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THE ROLE OF RISK PERCEPTION IN MEDIATING THE RELATIONSHIP BETWEEN DEMOGRAPHIC CHARACTERISTICS AND DRIVING BEHAVIOR IN INDONESIA

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SUMMARY

This paper explores the mediation effect of risk perception between demographic characteristics and motorized vehicle users' driving behavior in Indonesia. Driving behavior was evaluated on three categories: violation, error and lapse. A Partial Least Squares Structural Equation Modeling (PLS-SEM) was used for data analysis, which was carried out on 353 respondents who were selected using purposive sampling. The reliability and validity of constructs were tested through measurement model analyses, and the results showed the reliability and validity of the constructs met the criteria with Cronbach's alpha and composite reliability above 0.70 and AVE value above 0.50. Results of the structural models showed that age was a significant factor in reducing errors ($\beta = -0.712$) and violations ($\beta = -0.729$) while education was a positive factor for risk perception ($\beta = 0.714$) and unsafe behaviors (errors $\beta = -0.350$, violations $\beta = -0.372$). Lapses and risk perception were affected to a lesser extent by gender ($\beta = 0.163$; $\beta = 0.182$). Interestingly, errors ($\beta = 0.247$) and violations ($\beta = 0.266$) were positively related to risk perception, which is consistent with the Risk Homeostasis Theory that overconfidence or perceived attributes of "safety" may lead to increased risk taking. The model was a good predictor of perception (Adjusted $R^2 = 0.640$; $Q^2_{\text{predict}} = 0.639$), violation behavior (Adjusted $R^2 = 0.536$; $Q^2_{\text{predict}} = 0.510$), and errors (Adjusted $R^2 = 0.509$; $Q^2_{\text{predict}} = 0.487$), and a moderate predictor of lapses (Adjusted $R^2 = 0.093$; $Q^2_{\text{predict}} = 0.088$). The findings underscore the need for more specific interventions that involve education, experiential training, and enforcement measures to help curb unsafe driving behaviors. Development of program adaptations based on demographic features can improve the effectiveness of programs and can be used by policy makers for creating culturally responsive traffic safety programs in Indonesia.

Key words: risk perception, driving behavior, age, gender, education, structural model, violation error.

INTRODUCTION

Road traffic safety is a critical issue in developing sustainable transportation systems. According to the World Health Organization data, the number of fatalities caused by road traffic accidents is one of the major causes of death in the productive age group in many countries, such as Indonesia [8][12]. There is a high number of accidents that are mainly attributed to unsafe driving behavior [2]. Past research indicates that age, gender and education are all factors that impact driving behavior, and that driver perceptions are also important. Results are however often inconsistent and suggest that other mediators, like risk perception, could affect this relationship [1][3]. Risk perception is an active process in which people receive, structure and interpret information in their environment to evaluate the danger in their surroundings [4][5]. It can buffer the impact of demographic factors on driving behavior such as errors, violations, and lapses. This study shows that the role of risk perception is a mediator which has not been widely studied in road safety in Indonesia [6][7]. The psychological processes that influence a driver's decision-making process are investigated, giving empirical clues for targeted traffic safety interventions.

Key Contributions

1. Demonstrates the mediating role of risk perception between demographic factors (age, education, gender) and driving behavior.
2. Demonstrates evidence of an attitude-behaviour gap including how high safety perception can actually lead to higher risk behaviours in driving.
3. Provides a guideline for developing education- and policy-based interventions for driver demographics in Indonesia.

Research Objectives:

- To identify the demographic factors that affect driving behavior in Indonesia.
- To test the role of risk perception between the demographics and driving behavior.
- To inform decision makers on how to enhance the effectiveness of road safety interventions.

Research Questions:

1. What are the differences in driving behavior (errors, violations, lapses) between different age groups, genders, and levels of education?
2. Is the association between the demographic characteristics and driving behaviors explained by risk perception?
3. How do the findings apply to developing targeted traffic safety interventions?

Hypotheses:

- H1: Age negatively influences risky driving behaviors.
- H2: Education positively affects risk perception and reduces risky driving behaviors.
- H3: Gender has a significant impact on risk perception and driving behavior.
- H4: Risk perception mediates the association between demographic factors and driving behavior.

The paper is organized as follows. Section 2 shows the literature survey, which covers previous research regarding demographic factors, risk perception and driving behavior. The methodology is explained in Section 3, which focuses on the research approach, sampling procedures, and the procedures of PLS-SEM analysis. The results of measurement and structural model analyses and the path coefficients

and predictive validity are reported in Section 4. A discussion of the findings, with a connection to the existing theory and previous research, is included in Section 5. Lastly, Section 6 summarises the key findings and provides recommendations for enhancing the road safety interventions.

LITERATURE REVIEW

Violations, errors, and lapses are commonly used to evaluate driving behavior, and violations have the highest correlation with accidents. Age, gender, and education factors have a demographic effect on unsafe driving habits that affect decision-making and reactions to risky circumstances [9][10].

Younger and less-experienced drivers are more likely to commit traffic violations and be involved in accidents. Younger males are more likely to drive in risky and aggressive ways, whereas older and female drivers are more likely to drive in a safe and conservative manner [11][13]. Generally speaking, male drivers are faster and riskier drivers, although driving behavior cannot be entirely attributed to sex [14][15].

The degree of compliance with traffic regulations is also dependent on education. Motorists with lower levels of education will be more likely to make mistakes, while drivers with higher levels of education will be more likely to comply. However, the unsafe behavior of highly educated drivers can sometimes be observed, suggesting a complex interplay between education and other aspects, such as driving culture, legal awareness, and social environment.

