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Why Riders Break the Rules: A Structural Equation Modeling Approach to Traffic Violations in a Developing Region

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ABSTRACT

Traffic violations remain a major contributor to road traffic accidents in Indonesia. Despite government initiatives, limited research has examined the psychological and contextual factors driving this behavior. This study extends the Theory of Planned Behavior (TPB) by incorporating risk perception, habit, emotional condition, environmental condition, and legal knowledge and awareness. A structured questionnaire (N=100) was administered to motorcyclists and/or car drivers in East Java; items were derived from established scales and refined using field observations and a pilot test. Respondents were selected using stratified area sampling to ensure relevance. Data were analyzed using PLS-SEM (SmartPLS). Key findings: attitude and perceived behavioral control significantly predicted behavioral intention; intention strongly predicted actual violation behavior; risk perception negatively predicted permissive attitudes. Habit, subjective norms, emotional and environmental conditions, and legal knowledge were not significant predictors. The study contributes theoretically by refining TPB with risk perception as an antecedent of attitude, and practically by suggesting interventions targeting attitudes and risk awareness supported by technology-assisted enforcement in developing-country contexts.

1. Introduction

Unsafe driving behavior is a major contributor to global road accidents. The World Health Organization estimates that 1.19 million people die each year due to road traffic injuries, and 20–50 million suffer non-fatal injuries, many resulting in permanent disability. Vulnerable road users especially motorcyclists in low and middle-income countries are disproportionately affected (WHO, 2023). In Indonesia, traffic accidents remain a pressing public safety issue. According to the Integrated Road Safety Management System (IRSMS), a total of 79.220 traffic accidents were reported as of 5 August 2024, with motorcycles accounting for 76.42% of cases. April recorded the highest number of incidents, followed by slight declines in June and July.

This fluctuation highlights the dynamic nature of traffic conditions and underscores the urgent need to understand the behavioral drivers behind such incidents. While infrastructure and enforcement play important roles, the persistence of accidents despite ongoing government efforts suggests that individual behavior is a key determinant. This makes theory-driven behavioral frameworks essential to explain why drivers continue to engage in unsafe practices (Redaksi, 2024).

Numerous studies have identified driver behavior as one of the most critical contributors to both the frequency and severity of traffic accidents. Behavioral violations such as not wearing helmets, speeding, running red lights, driving under the influence, or driving while fatigued are common risk factors in both developing and developed nations (Scott-Parker et al., 2014; Dapilah et al., 2017). Notably, many traffic rule violations are not accidental but rather intentional and repetitive. Despite being aware of the potential risks, many drivers continue to engage in unsafe or unlawful behavior. This highlights the importance of exploring the cognitive and psychosocial mechanisms underlying traffic violations (Tang et al., 2025). However, most of these studies have not considered the complex interactions between habits, emotions, and environmental conditions in the context of driving in developing countries, where weak law enforcement and cultural permissiveness may further influence driving behavior (Hasan et al., 2024). To investigate these behavioral patterns, theory-based frameworks and advanced quantitative models have become increasingly relevant. Among the most widely used theories is the Theory of Planned Behavior (TPB) developed by Ajzen (1991), which explains behavior as a function of individual attitudes, subjective norms, and perceived behavioral control. This theory provides valuable insights into how individuals make decisions and act under specific circumstances. However, TPB alone may not sufficiently explain driving behavior in diverse sociocultural contexts. Therefore, researchers have increasingly incorporated additional psychological and contextual constructs to enhance explanatory power (Arslan et al., 2025; Brenner, 2024).

Several extensions to the TPB have been proposed, including the integration of risk perception, habitual behavior, emotional state, situational factors, and legal knowledge and awareness (Ajzen, 1991; Hai et al., 2024). Risk perception reflects an individual's awareness of the potential consequences of risky driving behavior (Teye-Kwadjo, 2019; Sayed et al., 2023). Low self-control is also linked to increased likelihood of rule violations and impulsive driving (Jin et al., 2021). Habits may lead to automatic behavior, especially in the context of minor and frequently repeated traffic violations (Love et al., 2022; Vinh et al., 2022). Emotional states such as stress, frustration, or anxiety also influence how drivers behave on the road, often leading to aggressive or unsafe actions (Roche et al., 2020; Liu et al., 2021). Environmental conditions, including slippery roads, heavy rain, poor road surfaces, or narrow lanes, can increase the likelihood of risky maneuvers (Sadia et al., 2018). Moreover, the lack of traffic law knowledge and low legal awareness have been recognized as aggravating factors (Love et al., 2022).

