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Effect of Distraction and Driving Behaviour to Traffic Accidents in Jakarta Using Partial Least Squares Structural Equation Modeling (PLS-SEM)

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Abstract. Traffic accidents are the eighth leading cause of death worldwide, and each year, Indonesia reports an increasing number of such incidents. Human error, specifically risky driving behaviour such as distraction, is the primary contributors to the accidents. A thorough understanding of the contributing factors to traffic accidents is crucial to enhancing road safety initiatives. Therefore, this study aimed to design a model to assess the effect of road distraction, driving behaviour, and perception of risk on self-reported crashes by private car drivers in Jakarta, Indonesia, as well as formulate strategies to improve safety. This study used a diverse group of 142 drivers from Jakarta as respondents, utilizing a combination of quantitative methods, such as Partial Least Squares Structural Equation Modelling (PLS-SEM) and Pearson's Chi-square tests, complemented by questionnaire instruments such as the Driving behaviour Questionnaire (DBQ), Road Distractions Scale (RDS), and Risk Perception and Regulation Scale (RPRS). The results showed that driver distractions significantly increase the possibility of lapses, while errors, violations, and risk perception significantly affect the incident of traffic incidents. Furthermore, chi-square analysis showed that men are more likely to commit violations and are more distracted by attractive roadside objects compared to women, who reported a higher incidence of lapses and greater disturbance from weather conditions. This study offered strategic recommendations with the potential to lower accident rates and improve driving safety overall.

Keywords: Driving behaviour; Distracted driving; Driving Behaviour Questionnaire (DBQ); Road safety; Structural Equation Modelling (SEM)

1. Introduction

Traffic accidents are the eighth leading causes of death in the world. According to the Global Status Report on Road Safety published by the World Health Organization (WHO), approximately 1.35 million people die in road traffic accidents yearly (WHO, 2018). As a result, most countries suffer significant economic losses, amounting to about 3% of their gross domestic product (WHO, 2022). In Indonesia, the number of traffic accidents reached 103,645 in 2021, an increase of 3.62% compared to 100,028 cases in 2020. There were 25,266 fatalities and material losses of up to Rp246 billion in 2021 (Kementerian

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Perhubungan RI, 2022). Most accidents occurred during rush hour when commuters were heading home using highways and main roadways. When the number of vehicles on the road increases, the probability of accidents also rises (Zainy *et al.*, 2023; Puspasari *et al.*, 2015).

The high number of traffic accidents can be attributed to the physical environment of the road and vehicle and human factors (Shope, 2006; Ulleberg and Rundmo, 2003). The term "physical environment factor" refers to unsupportive road conditions, including damaged or uneven roads, sharp curves, inadequate traffic signs, and faded road markings. Vehicle factors include issues such as malfunctioning brakes, tire blowouts, and defective lights. Human factors pertain to the abilities and characteristics of the drivers.

Data from the Indonesian National Police indicate that the predominant contributing factors to traffic accidents are human at 61%, followed by infrastructure and environment at 30%, and vehicle at 9%. Human factors contribute to the highest percentage of traffic accidents (Zuraida, Wijayanto, and Iridiastadi, 2022; Kementerian Komunikasi dan Informatika RI, 2017).

Manchester Driving Behaviour Questionnaire (DBQ) is popularly used to analyse driving behaviour (Hussain *et al.*, 2023; Jomnonkwao *et al.*, 2021; Shen *et al.*, 2018). Driving behaviour assessed using DBQ can be divided into 3 subscales, including error, lapse, and violation (Parker *et al.*, 1995; Bakhshi *et al.*, 2022; Wang and Xu, 2019). The term 'error' denotes instances of judgment mistakes or failures in observation that may endanger others. 'Lapses' are defined as unintentional deviations or behaviours caused by inattention or similar shortcomings. 'Violations' refer to deliberate departures from legally mandated or socially expected safe vehicle operation norms (Wang and Xu, 2019; Zhao *et al.*, 2012).