Social, cultural, psychological, and demographic factors influence the perception of risk, and this has a significant impact on driving behavior [16][17]. Younger drivers and sensation-seekers tend to overestimate risk and engage in more risky activities, while women tend to perceive risk more highly than men do [18][19]. Based on the Risk Homeostasis Theory, drivers are constantly assessing risk and their target risk [20]. In cases where perceived risk is less than the accepted level, drivers tend to be more aggressive, and when it is greater, more cautious [21]. This suggests that the demographic characteristics enter into the driving behavior through the risk perception.

Research in the literature suggests that the effect of demographic characteristics, like age, gender and education on driving behavior is mostly mediated by their effects on risk perception. Younger, less experienced and male drivers are risk takers and less experienced, more education and greater risk perception leads to safer driving. The findings indicate that investigating risk perception as a mediating variable may help shed light on the influence of demographic factors on driving behavior in the current study.

METHODS

Research Type and Approach

The study is explanatory quantitative approach that explain the relationship between demographic variables and the driving behavior variables by considering the mediating role of the driver perception variables. The choice of quantitative was made because it allows the hypotheses to be tested numerically and has the advantage of enabling generalization of results to a larger population. The current study aims to identify statistical relationships between variables, and to develop practical implications for the role of driver perception in the development of safe driving practices.

Specifically, the researcher does not stop at just observing bivariate relationships; they seek to understand how and to what degree the independent variables (age, education and gender) affect the dependent variable (driving behavior) directly and indirectly through the mediating construct, which is driving safety perception. The study design is designed in such a way that it allows for the rigorous testing of a conceptual model that is based on existing theory and previous empirical studies. The adoption of an explanatory approach digs deep into the complicated interrelationships and exposes the mediating role of perception, an area which has been little studied in the context of motorcycle riders in Indonesia, especially among the road users described by heterogeneous social attributes.

Conceptual Framework

The conceptual framework (see figure 1) created in this research aims to explain how individual demographic characteristics, namely age, education level, and gender, influence driving behavior through the role of risk perception as a mediating variable. In this model, age, education, and gender are positioned as independent variables because theoretically all three are believed to shape thinking patterns, levels of alertness, and tendencies in making decisions while driving. Meanwhile, driving behavior is positioned as a dependent variable, which is measured through three behavioral dimensions, namely: violations (intentional violations of traffic rules such as running red lights), lapses (negligence originating from attentional disturbances such as forgetting to turn on the turn signal), and errors (unintentional mistakes that occur due to errors in perception or interpretation while driving).

The center of this model is risk perception, or the perception of driving risk, which is positioned as an intervening or mediating variable. This model centers on the notion of risk perception (or driving risk perception) as an intervening or mediating variable. Risk perception is the subjective evaluation of potential risks that can arise during driving activities, as well as the ability to anticipate, control and respond to potential risks. Personal factors, including age (experience and maturity), education (legal knowledge and awareness), and gender (which is related to driving styles), are considered to be significant influences on perception of traffic risk, and this study assumes that this is true.

This model is theoretically based on cognitive psychology and risk-taking behaviour theory, which explain how a person's perception of risk is a significant factor in their tendency to commit violations or errors when operating a vehicle. Empirical works previously have shown that risk perception plays an important role between personal attributes and driving attitudes/behaviors. The conceptual framework in this study not only investigates the direct effect of demographic variables on driving behavior but also empirically examines the mediating mechanisms from demographic variables to driving behavior through risk perception.

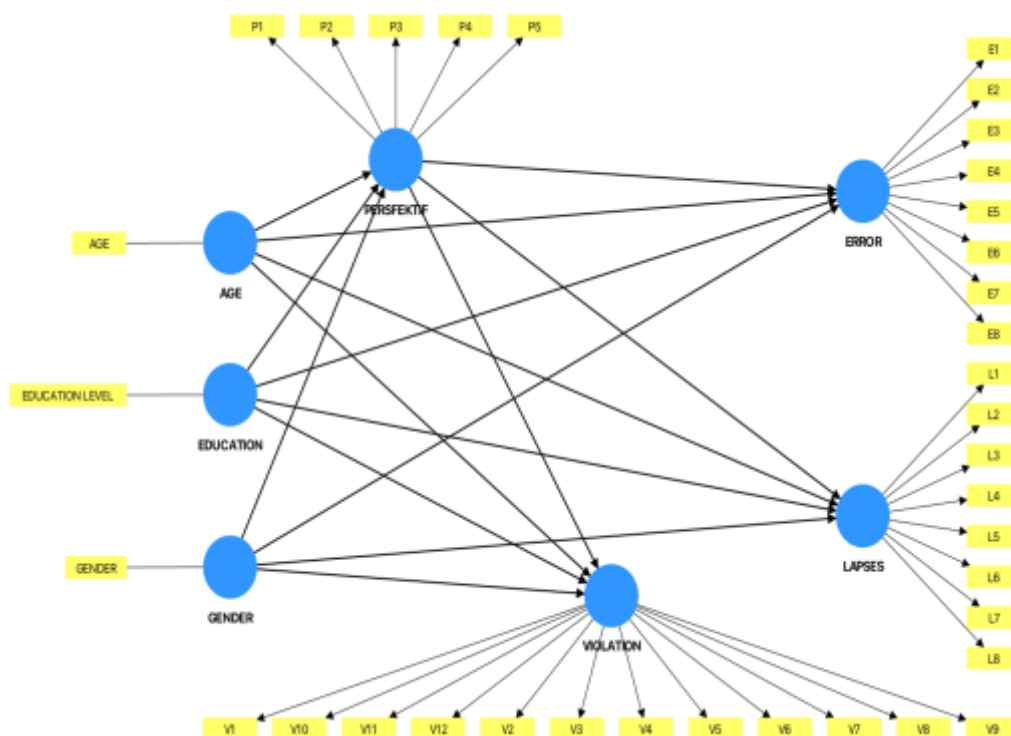


Figure 1. Research conceptual model

It is a model that is important for development in the context of Indonesia, since there are many traffic accidents that are thought to have been caused by recklessness by the driver, and not many empirical studies which map the road of psychological and demographic factors affecting driver behavior. In this research, the model will be tested systematically, so that it can be expected to make contributions in

theory and practice in traffic education planning more targeted and in implementing road safety campaigns, which take into account the demographic characteristics of the population of the Republic of Indonesia.