Few studies in Indonesia have tested an extended TPB model that simultaneously incorporates habit, emotion, environment, legal knowledge, and risk perception using PLS-SEM. This study fills that gap by first, it extends the traditional TPB framework by incorporating additional constructs: risk perception, habit, emotional condition, environmental condition, and legal knowledge and awareness. Second, this study introduces a dual classification system for driving behavior that distinguishes between legally classified violations that may appear safe to drivers and unsafe driving behaviors that are not necessarily classified as legal violations. Third, grounding item development in field observations across in East Java.

This study pursues three interrelated objectives to enhance understanding of, and to inform interventions for, traffic violations in developing-country contexts. First, it tests an extended TPB model to predict both behavioral intentions and actual traffic-violation behavior. Second, it assesses the influence of key factors, risk perception, habit, emotional and environmental conditions, and legal knowledge, on such behavior. Third, it derives evidence-based recommendations for policies and interventions aimed at improving road safety in developing countries.

2. Method

2.1. Preliminary Study

The initial phase of this research involved problem identification, literature review, field observations, and formulation of research objectives. The field observations were first conducted in urban, sub-urban, and peri-urban areas of East Java to identify common types of violations, situational triggers, and the expressions typically used by riders. These insights guided the selection and wording of questionnaire items, thereby enhancing ecological validity. The items themselves were adapted from established scales in the literature, translated into Bahasa Indonesia, and then refined through a pilot test with 30 respondents to assess clarity and face validity. Minor wording modifications were made based on this feedback.

2.2. Sampling and Data Collection

A stratified area sampling approach was used to ensure representation across urban, suburban, and rural strata. Within each stratum, convenience and purposive recruitment targeted motorcyclists and car drivers active in local communities and social media groups. The survey was disseminated via targeted messaging apps and social-media groups between April and June 2024. Inclusion criteria: age ≥ 17, possession of a valid driving license, and self-reported experience with traffic violations or unsafe driving behaviors. The final sample comprised 100 valid responses.

A total of 100 valid responses were collected to ensure statistical reliability. Although the sample size may appear limited, Partial Least Squares Structural Equation Modeling (PLS-SEM) is suitable for small to medium samples and complex models (Hair et al., 2018). Based on the "10 times rule," the minimum required sample size is ten times the maximum number of structural paths directed at a latent construct. In this study, the most complex construct had nine indicators, requiring at least 90 respondents. Thus, the sample size of 100 is considered adequate for reliable estimation and hypothesis testing.