Driver distraction includes activities that divert attention away from the primary task of driving (Carney, Harland, and McGehee, 2018; Regan, Hallett, and Gordon, 2011). These distractions are a significant factor in the loss of concentration on the road. Distractions can generally be classified into four categories: visual, cognitive, auditory, and manual, which include interacting with the vehicle or environment (Regan, Lee, and Young, 2008).

Numerous studies examined driving behaviour (Hussain *et al.*, 2023; Wang and Xu, 2019; Zhao *et al.*, 2012) and distractions (Carney, Harland, and McGehee, 2018; Ortiz *et al.*, 2018; Regan, Hallett, and Gordon, 2011; Kass, Cole, and Stanny, 2007) as separate topics. Some studies on driving behaviour focused on significant differences in DBQ variables across countries (Hussain *et al.*, 2023). Meanwhile, studies on driving distractions often examined cell phone use (Ortiz *et al.*, 2018; Kass, Cole, and Stanny, 2007). Carney, Harland, and McGehee (2018) examined the relationship between types of distractions and crashes. Additionally, other studies investigated the relationship between driving behaviour and self-reported crashes (Wang and Xu, 2019; Zhao *et al.*, 2012). However, study that integrates driving behaviour with distraction variables to assess traffic crashes is limited. Arevalo-Tamara *et al.* (2022) investigated a model that included distractions about risky road behaviours and traffic crashes in Bogota. The model did not account for the 'lapses' variable in driving behaviour. Definitively, lapses are unintentional actions resulting from inattention or a deficit, such as taking the wrong exit (Wang and Xu, 2019). The original DBQ comprises three subscales: errors, lapses, and violations (Parker *et al.*, 1995), which means including 'lapses' as a variable is crucial. Several studies showed traffic disruption was a critical factor that should be considered in road safety policymaking (Arevalo-Tamara *et al.*, 2022; Stanojević, Jovanović, and Lajunen, 2013).

This study aims to develop a model for assessing the impact of road distractions, driving behaviour, and perceived risk on self-reported crashes among private car drivers in Jakarta. Specifically, violations, errors, and lapses as the driving behaviour variables were considered and expected to help suggest strategies for enhancing road safety, drawing on insights from the driving behaviour model. The objectives can be summarised into two, including (1) creating a model that connects distractions and driving behaviour with traffic accidents, and (2) recommending effective strategies to bolster road safety.

2. Methods

2.1. *Study Object and Subject*

This study focused on private car drivers in Jakarta who use the vehicles for daily activities. The participants included 142 respondents, aged between 26 and 59. All respondents were confirmed to hold valid driving licenses (SIM A) and were deemed suitable for this study. This sample size surpasses the minimum requirement of 112 respondents for PLS-SEM, as calculated by the inverse square root method (Kock and Hadaya, 2016). Convenience sampling, a non-probability sampling method where participants self-select in response to an open invitation, was used (Stratton, 2021).

`Six latent variables were used, including Distractions (DS), Risk Perception (RP), Errors (E), Lapses (L), Violations (V), and Traffic Incidents (TI). DS evaluates the extent to which various commonly observed road disturbances influence drivers. RP assesses driver awareness of the risks and the understanding of traffic regulations (Arevalo-Tamara *et al.*, 2022; Useche *et al.*, 2018). E, L, and V are the subscales of DBQ that quantify driving behaviours related to inattention and distraction. TI captures the history of the respondent traffic incidents, including accidents/collisions and incidents/near misses.

2.2. *Model and Study Hypothesis*

This study adopts the study model from Arevalo-Tamara *et al.* (2022) to evaluate the effects of road distractions, driving behaviour, and risk perception on self-reported crashes. It hypothesizes that road distractions influencing drivers may significantly predict the risky driving behaviour, potentially leading to traffic accidents. Figure 1 shows the conceptual model, which has been augmented by including the 'Lapses' variable from DBQ as developed by Wang and Xu (2019). Additionally, the model features a refined 'Traffic Incidents' (TI) component that includes two indicators, accidents and incidents/near misses. A total of 11 hypotheses were developed as shown in Table 1.