Sampling and Population

In this method, the motorized users of vehicles in urban/suburban areas in Indonesia were the target. All the subjects were adults (age ≥ 17), had been issued with a driver's license and had had more than one year of driving experience to ensure stable safety perceptions. A purposive sampling method was used to recruit 353 people who met these criteria, who were informed of Google Forms through social media, driver communities and professional networks. This sample size was adequate for analysis. Risk perception was measured based on the answers given to the questions of a questionnaire regarding risky driving behaviors on a 5-point Likert scale, with higher scores which shows higher risk perception. The driving behavior was assessed with the 28-item Driving Behavior Questionnaire (DBQ) that includes violations, errors and lapses measured on a six-point Likert scale, with higher scores shows the higher risk behavior. Demographic analysis showed the average age of the population was 32 years (17-65), 77% were male and 50% had tertiary education. 41% of the vehicles on the road were motorcycles, 54% were passenger cars, 2% were freight vehicles, and 3% were buses (Figure 2).

Table 1. Demographic characteristics

Demographic Variable	Category	Percentage (%)
Age (years)	17–35	59
	36–65	41
Gender	Male	77
	Female	23
Education Level	$\leq$ High school	50
	Tertiary	50
Vehicle Type	Motorcycle	41
	Passenger car	54
	Freight/Bus	5

In this table 1 shows the age, gender, education, and vehicle type distribution of the 353 participants, providing a quick overview of the respondent profile for context in analyzing driving behavior and risk perception.

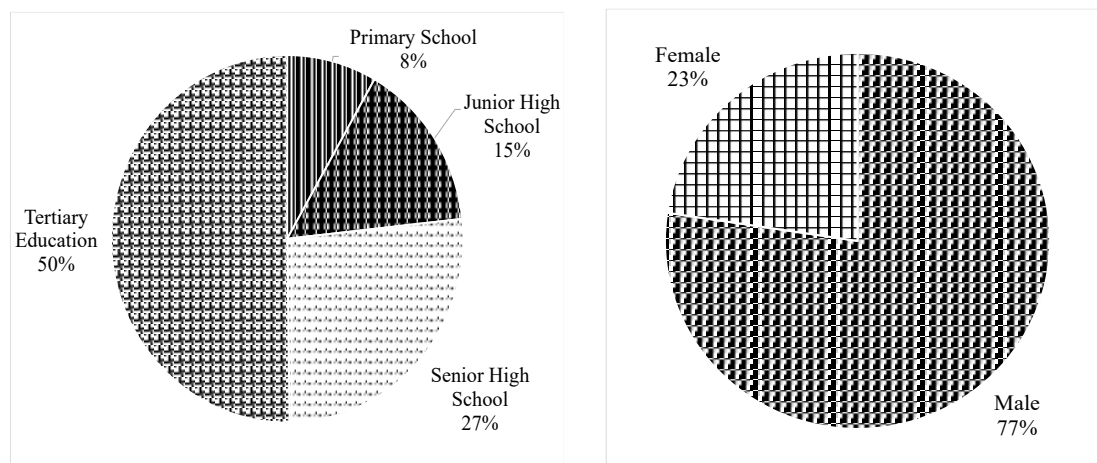


Figure 2. Respondents' education and age

Analysis Method

The analysis used the PLS-SEM approach with SmartPLS. This approach can be used when there are multiple latent constructs in the model and multiple mediating relationships and is not dependent on

multivariate normality. The model explored the effect of age, gender, and education on driving behavior and risk perception, which served as a mediator.

Reliability and validity tests were conducted to ensure that the items in the questionnaire reflected the latent variable (risk perception and driving behavior – lapses, errors, and violations). To guarantee the consistency of data and accuracy, convergent validity, construct reliability, and discriminant validity were tested.

The evaluation of structural models involved a multi-collinearity test by VIF and path coefficient analysis by bootstrapping with 5,000 sub-samples to test the significance. The predictive power was measured by R^2 , and the effect size (f^2) was used to measure the contribution of each exogenous construct with small, medium, and large categories. The model was assessed for predictive relevance by the Q^2 value using blindfolding procedures, with $Q^2 > 0$ being a good predictive ability. This type of PLS-SEM is able to deliver strong results when testing the mediating role of risk perception between demographic and driving behavior.

RESULT

The findings of the data analysis and its discussion were conducted to test the research model using the PLS-SEM approach. The analysis includes two main stages, namely the assessment of the measurement model to assess the validity and reliability of the constructs, and the assessment of the structural model to test the causal relationships between the formulated latent constructs. The empirical findings obtained from this process are then critically analyzed by linking them to theory and previous research results, to provide a deeper understanding of the role of perception in mediating the influence of age, gender, and education on driving behavior, especially in the dimensions of violation, error, and lapses.

Measurement Model Analysis

In this stage, the goal is to assess whether the concept is valid and reliable or not on the latent variables of driving behavior and risk perception. Construct validity is determined by its outer loading value. Based on the Smart PLS output, the outer loading value is obtained as shown in table 2, shows that several indicators in the Error construct have an outer loading value below 0.7 and an AVE value below 0.5, indicating that more than half of the error indicator variance is explained by measurement error rather than by the construct itself. Therefore, in accordance with the principle of convergent validity, indicators that do not meet these criteria are decided to be removed from the model. In addition to looking at the outer loading and AVE values, according to recent study, if the HTMT value is greater than 0.9, it indicates that the hypotheses are not empirically varies from one other. table 2 shows the HTMT value for each construct.