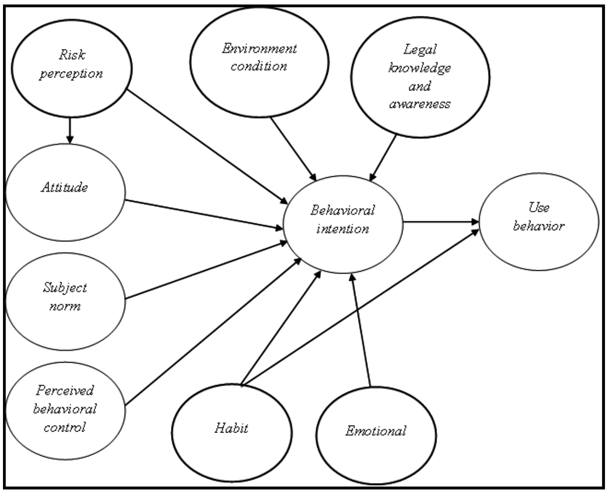

Fig. 1. The conceptual model of the proposed method

The questionnaire consisted of three sections, namely socio-demographic characteristics, types of traffic violations and unsafe driving behaviors, and items measuring latent constructs derived from the extended TPB. All items were measured using a five-point Likert scale (1 = strongly disagree to 5 = strongly agree) and were pre-tested for clarity and content validity. To enhance contextual accuracy, the development of the instrument was informed by preliminary field observations of common traffic behaviors in East Java. The conceptual model, presented in Fig. 1, extends the traditional TPB by integrating five additional constructs risk perception, habit, emotional condition, environmental condition, and legal knowledge and awareness hypothesized to influence behavioral intention and use behavior. In this model, risk perception is positioned as an antecedent of attitude toward traffic violations. The original TPB variables, subjective norm and perceived behavioral control, are retained as predictors of behavioral intention. Additional constructs, namely habit, emotional condition, environmental condition, and legal knowledge and awareness, are also hypothesized to exert direct effects on behavioral intention. Finally, behavioral intention is considered the primary determinant of use behavior on the road. This framework therefore emphasizes not only internal psychological factors but also situational conditions, habitual patterns, and legal awareness, which are highly relevant in the context of developing countries such as Indonesia.

2.3. Data Analysis

Data were analyzed using PLS-SEM, implemented via SmartPLS. PLS-SEM is a widely adopted technique in behavioral and social sciences for modeling complex relationships between latent constructs (Ping et al., 2018). The analysis followed a two-step process, measurement model assessment for evaluating construct validity and reliability and structural model evaluation for hypothesis testing and path analysis. A construct was considered valid and reliable if it met the following criteria: outer loading, Cronbach's alpha, and composite reliability > 0.70, Average Variance Extracted (AVE) > 0.50 (Hair et al., 2018).

Discriminant validity was assessed using the Heterotrait-Monotrait (HTMT) ratio, with a threshold of < 0.90 (Henseler, 2017). The structural model was evaluated through the coefficient of determination (R^2), representing the proportion of variance in the dependent variables explained by the model. An R^2 value of 0.25 or higher is considered acceptable for behavioral studies (Hair et al., 2018). In addition, overall model fit was examined using the Standardized Root Mean Square Residual (SRMR), with values below 0.08 indicating a good fit. Complementary indices such as the Normed Fit Index (NFI) and chi-square were also considered to provide further evidence of model adequacy, ensuring that the proposed framework adequately represents the observed data (Henseler et al, 2015).

The proposed research model extends the TPB by integrating five additional constructs: risk perception, habit, emotional condition, environmental condition, and legal knowledge and awareness. Each hypothesis was formulated based on prior theoretical frameworks and empirical studies.

H1: Risk perception has a positive effect on attitude toward the behavior.
H2: Risk perception has a positive effect on behavioral intention.
H3: Attitude toward the behavior has a positive effect on behavioral intention.
H4: Subjective norm has a positive effect on behavioral intention.
H5: Perceived behavioral control has a positive effect on behavioral intention.
H6: Habit has a positive effect on behavioral intention.
H7: Habit has a positive effect on use behavior.
H8: Emotional condition has a positive effect on behavioral intention.
H9: Environmental condition has a positive effect on behavioral intention.
H10: Legal knowledge and awareness have a positive effect on behavioral intention.
H11: Behavioral intention has a positive effect on use behavior.

3. Results and Discussion

3.1. Respondent Profile

This study involved respondents from various regions of East Java Province. A purposive sampling technique was employed, targeting individuals who were active motorcycle users and likely to have engaged in traffic violations or unsafe driving practices. The demographic characteristics of the respondents are summarized in Table 1.

The sample was 53% male and 47% female. Most respondents were aged between 25 and 34 years (38%), a group empirically associated with high mobility, increased exposure to road risk, and greater likelihood of engaging in violations due to lifestyle and travel frequency. In terms of vehicle type, 88% of the respondents reported using motorcycles as their primary mode of transportation. This figure reflects the dominant transportation mode in both East Java and Indonesia at large, where motorcycles are associated with higher traffic violation rates due to their maneuverability, flexibility, and relatively limited enforcement (Wegman, 2017).