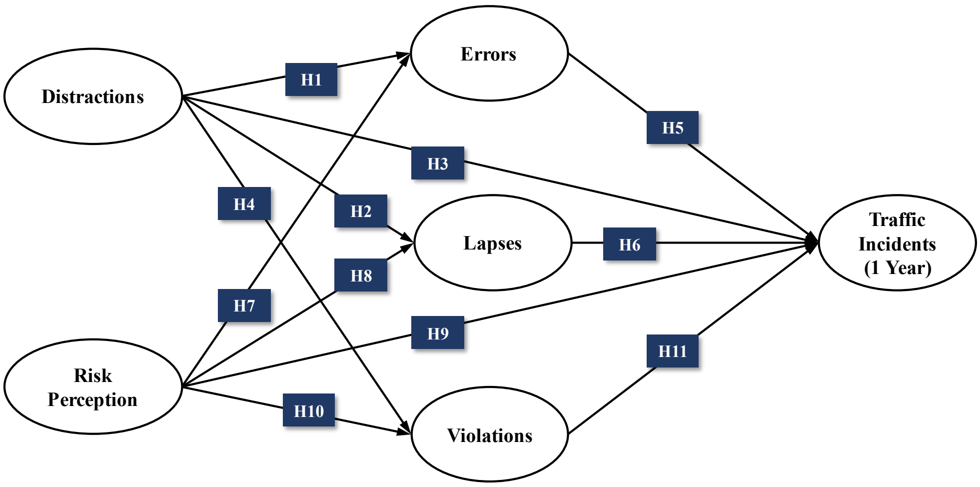

Figure 1 Conceptual model for predicting traffic incidents

Table 1 Study Hypotheses

Hypotheses	Information	Source
H1	Distractions have a direct impact on errors	Arevalo-Tamara *et al.*, (2022)
H2	Distractions have a direct impact on Lapses	Feng, Marulanda, and Donmez, (2014)
H3	Distractions have a direct impact on Traffic Incidents	Arevalo-Tamara *et al.*, (2022)
H4	Distractions have a direct impact on Violations	Arevalo-Tamara *et al.*, (2022)
H5	Errors have a direct impact on Traffic Incidents	Arevalo-Tamara *et al.*, (2022)
H6	Lapses have a direct impact on Traffic Incidents	Sullman, Stephens, and Taylor, 2019
H7	Risk Perception has a negative direct impact on Error	Arevalo-Tamara *et al.*, (2022)
H8	Risk Perception has a negative direct impact on Lapses	Liu *et al.*, 2021
H9	Risk Perception has a direct negative impact on Traffic Incidents	Arevalo-Tamara *et al.*, (2022)
H10	Risk Perception has a negative direct impact on Violations	Arevalo-Tamara *et al.*, (2022)
H11	Violations have a direct impact on Traffic Incidents	Arevalo-Tamara *et al.*, (2022)

Data collected from surveys, including DBQ, Road Distraction Scale (RDS), and Risk Perception Rating Scale (RPRS), along with traffic incident histories were analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM) and the Chi-square test. The results helped design strategies, which would be developed through a literature review and validated by experts and stakeholders.

2.3. Data Collection

The data collection phase includes discussing the types and methods of data collection, designing conceptual models and hypotheses based on a literature review, creating questionnaires, and analysing the results obtained from these questionnaires. The data processing phase includes testing the validity and reliability of the questionnaires, specifying the model, analysing SEM model, which includes testing both the measurement model (outer model) and the structural model (inner model) and conducting the Chi-square test.

Data were collected through questionnaires comprising five parts, including driver demographics and characteristics, DBQ, RDS, RPRS, and information on driving experience and accident/incident history. According to Arevalo-Tamara *et al.* (2022), RDS includes eight types of distractions, specifically text messaging/chatting (DS1), phone calls (DS2), billboards (DS3), attractive roadside objects (DS4), personal thoughts/concerns (DS5), weather conditions (DS6), behaviour of other road users (DS7), and road obstacles (DS8). In addition to questionnaire data, further information was collected to inform the formulation of strategic recommendations at the conclusion. This additional data collection involved validating the prepared strategies based on the results of hypothesis testing, Chi-square analysis, and literature review with relevant experts.

