→	Error	0.933	0.127	0.000	Accepted
V1	→	Violation	1.000			
V3	→	Violation	0.980	0.121	0.000	Accepted
V4	→	Violation	0.940	0.112	0.000	Accepted
V5	→	Violation	0.964	0.094	0.000	Accepted
V7	→	Violation	1.117	0.113	0.000	Accepted
E1	→	Error	1.000			
E3	→	Error	0.981	0.086	0.000	Accepted
E4	→	Error	1.042	0.062	0.000	Accepted
E5	→	Error	0.968	0.063	0.000	Accepted
E6	→	Error	0.854	0.061	0.000	Accepted
E7	→	Error	1.094	0.070	0.000	Accepted
E8	→	Error	0.908	0.061	0.000	Accepted
L3	→	Lapses	1.000			
L4	→	Lapses	1.033	0.083	0.000	Accepted
L5	→	Lapses	1.183	0.081	0.000	Accepted
L6	→	Lapses	1.048	0.079	0.000	Accepted
L7	→	Lapses	1.057	0.089	0.000	Accepted
L8	→	Lapses	0.933	0074	0.000	Accepted

4. Conclusions

In the context of driver behavior in Malaysia, which is aggressive or passive, the hypothesis testing outcomes presented the factor of the behavior. The relationship between lapses and errors is rejected, while the others are accepted, as indicated in Table 6. For instance, the driver behavior perception of aggressive and passive could be influenced by factors such as Violation, Error and Lapses, similar to what the table provided. Moreover, the lapses to error hypothesis were rejected, and maybe these factors might not be applied by drivers in Malaysia. A law, rule, regulation, or code of behavior is broken or infringed upon when violated. It usually entails willfully flouting accepted norms, standards, or moral precepts. Furthermore, depending on the situation and the seriousness of the breach, violations may result in disciplinary actions or legal repercussions. A mistake or inaccuracy in a procedure, computation, opinion, or action is referred to as an error. Unintentional mistakes might result from negligence, a lack of knowledge, or human fallibility. Additionally, depending on the situation, errors can have a range of effects, from small annoyances to serious repercussions. A momentary and frequently inadvertent failure to uphold a job, obligation, or responsibility generally defines lapses. They frequently come from brief failures in judgement, memory, or concentration. Most of the time, lapses are deemed temporary departures from anticipated behavior rather than intentional infractions.

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