Table 1. Demographic data

Description	Percentage
Gender	
Male	53%
Female	47%
Age	
18 – 24 years	35%
25 – 34 years	38%
35 – 44 years	16%
45 – 54 years	5%
55 – 64 years	6%
Purpose of Riding	
Daily activities (e.g., work, school, errands)	93%
Leisure	4%
Visiting friends/relatives	2%
Religious activities	1%

3.2. Descriptive Statistics and Types of Violations

The types of traffic violations committed by respondents are presented in Table 2. The data indicate a distribution of both minor and serious offenses, ranging from the failure to wear a helmet or seatbelt to driving under the influence of alcohol. The most frequent violations relate to basic compliance with highly visible rules. For instance, not wearing a helmet or seatbelt (16.13%) indicates a low level of personal safety awareness and poor risk perception. Similarly, administrative violations such as driving without a license or registration (12.90%) and disobeying traffic signs or signals (over 12%) point to inadequate traffic education, weak enforcement, and a public perception that the likelihood of apprehension is minimal, especially outside of official checkpoints or traffic patrol hours.

From the perspective of the TPB, these violations are associated with permissive attitudes, low perceived behavioral control over enforcement, and social norms that tolerate minor rule-breaking.

Table 2. Types of traffic violations committed

No.	Type of Traffic Violation	%
1	Not wearing a helmet or seatbelt	16.13
2	Driving without a license and/or vehicle registration	12.90
3	Violating traffic signs	12.54
4	Running red lights	12.19
5	Driving against the flow of traffic	8.24
6	Speeding	8.60
7	Vehicle incompleteness (missing mirrors, plate, exhaust)	5.73
8	Overtaking from the wrong side	6.10
9	Failing to signal when turning	4.30
10	Driving on pedestrian sidewalks	3.94
11	Carrying excessive passengers	4.30
12	Driving without headlights	3.23
13	Causing an accident (e.g., hitting another rider)	1.08
14	Driving under the influence of alcohol or drugs	0.72
15	Damaging or obstructing road functions	0.00
16	Street racing	0.00

3.3. Descriptive Statistics and Types of Unsafe Driving Behavior (Non-Violations)

In addition to legal violations, the study also examined unsafe driving behaviors that may not be classified as illegal but pose significant risks. These are detailed in Table 3. Such behaviors include activities that distract attention, reduce physical control, or impair decision-making while driving.

Among all the unsafe behaviors analyzed, distraction-related behaviors were the most prevalent. These include using mobile phones while driving (22.19%), driving while fatigued or sleepy

(16.89%), and operating a vehicle with one hand (11.92%). These behaviors often go unnoticed by law enforcement because they do not constitute formal violations, yet they significantly increase the likelihood of accidents.

Psychological factors such as fatigue and emotional instability (e.g., stress, anger, or panic) were also prominent. These findings emphasize the need to address not only rule-breaking behavior but also risky behavioral patterns that are not currently addressed through enforcement or regulation.

Table 3. Types of unsafe driving behavior (non-violative)

No.	Type of Unsafe Driving Behavior	%
1	Using a mobile phone (music, calls, messages) while driving	22.19
2	Driving while fatigued or sleepy	16.89
3	Driving with one hand (e.g., holding a phone or object)	11.92
4	Intense conversation with passengers while driving	10.60
5	Driving with unstable emotions (anger, sadness, panic)	10.26
6	Eating, drinking, or smoking while driving	9.27
7	Not maintaining a safe distance from the vehicle ahead	7.95
8	Carrying overweight or oversized items	6.95
9	Driving under the influence of legal medications (e.g., sedatives)	3.97

These behaviors highlight the importance of enhancing driver education and integrating emotional regulation and situational awareness into safety training programs. The data show that distraction-related behaviors, particularly mobile phone use while driving (22.19%) and driving while fatigued (16.89%), were the most frequent unsafe practices. This indicates that many violations are not purely legal in nature but stem from everyday habits that reduce driver attention and control. Such patterns suggest that unsafe driving is often linked to reduced self-regulation rather than deliberate defiance of rules. Therefore, future policy frameworks should not only reinforce compliance with existing traffic laws but also address high-risk behaviors not yet regulated, such as driving while distracted or fatigued, which represent a significant portion of unsafe practices in East Java.