Validation with these experts aimed to ensure the content of the questionnaire was accurate and relevant before distribution. This validation process included assessing the accuracy and relevance of the content and incorporating any significant aspects that may have been initially overlooked. The experts who validated this study included an Associate Expert Researcher from the BRIN Transportation Safety Research Group and the Head of the Work System Engineering & Ergonomics Laboratory at the Bandung Institute of Technology.

2.4. Validity and Reliability Test

After collection, the data is tested for validity and reliability using IBM SPSS Statistics 29 to ensure it is consistent and accurately reflects the conditions being measured. An item is considered valid in case it has a positive correlation value (r-value) and the calculated r (r count) is greater than the critical r (r table). Meanwhile, an item is invalid suppose the r count is less than or equal to the r table (Silvia and Irwansyah, 2023). The Pearson Correlation test results for 41 items all exceed 0.1743, indicating that the questionnaire is valid. Following the validity test and confirming that all indicators are valid, a reliability test is performed. The reliability test results for the 41 indicators yield a Cronbach's alpha value of 0.875, which is above the acceptable threshold, confirming the reliability of the questionnaire as a measurement instrument.

2.5. PLS-SEM Processing

PLS-SEM processing is carried out using SmartPLS 4 application. PLS-SEM processing consists of three stages, including model specification, evaluation of the measurement model (outer model), and evaluation of the structural model (inner model). The circle symbols on the model represent latent variables, while the rectangular symbols represent indicators. In the model, arrows represent the relationships between indicators and latent variables, as well as the among the latent variables themselves. The type of model used in this study is a reflective measurement model. Figure 2 shows the model while Table 2 explains the codes used for each latent variable.