Based on the results presented in table 3, it was found that the HTMT value between the Violation and Error constructs reached 1.061, indicating a serious problem in the discriminant validity between the two constructs. This condition is most likely caused by the presence of indicators that have a higher correlation with other constructs compared to the original construct. The findings of the cross-loading analysis support this indication, where the V10 indicator, which should reflect the Violation construct, actually shows a higher loading value for the Error construct (0.844) compared to Violation (0.764). Similarly, the V11 indicator shows a similar pattern, with a loading for Error of 0.769 and for Violation of 0.726. This discrepancy indicates that the two indicators no longer represent the original construct validly. Therefore, to improve discriminant validity and conceptual clarity between the constructs, indicators V10 and V11 were decided to be removed from the model.

After eliminating indicators that did not meet the above requirements, the AVE value was increased above 0.5. The results of the calculation are shown in table 4. The table shows that all constructs in this study, namely Error, Lapses, Violation, and Perception on Risk, have met the required statistical criteria for convergent validity and construct reliability. All indicators measuring the four constructs have outer loading values above 0.70, which indicates that each indicator has a strong and significant contribution in representing the latent construct it measures. This condition shows that each indicator is individually

able to capture the essence of the intended construct, so it can be retained in the model without the need for elimination.

Table 2. Outer loading, CR and AVE

Indicator	Outer Loading	Composite Reliability (CR)	Average Variance Extracted (AVE)	Decision
E1	0.504	0.842	0.407	Delete
E2	0.491	0.842	0.407	Delete
E3	0.59	0.842	0.407	Delete
E4	0.6	0.842	0.407	Delete
E5	0.773	0.842	0.407	Retain
E6	0.725	0.842	0.407	Retain
E7	0.575	0.842	0.407	Delete
E8	0.772	0.842	0.407	Retain
L1	0.594	0.882	0.486	Delete
L2	0.765	0.882	0.486	Retain
L3	0.673	0.882	0.486	Delete
L4	0.724	0.882	0.486	Retain
L5	0.669	0.882	0.486	Delete
L6	0.807	0.882	0.486	Retain
L7	0.704	0.882	0.486	Retain
L8	0.618	0.882	0.486	Delete
V1	0.718	0.887	0.404	Retain
V2	0.711	0.887	0.404	Retain
V3	0.678	0.887	0.404	Delete
V4	0.408	0.887	0.404	Delete
V5	0.711	0.887	0.404	Retain
V6	0.739	0.887	0.404	Retain
V7	0.447	0.887	0.404	Delete
V8	0.547	0.887	0.404	Delete
V9	0.518	0.887	0.404	Delete
V10	0.708	0.887	0.404	Retain
V11	0.712	0.887	0.404	Retain
V12	0.613	0.887	0.404	Delete
P1	0.783	0.925	0.711	Retain
P2	0.872	0.925	0.711	Retain
P3	0.891	0.925	0.711	Retain
P4	0.839	0.925	0.711	Retain
P5	0.827	0.925	0.711	Retain

Table 3. Heterotrait–monotrait (HTMT) ratio of correlations

Variable	Demographic			Behaviour			
	Age	Education	Gender	Perception	Violation	Error	Lapses
Age							
Education	0.377						
Gender	0.059	0.065					
Perception	0.188	0.147	0.101				
Violation	0.11	0.072	0.082	0.243			
Error	0.112	0.082	0.051	0.32	1.061		
Lapses	0.175	0.067	0.193	0.164	0.899	0.863	

Furthermore, the Cronbach's Alpha and CR values for all constructs were also recorded above 0.70, indicating an excellent level of internal consistency. This means that the indicators within each construct are homogeneous and mutually supportive in measuring the same concept. In addition, the AVE values for all constructs were above 0.50, indicating that more than 50% of the indicator variance can be explained by the latent constructs they represent.

After convergent validity is conducted, discriminant validity is then conducted. There are two criteria for discriminant validity: first, the Fornell-Larcker criterion, which requires that the square root of the AVE of each construct must be higher than the correlation between the other constructs. Second, the Heterotrait-Monotrait Ratio of Correlations (HTMT) approach.

Table 4. Outer loadings, cronbach's alpha (CA), composite reliability (CR), and AVE after indicator removal

Indicator	Outer Loading	Cronbach's Alpha (CA)	Composite Reliability (CR)	Average Variance Extracted (AVE)
E5	0.843	0.748	0.855	0.662
E6	0.769	0.748	0.855	0.662
E8	0.828	0.748	0.855	0.662
L2	0.802	0.777	0.853	0.593
L4	0.702	0.777	0.853	0.593
L6	0.835	0.777	0.853	0.593
L7	0.736	0.777	0.853	0.593
V1	0.816	0.818	0.877	0.642
V2	0.725	0.818	0.877	0.642
V5	0.839	0.818	0.877	0.642
V6	0.82	0.818	0.877	0.642
P1	0.778	0.898	0.925	0.711
P2	0.872	0.898	0.925	0.711
P3	0.894	0.898	0.925	0.711
P4	0.839	0.898	0.925	0.711
P5	0.828	0.898	0.925	0.711

The results of the discriminant validity evaluation using the Fornell-Larcker criteria (Table 5) show that each construct in the model has a higher AVE (Average Variance Extracted) square root value compared to the correlation between other constructs.

This indicates that each construct is unique and is able to explain the variance of its indicators more dominantly compared to other constructs, so it can be concluded that discriminant validity has been met. Thus, there is no indication that the constructs in the model overlap empirically, and all constructs can be distinguished from each other statistically.