3.4. Structural Equation Modeling Analysis

This study employed Structural Equation Modeling (SEM) using the Partial Least Squares (PLS) approach to examine the influence of attitude, perceived behavioral control, subjective norms, habit, environmental condition, emotional condition, risk perception, and legal knowledge on behavioral intention and use behavior related to traffic violations. The detailed measurement items for each construct are presented in Table 4.

Table 4. Construct items and measurement statements

Construct	Code	Statement
Risk Perception (RP)	RP1	I realize that unsafe driving and violating traffic rules can result in serious consequences.
	RP2	I am aware that even minor traffic violations and unsafe driving can lead to fatal accidents.
	RP3	I understand that unsafe driving and minor violations can harm others.
Habit (H)	H1	I am used to driving unsafely and violating traffic rules without much thought.
	H2	I often drive unsafely and violate traffic rules without even realizing it.
	H3	I tend to drive unsafely and break traffic rules when there are no traffic officers around.
	H4	I tend to drive unsafely and violate rules when on quiet or non-main roads at certain times.
	H5	I tend to drive unsafely and break rules during short trips.
Emotional Condition (E)	E1	I am impatient while driving.
	E2	Negative emotions (anger, stress, anxiety) affect my ability to drive safely and obey traffic laws.
	E3	I tend to be easily provoked by other drivers and act aggressively on the road.

Construct	Code	Statement
	E4	Sometimes, my arrogance appears while driving, making me less considerate toward other road users.
Environmental Condition (EC)	EC1	Traffic congestion makes it difficult for me to follow traffic rules.
	EC2	Poor road conditions force me to drive unsafely and break the rules to avoid vehicle damage.
	EC3	Road geometry (slopes, curves, etc.) forces me to drive unsafely and violate traffic regulations.
	EC4	Traffic situations often compel me to break the rules.
Legal Knowledge and Awareness (LK)	LK1	I am unaware that traffic violations may result in fines, imprisonment, or license revocation.
	LK2	I do not know the correct procedures when involved in a traffic violation.
	LK3	I am not aware that following traffic rules is a legal obligation.
Subjective Norms (SN)	SN1	People close to me often drive unsafely and commit traffic violations.
	SN2	My friends tend to drive unsafely and break traffic rules.
	SN3	Those close to me and my friends do not correct me if I drive unsafely or violate traffic laws.
	SN4	Others' opinions can influence my traffic behavior.
Perceived Behavioral Control (PB)	PB1	I find it hard to control myself to drive safely and follow traffic rules.
	PB2	I find it difficult to avoid unsafe driving and violations in certain situations.
	PB3	I find it easy to break traffic rules.
Attitude Toward the Behavior (ATB)	ATB1	Safe driving and following traffic rules are not very important to me.
	ATB2	Not all traffic violations are dangerous to myself or others.
	ATB3	I do not feel guilty when I drive unsafely or break traffic rules.
	ATB4	I believe that unsafe driving and breaking the rules can sometimes benefit the trip.
	ATB5	I feel that following traffic rules is often inefficient, especially in certain situations.
	ATB6	I believe I will not be penalized even if I drive unsafely or break the rules.
	ATB7	I consider some traffic rules not important enough to follow.
Behavioral Intention (BI)	BI1	I intend to violate traffic rules even if my driving is safe.
	BI2	I will drive unsafely even though it does not involve traffic violations.
	BI3	I have thought about driving unsafely and violating traffic rules.
	BI4	I will drive unsafely and break rules if it helps me reach my destination faster.
	BI5	I will ignore traffic rules if the sanctions are not enforced.
Use Behavior (UB)	UB1	I often violate traffic rules even if my driving is otherwise safe.
	UB2	I often drive unsafely but do not necessarily violate any laws.
	UB3	I have driven unsafely and violated traffic rules.
	UB4	I often drive unsafely and break traffic rules if it helps me arrive faster.
	UB5	I have ignored traffic rules when enforcement is weak or absent.