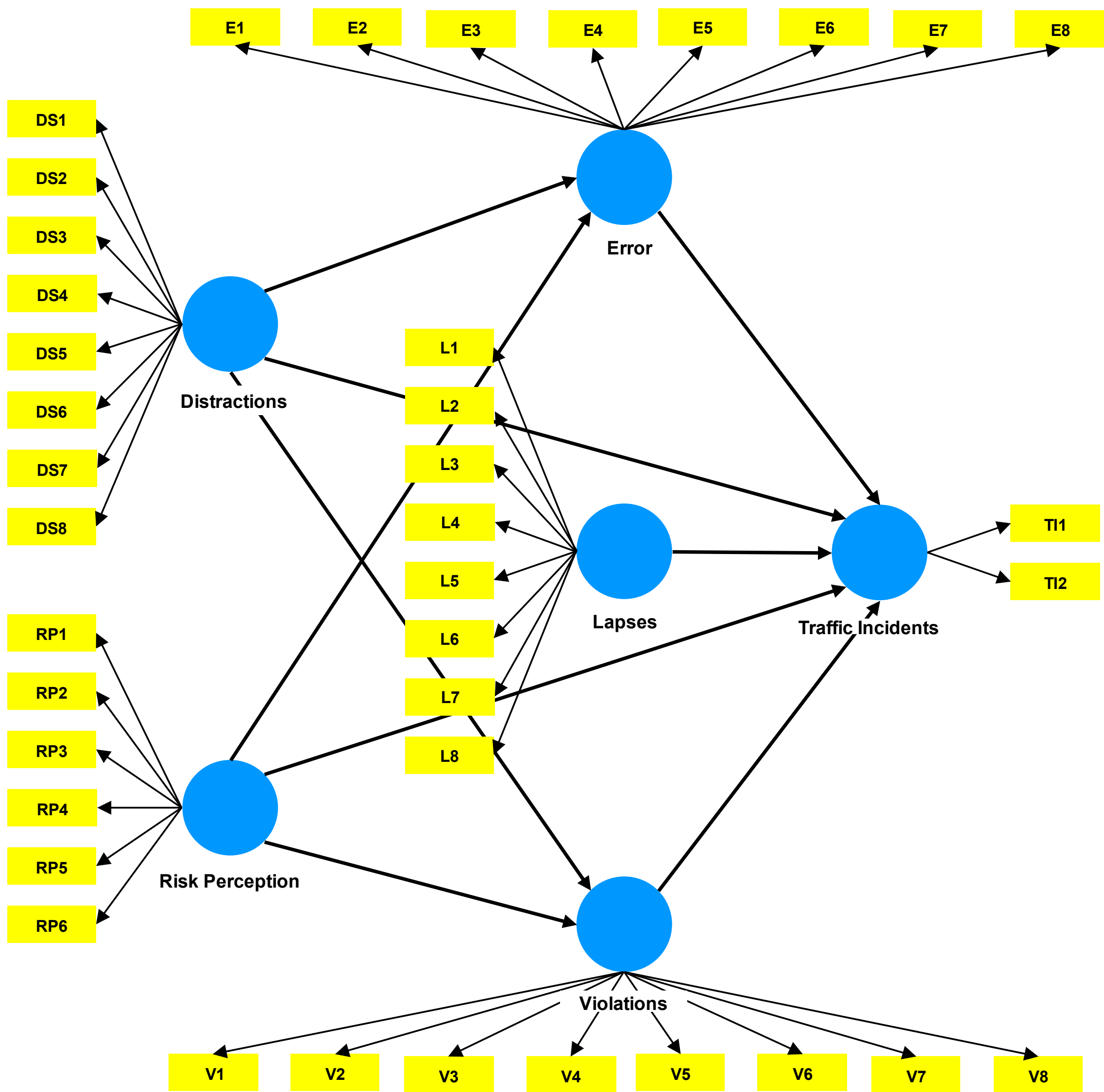

Figure 2 PLS-SEM model for predicting traffic incidents

Table 2 Codes used for each latent variable

Latent Variable	Code	Indicators
Distractions	DS	DS1, DS2, DS3, DS4, DS5, DS6, DS7, DS8
Risk Perception	RP	RP1, RP2, RP3, RP4, RP5, RP6. RP7
Error	E	E1, E2, E3, E4, E5, E6, E7, E8
Lapses	L	L1, L2, L3, L4, L5, L6, L7, L8
Violations	V	V, V2, V3, V4, V5, V6, V7, V8
Traffic Incidents	TI	TI1, TI2
Total Indicators	41	

SEM processing was carried out on 142 respondent data, a number that already exceeds PLS-SEM minimum sample requirements calculated using the inverse square root method. The formulation of SEM processing stages is as follows:

2.5.1. Measurement Model (Outer Model)

This test is conducted to determine the validity and reliability of the constructs used. Reflective indicator testing includes indicator reliability, internal consistency reliability, convergent validity tests, and discriminant validity tests with each measurement having different approaches and requirements. The steps consist of indicator and internal consistency reliability, as well as convergent and discriminant validity (Ahdika, 2017; Hair *et al.*, 2017).

2.5.2. Structural Model (Inner Model)

a. **Multiple collinearity test**. All indicators show a VIF value of <3 which means there is no collinearity problem in the study model. All VIF tests on the hypothesis show good and acceptable results.
b. **Coefficient of determination.** According to Cohen (1988), the value of R^2 can be categorized into: > 0.26 (Strong), 0.13 - 0.26 (Moderate), and < 0.13 (Weak). R^2 values in social and behavioural study tend to have low values (Hair *et al.*, 2017). Traffic Incidents have moderate predictive power (R^2 = 0.228), while Errors, Lapses, and Violations have weak predictive power (R^2 below 0.13).
c. **Predictive relevance.** Hair *et al.* (2017) recommends cross-validated redundancy as chosen as the best approach. According to Hair *et al.* (2017), a good Q^2 value is > 0 and that can be said to have good predictive ability. The Q^2 value on the latent variable listed already shows a value > 0. Therefore, these endogenous latent variables have good predictive relevance and are acceptable.
d. **Path coefficient.** The Rule of Thumb for path coefficient value is that the hypothesis will be accepted if the p-value < 0.05 and t-value > 1.96.