Table 5. Fornell-larcker criterion

Variable	Demographic		Perception		Behaviour		
	Age	Education	Gender		Violation	Error	Lapses
Age	1						
Education	0.377	1					
Gender	0.059	0.065	1				
Perception	0.179	0.14	0.079	0.843			
Violation	0.084	0.005	-0.008	-0.169	0.801		
Error	0.088	-0.069	0.008	-0.276	0.649	0.814	
Lapses	0.168	0.059	0.171	-0.118	0.68	0.658	0.77

In this table 6 presents the results of the HTMT evaluation after removing indicators that did not meet the measurement validity criteria. Based on the table, all HTMT values were recorded below the threshold of 0.90, indicating that each construct in the model has a clear empirical distinction. This indicates that there is no overlap between constructs, and each construct is capable of representing a statistically distinct concept. By meeting these criteria, it can be concluded that the model's discriminant validity has been adequately confirmed. Overall, these findings strengthen the reliability of the model structure in differentiating the analyzed constructs and provide a strong basis for proceeding to the structural model evaluation stage (inner model) in the PLS-SEM analysis process.

Table 6. HTMT ratios after indicator removal

Variable	Demographic		Perception		Behaviour		
	Age	Education	Gender		Violation	Error	Lapses
Age							
Education	0.377						
Gender	0.059	0.065					
Perception	0.188	0.147	0.101				
Violation	0.087	0.066	0.086	0.186			
Error	0.112	0.082	0.051	0.32	0.848		
Lapses	0.175	0.067	0.193	0.164	0.86	0.863	

Structural Model Analysis

After the measurement model has been declared to meet the validity and reliability criteria, the next stage is to evaluate the structural model to test the causal relationships between the latent constructs formulated in the research conceptual framework. Structural model analysis aims to assess the strength and direction of influence between constructs, as well as to evaluate the model's adequacy in explaining the dependent variable studied. Structural analysis is conducted in stages to ensure that the constructed model meets statistical and substantive criteria. This stage begins with an examination of potential collinearity issues between exogenous constructs, to ensure that the path coefficient estimates are not distorted by excessively high correlations. Subsequently, the significance and relevance of the structural relationships between constructs are tested through path coefficient analysis and bootstrap statistical tests. Next, the model's predictive power is assessed through the coefficient of determination (R^2), followed by the calculation of the effect size (f^2) to measure the relative contribution of each exogenous construct. The next step is an evaluation of predictive relevance (Q^2) using a blindfolding procedure, and finally, an assessment of the Q^2 effect size is performed to assess the predictive power of the exogenous construct on the indicators in the endogenous construct. This entire process aims to gain a comprehensive understanding of the reliability and capability of the structural model in explaining and predicting the phenomena under study.

Based on the table 7 presented, all VIF values are below the threshold of 5, which indicates there is no serious multicollinearity between predictor constructs in influencing the same endogenous construct (Hair et al., 2017). Based on the results of the VIF calculation, all values obtained are below the critical limit, which indicates there is no serious multicollinearity problem in the model. For the endogenous construct ERROR, the paths of AGE, EDUCATION LEVEL, GENDER, and PERCEPTION show VIF values of 1.236, 2.696, 1.104, and 2.797, respectively. Although PERCEPTION and EDUCATION LEVEL have higher VIF values than the other constructs, all are still far below the threshold of 5, so it can be concluded that the four constructs can be used simultaneously as predictors of ERROR without the risk of multicollinearity damaging the estimation. Similarly, for the endogenous construct LAPSES, the VIF values for the AGE, EDUCATION LEVEL, GENDER, and PERCEPTION paths are identical to those for the ERROR construct, namely 1.236, 2.696, 1.104, and 2.797. The consistency of these values indicates the stability of the relationship structure between the constructs and the absence of excessive interactions among the exogenous constructs in explaining LAPSES. For the endogenous construct VIOLATION, the same pattern was again found. The VIFs for AGE, EDUCATION LEVEL, GENDER, and PERCEPTION were 1.236, 2.696, 1.104, and 2.797, respectively. These values are still within the safe range and strengthen the conclusion that the path structure in the model is not disturbed by high correlations between predictors. Meanwhile, for the PERCEPTION construct which is also endogenous, influenced by AGE, EDUCATION LEVEL, and GENDER, the VIF values are 1.185, 1.268, and 1.090, respectively. These values are low and indicate the absence of high correlations between predictor constructs that can interfere with the estimation of structural relationships with PERCEPTION. Thus, based on the VIF evaluation per endogenous construct, it can be concluded that no significant multicollinearity was found in this model, because all VIF values are well below the threshold limit of 5. This condition supports the reliability of the path parameter estimates in the constructed structural model.

After evaluating the statistical significance of the relationships between constructs, the next, equally important step is to assess the practical relevance of those relationships. Unfortunately, many studies stop at the statistical significance stage, neglecting to analyze the relative strength of the constructs' influence within the model. However, in the context of structural models, a statistically significant path coefficient does not necessarily have a substantively meaningful impact, especially in studies with large sample sizes, where even small coefficient values can easily reach significance. Therefore, it is important to consider the magnitude of the path coefficients as a measure of the strength of each construct's contribution to the latent construct it influences, in order to produce more valuable interpretations and support informed decision-making.

Table 7. Variance inflation factor (VIF) values

PATH	Original Sample (O)	Sample Mean (M)	2.50%	97.50%
AGE -> ERROR	1.236	1.245	1.15	1.362
AGE -> LAPSES	1.236	1.245	1.15	1.362
AGE -> PERCEPTION	1.185	1.19	1.11	1.289
AGE -> VIOLATION	1.236	1.245	1.15	1.362
EDUCATION LEVEL -> ERROR	2.696	2.729	2.276	3.255
EDUCATION LEVEL -> LAPSES	2.696	2.729	2.276	3.255
EDUCATION LEVEL -> PERCEPTION	1.268	1.273	1.177	1.389
EDUCATION LEVEL -> VIOLATION	2.696	2.729	2.276	3.255
GENDER -> ERROR	1.104	1.11	1.074	1.155
GENDER -> LAPSES	1.104	1.11	1.074	1.155
GENDER -> PERCEPTION	1.09	1.093	1.06	1.134
GENDER -> VIOLATION	1.104	1.11	1.074	1.155
PERSFEKTIF -> ERROR	2.797	2.836	2.345	3.431
PERSFEKTIF -> LAPSES	2.797	2.836	2.345	3.431
PERSFEKTIF -> VIOLATION	2.797	2.836	2.345	3.431

Path coefficients in PLS-SEM can be compared relative to each path to determine which contributes most to explaining the endogenous construct. Each coefficient can be understood similarly to the standardized beta coefficient in OLS regression, where a one-unit change in the exogenous construct will result in a change in the value of that coefficient in the endogenous construct, assuming all other variables remain constant. When the coefficient is significant, its value reflects the strength of the association between the predictor construct and the outcome construct. Furthermore, certain contexts recommend formal testing of differences between path coefficients within a single model to compare whether the effects of two constructs differ significantly. However, such tests are usually only used when the research hypothesis specifically compares two or more paths within the model structure.