3.5. Measurement Model Evaluation

Convergent validity was assessed through outer loading and Average Variance Extracted (AVE) values. Indicators with loadings >0.70 and AVE >0.50 were considered valid. In this study, no indicators had loadings below 0.70; therefore, all items were retained in the model. The AVE values across all constructs ranged from 0.650 to 0.758, and all outer loadings exceeded 0.70, confirming acceptable convergent validity (Hair et al., 2018). For instance, Attitude Toward Behavior had an AVE of 0.650, and Perceived Behavioral Control showed an AVE of 0.752 with outer loadings ranging from 0.800 to 0.906.

Internal consistency reliability was verified using Cronbach's Alpha and Composite Reliability (CR). All constructs exceeded the recommended thresholds (>0.70), indicating strong reliability (Nunnally & Bernstein, 1994). For example, the Habit construct yielded $\alpha = 0.905$ and CR = 0.930. Detailed results are provided in Table 5.

Table 5. Validity and reliability of constructs

Construct		Outer loading	VIF	Cronbach's alpha	Composite reliability	AVE
ATB	ATB1	0.721	2.007	0.910	0.928	0.650
	ATB2	0.770	1.840			
	ATB3	0.791	2.087			
	ATB4	0.799	2.458			
	ATB5	0.873	3.832			
	ATB6	0.842	2.746			
	ATB7	0.840	2.772			
BI	BI1	0.868	2.763	0.913	0.935	0.743
	BI2	0.888	3.188			
	BI3	0.847	2.746			
	BI4	0.865	2.655			
	BI5	0.839	2.497			
E	E1	0.793	1.747	0.833	0.888	0.665
	E2	0.855	2.358			
	E3	0.822	2.105			
	E4	0.790	1.490			
EC	EC1	0.832	1.994	0.877	0.915	0.730
	EC2	0.850	2.257			
	EC3	0.876	2.447			
	EC4	0.859	2.185			
H	H1	0.789	2.235	0.905	0.93	0.726
	H2	0.904	3.824			
	H3	0.926	4.482			
	H4	0.849	2.808			
	H5	0.783	1.973			
LK	LK1	0.873	2.180	0.838	0.901	0.753
	LK2	0.850	1.991			
	LK3	0.880	1.815			
PB	PB1	0.893	2.417	0.834	0.901	0.752
	PB2	0.906	2.597			
	PB3	0.800	1.567			
RP	RP1	0.833	1.995	0.840	0.904	0.758
	RP2	0.861	1.897			
	RP3	0.915	2.743			
SN	SN1	0.860	2.437	0.876	0.915	0.729
	SN2	0.884	2.701			
	SN3	0.889	2.641			
	SN4	0.779	1.846			
UB	UB1	0.913	4.714	0.904	0.929	0.725
	UB2	0.861	3.860			
	UB3	0.755	2.300			
	UB4	0.891	3.098			
	UB5	0.828	2.478			

Discriminant validity was assessed using the Heterotrait-Monotrait Ratio (HTMT). All construct pairs scored below 0.90, confirming that the constructs are empirically distinct (Henseler et al, 2015). HTMT values are presented in Table 6.

Overall, the SmartPLS output demonstrates strong reliability and validity across all constructs, indicating that the measurement instrument can be confidently used to analyze traffic violation behavior among road users in East Java.

Table 6. HTMT scored

	ATB	BI	E	EC	H	LK	PB	RP	SN	UB
ATB										
BI	0.801									
E	0.637	0.634								
EC	0.723	0.646	0.606							
H	0.635	0.613	0.474	0.522						
LK	0.481	0.619	0.513	0.360	0.637					
PB	0.798	0.872	0.730	0.678	0.705	0.802				
RP	0.269	0.373	0.154	0.135	0.273	0.282	0.231			
SN	0.659	0.737	0.725	0.637	0.527	0.706	0.890	0.211		
UB	0.804	0.897	0.613	0.593	0.609	0.565	0.892	0.279	0.727	