3. Results and Discussion

3.1. Analysis of Significance Test

The analysis of the significance test is conducted to determine whether the relationship between latent variables has statistical significance (Sarstedt, Ringle, and Hair, 2021). Hypothesis testing was conducted using the bootstrapping method using a two-tailed test scheme with a significance level of 5% (α = 0.05).

Table 3 shows all the hypotheses for this study. A total of 4 hypotheses out of 11 were accepted, specifically H2, H5, H9, and H11. The final PL et alS-SEM model is shown in Figure 3.

Table 3 Significance Test

Hypothesis	*t-value*	*p-value*
H1: Distractions → Error	1.222	0.222
H2: Distractions → Lapses	**2.359***	**0.018**
H3: Distractions → Traffic Incidents	1.254	0.210
H4: Distractions → Violations	1.883	0.060
H5: Error → Traffic Incidents	**3.502****	**0.000**
H6: Lapses → Traffic Incidents	0.567	0.571
H7: Risk Perceptions → Error	1.221	0.222
H8: Risk Perceptions → Lapses	1.206	0.228
H9: Risk Perceptions → Traffic Incidents	**2.113***	**0.035**
H10: Risk Perceptions → Violations	0.095	0.924
H11: Violations → Traffic Incidents	**2.300***	**0.022**