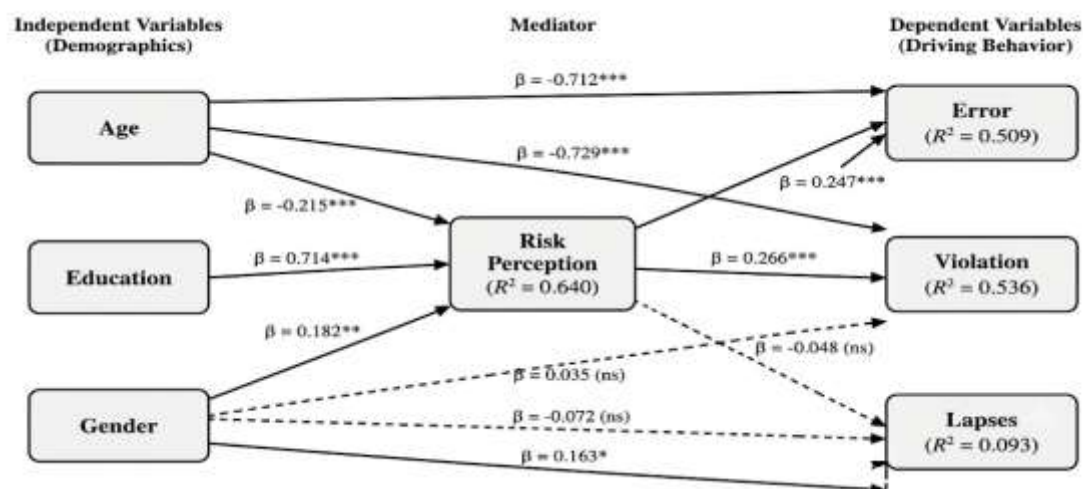


Figure 3. Path diagram showing hypothesis support in driving behavior study

In this figure 3 shows that the relationships between demographic variables (Age, Education, Gender) and driving behavior outcome variables (Error, Violation, Lapses) were mediated by Risk Perception. Statistically significant ($p < 0.05$) hypotheses are presented as solid arrows, while dashed arrows represent paths that were not significant. For interpretation purposes, the path coefficients (β) and R^2 values are provided showing direct and indirect effects of the demographics on driving.

The results of the path analysis (path coefficients) show that of the overall relationship between constructs in the model (see table 8), most paths show a statistically significant effect at the 95% confidence level. The AGE variable significantly negatively affects ERROR ($\beta = -0.712$), PERCEPTION ($\beta = -0.136$), and VIOLATION ($\beta = -0.729$), but does not affect LAPSES ($\beta = 0.008$; $p > 0.05$). EDUCATION LEVEL has a significant effect on all endogenous constructs, namely negatively on ERROR ($\beta = -0.350$) and VIOLATION ($\beta = -0.372$), and positively on LAPSES ($\beta = 0.242$) and PERCEPTION ($\beta = 0.714$). For GENDER, only the paths to LAPSES ($\beta = 0.163$) and PERCEPTION

($\beta = 0.182$) were significant, while the effects on ERROR and VIOLATION were not significant. Meanwhile, the PERCEPTION construct had a significant effect on ERROR ($\beta = 0.247$) and VIOLATION ($\beta = 0.266$), but not on LAPSES ($\beta = -0.020$; $p > 0.05$). These findings indicate that not all relationships in the model have statistically significant contributions, and the relative strength of influence between constructs varies according to the direction and magnitude of their coefficients.

In regression analysis, the coefficient of determination (R^2) is used to measure the proportion of variation in the dependent variable that can be explained by the independent variables in the model. However, the R^2 value has a weakness because it tends to increase with the addition of the number of independent variables, even though these variables are not statistically significant. Therefore, the adjusted R^2 is used as a more reliable measure because it has been adjusted for the number of predictor variables in the model and the sample size used. Adjusted R^2 provides more accurate information in evaluating model fit, especially when the model involves many variables. Analysis of the adjusted R^2 value in this study aims to assess how effective the regression model is in explaining variation in the dependent variable by considering the complexity of the model used.

Table 8. Path coefficients

Path	Original Sample (O)	Sample Mean (M)	P-values
AGE -> ERROR	-0.712	-0.713	0
AGE -> LAPSES	0.008	0.008	0.895
AGE -> PERCEPTION	-0.136	-0.136	0
AGE -> VIOLATION	-0.729	-0.73	0
EDUCATION LEVEL -> ERROR	-0.35	-0.351	0
EDUCATION LEVEL -> LAPSES	0.242	0.243	0.001
EDUCATION LEVEL -> PERCEPTION	0.714	0.714	0
EDUCATION LEVEL -> VIOLATION	-0.372	-0.373	0
GENDER -> ERROR	0.04	0.04	0.331
GENDER -> LAPSES	0.163	0.164	0.001
GENDER -> PERCEPTION	0.182	0.184	0.01
GENDER -> VIOLATION	0.026	0.026	0.508
PERCEPTION -> ERROR	0.247	0.247	0
PERCEPTION -> LAPSES	-0.02	-0.02	0.783
PERCEPTION -> VIOLATION	0.266	0.266	0