3.6. Structural Model and Hypothesis Testing

Bootstrap results (5.000 resamples) show the following key relationships:

1. Attitude Toward Behavior → Behavioral Intention ($\beta = 0.339$, $p = 0.015$)
2. Behavioral Intention → Use Behavior ($\beta = 0.739$, $p < 0.001$)
3. Perceived Behavioral Control → Behavioral Intention ($\beta = 0.317$, $p = 0.026$)
4. Risk Perception → Attitude Toward Behavior ($\beta = -0.261$, $p = 0.003$)

Other hypothesized paths (habit, subjective norms, emotional condition, environmental condition, legal knowledge) were not statistically significant. A full list of results is provided in Table 7. The model fit assessment was conducted using SmartPLS, and the Standardized Root Mean Square Residual (SRMR) value for the saturated model was 0.072, which is below the recommended threshold of 0.08, indicating an acceptable model fit. In contrast, the SRMR value for the estimated model was 0.198, which exceeds the recommended cutoff, suggesting that while the measurement model shows an adequate fit, the structural model may still be improved. The Normed Fit Index (NFI) values were 0.611 for the saturated model and 0.586 for the estimated model, both of which fall below the conventional threshold of 0.90, but are considered acceptable for exploratory studies in behavioral and social sciences, particularly when using PLS-SEM with complex models (Hair et al., 2018).

Table 7. Hypothesis testing results (sample mean, SD, t-statistics, p-values)

Hypothesis	Path	Sample Mean (β)	Std. Deviation	t-Statistics	p-Value	Result
H1	RP → ATB	-0.261	0.084	2.947	0.003	Supported
H2	RP → BI	-0.134	0.079	1.780	0.075	Not supported
H3	ATB → BI	0.339	0.131	2.433	0.015	Supported
H4	SN → BI	0.062	0.098	0.816	0.415	Not supported
H5	PB → BI	0.317	0.151	2.222	0.026	Supported
H6	H → BI	0.039	0.121	0.132	0.895	Not supported
H7	H → US	0.149	0.094	1.573	0.116	Not supported
H8	E → BI	0.040	0.081	0.500	0.617	Not supported
H9	EC → BI	0.070	0.078	0.919	0.358	Not supported
H10	LK → BI	0.059	0.098	0.617	0.537	Not supported
H11	BI → UB	0.739	0.076	9.723	0.000	Supported

Additional fit indices included the squared Euclidean distance (d_ULS) and the geodesic distance (d_G). For the saturated model, d_ULS = 4.862 and d_G = 3.953, whereas for the estimated model, d_ULS = 37.161 and d_G = 4.701. These values provide further evidence that the measurement model exhibits satisfactory approximation, while some discrepancies remain at the structural level. The chi-square values (1782.684 for the saturated model and 1899.754 for the estimated model) are relatively high, which is common in models with a large number of indicators and paths. Overall, the fit indices suggest that the extended TPB model employed in this study achieves a reasonable degree of approximation, supporting its adequacy for explaining behavioral intentions and actual traffic violation behavior in the Indonesian context.

3.6.1. Influence of Attitude Toward Behavior on Behavioral Intention

Hypothesis testing was conducted using path coefficients (β), t-statistics, and p-values. A path was considered significant at $p < 0.05$. To aid interpretation, the effect size of the path coefficients was categorized as follows: weak ($\beta < 0.20$), moderate ($\beta = 0.20$–0.39), and strong ($\beta \geq 0.40$). Attitude toward the behavior significantly influenced behavioral intention ($\beta = 0.339$, $p = 0.015$), representing a moderate positive effect. This indicates that drivers with more permissive attitudes are moderately more inclined to form intentions to violate traffic rules. Negative attitudes toward traffic rules, such as the belief that regulations are not always important or that they hinder driving efficiency, can foster a greater propensity to violate them. In some local cultural contexts, minor violations such as running red lights at night or driving on sidewalks are often considered "normal" or socially acceptable behaviors. This permissive attitude reflects a form of social justification for deviant behavior, especially in urban areas with high traffic congestion. This pattern aligns with empirical evidence in other settings, Wang & Xu (2024) reported that in the context of queue-jumping at urban intersections attitude had the strongest predictive effect on intention among all constructs considered