$^{**}p < 0.010$; $^{*}p < 0.050$

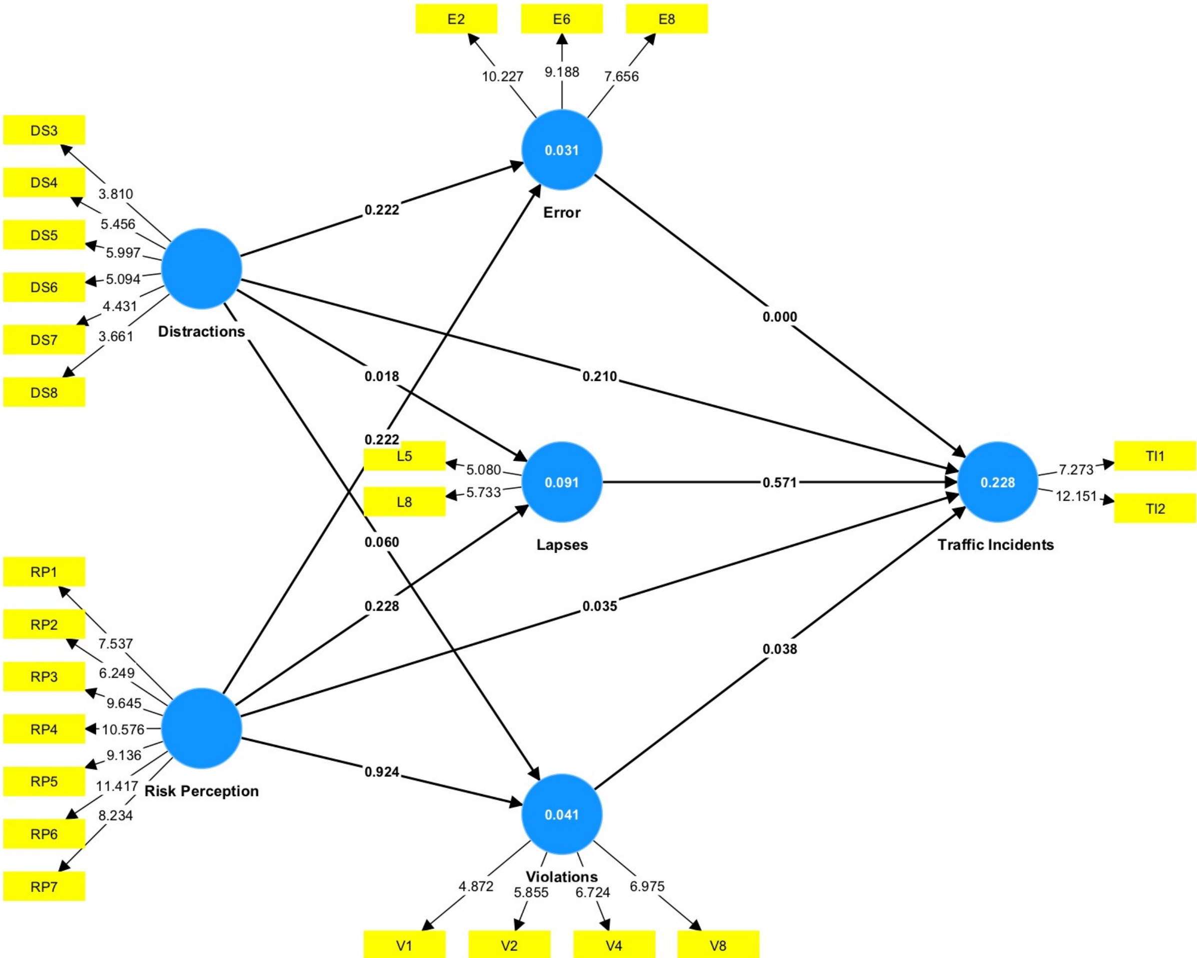

Figure 3 Final PLS-SEM model

The hypotheses confirmed a direct impact of distractions on lapses (H2). Additionally, cognitive limitations in middle-aged drivers may influence the response to distractions, manifesting as delayed reactions in intermediate or middle-aged drivers, which is evident through deviant road behaviour. The results were in line with Feng, Marulanda, and Donmez (2014), reporting that involuntary distractions significantly correlated with lapses. Similarly, Chen *et al.* (2016) found a positive correlation between self-reported distraction involvement and all four categories of unsafe driving behaviours identified in

DBQ, including lapses. According to Zhao *et al.* (2012), there is a correlation between a high frequency of lapses increased steering reversal rates and inconsistent throttle control, both of which can compromise driving safety.

The results of this study show that driving errors have a significant effect on traffic incidents (H5). Such errors, including near-misses, misinterpreting traffic signs, or failing to use the rearview mirror, directly influence the frequency of traffic incidents. These mistakes heighten the risk of accidents or lead to other hazardous situations if drivers are unaware of the actions. However, the results were not in line with Arevalo-Tamara *et al.* (2022), which did not observe a significant relationship between driving errors and traffic accidents. This discrepancy may highlight the differences between the driving contexts in Bogota, Colombia (Arevalo-Tamara *et al.*, 2022), and Jakarta (the current study), where drivers in Jakarta appear to commit more judgment-impairing driving errors, leading to traffic incidents. Additionally, this study supports the results of Wang and Xu (2019), establishing that high-risk drivers could commit errors due to inattention.

The results show that risk perception has a negative direct impact on traffic incidents (H9). Specifically, an improved awareness of risk correlates with a reduction in unwanted traffic events. Drivers with a keen sense of risk are usually more vigilant, can recognize potential hazards, assess the consequences of their actions, and act accordingly to mitigate risks. The results are in line with Arevalo-Tamara *et al.* (2022), which indicated a negative correlation between risk perception and the frequency of traffic accidents. Additionally, the study showed that violations had a direct positive impact on traffic incidents (H11). Traffic violations, which reflect non-adherence to road rules, can lead to an increase in dangerous situations. These behaviours were observed both in younger drivers who were associated with higher-risk driving as well as in more seasoned middle-aged drivers. This is in line with Zhao *et al.* (2012) and Arevalo-Tamara *et al.* (2022), which established that drivers who commit violations demonstrate poorer lateral control, more frequent sudden changes, and increased rates of sudden acceleration. Behaviours associated with traffic violations are significantly correlated with an increased rate of traffic accidents.

3.2. Analysis of Chi-Square Test

Pearson's Chi-square test is used to examine the relationship between two or more categorical variables or nominal data in the form of contingency tables. This test is meant to determine whether there is a significant relationship or association between the variables tested. Chi-square test processing was conducted based on gender groups, specifically male and female, as shown in Table 4.