Based on the PLS-SEM analysis (Table 9), the Adjusted R^2 values for each endogenous construct indicate the extent of variation explained by the exogenous constructs in the model. The PERCEPTION construct has the highest Adjusted R^2 value of 0.640, indicating that 64% of the variation in perceptions of accidents can be explained by the predictor variables in the model, while the remainder is influenced by other factors outside the model. Furthermore, the VIOLATION construct shows an Adjusted R^2 value of 0.536, meaning the model is able to explain 53.6% of the variation in violation behavior in driving. Meanwhile, the ERROR construct obtained an Adjusted R^2 value of 0.509, indicating that the model explains approximately 50.9% of the variation in errors while driving. In regard to the LAPSES construct, the Adjusted R^2 value obtained is the lowest at 0.093, implying that only 9.3% of the variance in the negligent behavior can be explained using the model, while most of the variance will still be due to factors other than those within the analyzed construct. From the above analysis, it can be deduced that the model functions effectively in explaining the PERCEPTION, VIOLATION, and ERROR constructs but performs poorly when trying to explain the LAPSES construct.

The Adjusted R^2 value obtained for the LAPSES construct of 0.093 indicates that the proportion of negligent behavior variance that can be explained by the exogenous construct in this model is relatively low. However, the decision not to add additional constructs to the model remains theoretically and methodologically justifiable. This study was specifically designed to examine the influence of demographic variables such as age, education level, and gender on three forms of driving behavior: violations, errors, and lapses, with risk perception as a moderator variable. Thus, the exogenous constructs used have been adjusted to the main objective of the study, namely to assess the extent to which demographic factors can influence the dimensions of driving behavior studied. The low Adjusted R^2 value for the LAPSES construct may reflect that negligent driving is likely more influenced by internal psychological factors such as stress, fatigue, or concentration levels, which are not explicitly

included in the scope of this model. Therefore, the low predictive power of the model on the LAPSES construct is not a methodological weakness, but rather a consequence of the focus and limitations that have been consciously established in the conceptual framework of this study.

In order to establish the contribution of each independent latent variable towards the dependent latent variable in the structural model, f-square (f^2) test was carried out. F-square (f^2) gives the magnitude of the effect of each independent construct towards the dependent construct. Unlike the R-square (R^2), which shows the contribution of all the exogenous variables in explaining the dependent variable, the f^2 only measures the magnitude of the effect of each individual exogenous variable towards the dependent variable. From a study, generally, there are some rules of thumb about f^2 . That is, $f^2 = 0.02$ is small effect, $f^2 = 0.15$ is medium effect, while $f^2 = 0.35$ is large effect. Through this analysis, it is hoped that it will be possible to determine the extent to which each construct has a significant and substantive influence on the intended construct, thereby strengthening the interpretation of the influence paths found in the model.

Table 9. Adjusted R^2 values

	Original sample (O)	Sample mean (M)	P values
ERROR	0.509	0.513	0
LAPSES	0.093	0.097	0
PERCEPTION	0.64	0.642	0
VIOLATION	0.536	0.54	0

Based on the results of the effect size analysis using the f-squared (f^2) value (Table 10), it was found that several paths in the model had a strong substantive contribution, while others showed a smaller but still significant influence. The paths AGE → VIOLATION and AGE → ERROR showed large effects, indicating that age is a dominant factor in explaining variations in violation and error behavior while driving. In addition, EDUCATION LEVEL → PERCEPTION also showed a large effect, indicating that education level plays a significant role in shaping drivers' risk perceptions regarding safety. In contrast, paths such as GENDER → LAPSES, GENDER → PERCEPTION, and PERCEPTION → ERROR and PERCEPTION → VIOLATION showed relatively small f^2 values, although statistically significant, which means that the practical contribution of these variables to the endogenous construct is relatively limited in the context of this model. The results highlight the relevance of age and education as factors determining driving behavior, with gender and safety perceptions having secondary roles which complement the general picture of the model. The results also show that the effects of education are not as strong as the effects of age and gender on risk perception, although they are also present.

The PLS Predict approach was used for an analysis of the predictive Q-squared (Q^2 predict) value, used to assess the ability of the model to predict values for the endogenous variables that are not included in the estimation. The Q^2 predict value indicates out-of-sample predictive validity, or how well the model can predict new data that was not part of the sample for the modeling. This analysis is necessary to make sure that the model is not only a good fit (in-sample fit), but can be practically applied as well.

Table 10. Effect-size (f^2) values

Path	Original sample (O)	Sample mean (M)	P values
AGE -> ERROR	0.841	0.848	0
AGE -> PERCEPTION	0.043	0.046	0.035
AGE -> VIOLATION	0.933	0.942	0
EDUCATION LEVEL -> ERROR	0.091	0.094	0.001
EDUCATION LEVEL -> LAPSES	0.051	0.053	0.006
EDUCATION LEVEL -> PERCEPTION	1.126	1.145	0
EDUCATION LEVEL -> VIOLATION	0.11	0.114	0.001
GENDER -> LAPSES	0.057	0.059	0.031
GENDER -> PERCEPTION	0.04	0.042	0.044
PERCEPTION -> ERROR	0.048	0.051	0.024
PERCEPTION -> VIOLATION	0.058	0.061	0.022

Interpretation of the Q^2 predict value is based on the general guideline that values > than 0.35 are considered to represent high predictive ability, 0.15 – 0.35 are considered to represent moderate predictive ability, and 0 – 0.15 are considered to represent low predictive ability, but are still considered

to be predictively relevant. The Q^2_{predict} is therefore highly informative about the "generalization" quality of the model's prediction in contexts other than the one the model was built on. The evaluation results of predictive relevance using Q^2_{predict} values indicate that the PLS-SEM model has varying predictive capabilities for each endogenous construct. The PERCEPTION construct shows the highest Q^2_{predict} value of 0.639, indicating that the model has high predictive capabilities in explaining drivers' perceptions of traffic safety. The VIOLATION and ERROR constructs also show strong Q^2_{predict} values, at 0.510 and 0.487, respectively, so both are included in the high prediction category, and confirm that the model has substantial predictive power for violation behavior and driving errors. Meanwhile, the LAPSES construct shows a Q^2_{predict} value of 0.088, which is still relatively low but still positive, meaning that the model still has relevance in predicting this variable, although its predictive contribution is not as strong as the other constructs. Overall (see table 11), these results confirm that the PLS-SEM model used in this study has good out-of-sample predictive validity for most constructs, particularly those related to driving perceptions and behavior.