Table 4 Chi-Square Test Results

Variables	Pearson Chi-Square	Asymptotic Significance Value
Gender – Error	1.391	0.708
Gender – Lapses	**9.530***	**0.049**
Gender – Violations	**22.759****	**0.000**
Gender – Risk Perception	1.641	0.801
Gender – Traffic Incidents	1.891	0.388
Gender – Distractions (DS1)	4.869	0.381
Gender – Distractions (DS2)	2.030	0.730
Gender – Distractions (DS3)	7.974	0.093
Gender – Distractions (DS4)	**12.174***	**0.016**
Gender – Distractions (DS5)	9.381	0.052
Gender – Distractions (DS6)	**15.783****	**0.003**
Gender – Distractions (DS7)	3.363	0.499
Gender – Distractions (DS8)	4.589	0.332

$^{**}p < 0.010$; $^{*}p < 0.050$

The analysis showed gender-based correlations with latent variables. Men tend to commit more traffic violations and have a higher incidence of traffic accidents. Additionally, men were more susceptible to distraction by DS4 (Attractive objects). This in line with Arevalo-Tamara *et al.* (2022), which established a significant distraction in men when encountering visually appealing objects while driving. Meanwhile, women were more prone to lapses and reported being more affected by DS6 (Weather Conditions), contrasting with Arevalo-Tamara *et al.* (2022). This suggests that in Jakarta, female respondents can be distracted by weather conditions and are more susceptible to lapses. The strategy recommendations to minimize traffic accidents from driving distractions are built based on the significant relationships between each latent variable, a study from the literature review, and expert validations, as shown in Table 5.

Table 5 Proposed Strategies

Strategy			Literature
H2	Distractions have a direct impact on Lapses	Increase the efforts of regulatory authorities in enforcing laws relating to Information and Communication Technology (ICT) while driving to reduce the prevalence and impact of disruptive sources on the road	Arevalo-Tamara *et al.* (2022)
H5	Errors have a direct impact on Traffic Incidents	Develop a system that guides human judgment and behaviour on the road through the adaptation of the Advanced Driver Assistance System	Kimura *et al.* (2022)
H9	Risk Perception has a direct negative impact on Traffic Incidents	Develop interventions focused on strengthening road safety skills such as risk perception, learning traffic rules, and anger management	Arevalo-Tamara *et al.* (2022)
H11	Violations have a direct impact on Traffic Incidents	Using applications that utilize sensors and features (text blocking, collision warning, voice control, feedback, and driving data recorder) on smartphones	(Botzer *et al.,* 2017; Albert, Musicant, and Perry, 2016)

The results of this study offer valuable insights for the development of new traffic policies for policymakers. These policies aim to substantially reduce traffic accidents in Jakarta while carefully considering critical factors such as driver distraction, age group, and driving behaviour.

4. Conclusions

In conclusion, this study aimed to design a model to assess the effect of road distraction, driving behaviour, and risk perception on traffic accidents using PLS-SEM and Chi-square analysis as well as to develop strategies for improving road safety for private car drivers in Jakarta, Indonesia. The study novelty lay in the inclusion of the 'lapses' variable within the model of distraction and driving behaviour, a distinction that differentiated it apart from previous studies. The results show that both errors and violations contributed to traffic incidents, while a heightened risk perception negatively correlated with such incidents. Additionally, the role of distractions in causing lapses was emphasized. Chi-square analysis showed that violations and susceptibility to distractions from attractive roadside objects were higher in men than women. Meanwhile, women were more prone to lapses and more affected by weather conditions. The theoretical implications of this study included providing new insights into the relationship between distraction and driving behaviour on the road, focusing on distractions that interfere with driver abilities. Several strategies for improving road safety were proposed in this study. The practical implications related to policy measures that stakeholders could adopt include law enforcement, system development, interventions to enhance road safety skills, and the use of sensor-based applications. These recommendations presented viable options to reduce accident rates, improve driving safety, as well as contributing to the evolution of previous studies and providing a reference for future ones. There were certain limitations in this study, such as focusing only on private car drivers in DKI Jakarta, not considering factors such as fatigue and exhaustion, and was conducted over a brief period from April to June 2023. Future studies should consider including other types of road users and different regions. It was also essential to include a larger number of experts from various fields to obtain more representative data and broader insights.

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