Table 11. Q^2_{predict} values

Construct	Q^2_{predict}
ERROR	0.487
LAPSES	0.088
PERCEPTION	0.639
VIOLATION	0.51

Based on a series of measurement model and structural model analyses conducted, it can be concluded that the PLS-SEM model constructed has met the requirements for statistical and substantive feasibility evaluation. Convergent validity and discriminant validity analyses were conducted at the measurement analysis stage. After the validity and reliability requirements were met, the structural model analysis stage was continued. At the structural model analysis stage, the multicollinearity test showed that all constructs had VIF values below the recommended threshold (<5), so there was no indication of multicollinearity between predictors. Furthermore, path coefficient analysis showed a number of significant relationships between exogenous and endogenous variables, which was then reinforced by the results of the f-squared (f^2) analysis which identified that the influence of constructs such as AGE, EDUCATION LEVEL, and PERCEPTION had a large substantive contribution to variables such as ERROR, VIOLATION, and PERCEPTION. Furthermore, the Q^2 values from blindfolding and Q^2_{predict} from PLS Predict consistently show high predictive ability for most constructs, with the highest values found in PERCEPTION and VIOLATION, while LAPSES still shows relevant predictions albeit in the low category. These results confirm that the model is not only theoretically and statistically feasible but also has good predictive validity for real-world applications. Based on the significant paths in the model, the resulting structural equations are as follows:

$$ERROR = -0.712(AGE) - 0.350(EDUCATION) + 0.247(PERCEPTION) \quad (1)$$

$$LAPSES = 0.242(EDUCATION) + 0.163(GENDER) \quad (2)$$

$$VIOLATION = -0.729(AGE) - 0.372(EDUCATION) + 0.266(PERCEPTION) \quad (3)$$

$$PERCEPTION = -0.136(AGE) + 0.714(EDUCATION) + 0.182(GENDER) \quad (4)$$

These equations (1 to 4) reflect the statistically significant main influence paths and form the basis for interpreting the relationships between constructs in explaining driving behavior and safety perceptions.

DISCUSSION

The results validate a key role for risk perception as a core mediator between demographics and driving behavior. There is a relationship between age, education and perception, with older drivers showing a lower risk perception and potentially not having risky behavior as they are experienced and cautious. In most cases, women had more perception and lower risk than men, and education had the greatest positive impact, increasing their awareness and understanding of traffic safety. These findings show that demographic factors affect not only how people perceive the issue of driving but also their driving

behavior, with their impact differing between different groups. However, results revealed an unexpected link between risk perception and the number of errors and violations: The riskier, the more errors and violations. This is in line with Risk Homeostasis Theory, which suggests that when drivers perform a risky behavior, they attempt to compensate in order to maintain the risk within a preferred range. A false feeling of security, or safety features of the car can lead to dangerous actions. The attitude-behavior gap indicates that simply being aware is not sufficient – it does not necessarily lead to safer driving.

The study points to the need for context-specific, focused interventions. Programs addressing traffic safety should incorporate education with hands-on, real-life approaches like driving simulations, scenario-based training, and reflective exercises. Adjusting the interventions according to age, gender, and education level may improve the effectiveness of the intervention, such as by using immersive simulations for younger drivers and light community-based modules for older drivers. There are a number of recommendations, including the adoption of law enforcement measures, including digital monitoring and penalties; enhanced vehicle safety design; and the integration of continuous feedback mechanisms. The integration of these can help reinforce safe driving practices, and may help bridge the gap between what they see and what they are driving.

CONCLUSION AND RECOMMENDATIONS

The analysis shows that perception has an important mediating function between demographic characteristics and risky driving. The child's education score (0.714), gender (0.182), and age (-0.136) had significant effects on perception; however, the risk perception score had unexpected positive effects on errors (0.247) and violations (0.266), indicating that higher safety awareness and/or safety aids might lead to higher levels of overconfidence, increasing the risk of driving. Targeted interventions were important, as age was consistently associated with decreased errors and violations, while higher levels of education were associated with decreased negative behaviors. Therefore, traffic safety education should not just be about increasing awareness of traffic risks but also include hands-on learning experiences like driving simulators, videos that show the consequences of traffic violations, and discussions of accidents and scenarios that occur in the community. When making interventions, it is important to consider demographic-specific strategies to improve intervention efficacy: younger drivers might be reached through practical simulations or campaign-based commitments; adult drivers may be reached by vision assessments and light community-based education; highly educated drivers may be reached through features such as "Do Not Disturb While Driving" and multitasking avoidance campaigns; older drivers may be reached through vision assessments and light community-based education. Authorities, educational and transport agencies are urged to roll out contextually relevant safety modules, based on empirical evidence, that incorporate the findings of research into their programs, and to simultaneously use consistent, evidence-based strategies like e-ticketing and digital patrols to help promote behavior change. Longitudinal and triangulated studies are recommended for future research to observe the changing relationship between perception, self-confidence, and driving behavior, and to ensure that repeated measurements of behavioral change can be used to provide a solid evidence base to guide the development and evolution of traffic safety policies and interventions.

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