3.6.2. Influence of Behavioral Intention on Use Behavior

Behavioral intention was confirmed as the strongest predictor of use behavior ($\beta = 0.739$, $p < 0.001$), representing a strong positive effect. This demonstrates that drivers who already intend to commit violations are highly likely to translate those intentions into actual unsafe or unlawful behavior. Overall, the findings indicate that in the East Java context, traffic violation behavior is primarily shaped by internal cognitive factors particularly attitude, perceived behavioral control, and intention while external or social factors such as norms, emotions, habits, environment, and legal awareness play a limited role.

According to Conner & Armitage (1998), intention serves as the immediate antecedent to behavior, assuming the absence of substantial contextual barriers. In the case of East Java, legal barriers such as traffic enforcement or electronic ticketing are often perceived as weak or inconsistently applied, thereby facilitating the transition from intention to action. To effectively reduce actual violations, interventions should target the formation of intention itself. Educational campaigns that focus on the real-life consequences of violations (e.g., accidents, injuries) are likely to be more effective than merely increasing legal knowledge.

3.6.3. Influence of Perceived Behavioral Control on Behavioral Intention

Perceived behavioral control had a significant effect on behavioral intention ($\beta = 0.317$, $p = 0.026$), also a moderate positive effect, implying that when drivers perceive traffic violations as easy to commit, their intention to violate increases. Additionally, Li et al. (2021) reported that perceived behavioral control was a significant predictor of risky driving intentions in an extended TPB model among truck drivers, highlighting the robust role of control perceptions in shaping violation intentions. This suggests that individuals who perceive traffic violations as easy to commit due to the absence of surveillance or penalties are more inclined to form the intention to violate (Cheng et al., 2021). In regions where traffic law enforcement is weak or electronic ticketing systems are inconsistently implemented, drivers are more likely to believe that violations carry no real consequences. This perception fosters a sense of confidence in breaking the rules without fear of being caught, thus reinforcing the intention to do so. These findings are consistent with Iversen & Rundmo (2004), who demonstrated that perceived behavioral control is closely associated with an individual's efficacy in violating traffic laws without being penalized.

3.6.4. Influence of Risk Perception on Attitude Toward Behavior

Risk perception had a significant negative effect on attitude toward the behavior ($\beta = -0.261$, $p = 0.003$), indicating a moderate effect. the higher an individual's awareness of the risks associated with violating traffic rules, the more negative their attitude becomes toward such behavior. In this context, risk perception functions as a preventive cognitive mechanism that discourages deviant attitudes and strengthens safety-oriented evaluations.

This result supports the findings of Carter et al. (2014) and Teye-Kwadjo (2019), who suggested that risk perception alters both affective and cognitive dimensions of attitude in driving behavior. Educational campaigns that highlight the social and human consequences of traffic violations, such as hitting a pedestrian or causing fatal injuries, may be more effective in shaping negative attitudes than those focusing solely on legal sanctions.

3.6.5. Non-Significant Relationships

Several hypothesized relationships in the model were found to be statistically non-significant, offering valuable insights into the nature of traffic violation behavior within the East Java context. Subjective norms ($\beta = 0.062$, $p = 0.415$), habit ($\beta = 0.039$, $p = 0.895$), emotional condition ($\beta = 0.040$, $p = 0.617$), environmental condition ($\beta = 0.070$, $p = 0.358$), and legal knowledge ($\beta = 0.059$, $p = 0.537$) were not significantly associated with behavioral intention. Habit also did not significantly affect use behavior ($\beta = 0.149$, $p = 0.116$), suggesting only a weak and nonsignificant tendency.

Emotional condition, for instance, did not significantly influence behavioral intention. Although negative emotional states (e.g., anger, stress, sadness) are often presumed to trigger traffic violations, the results suggest that such violations are not primarily driven by transient affective responses. Rather, they may stem from more rational calculations or habitual patterns. This finding challenges the assumption that emotional impulsivity is a primary driver of deviant driving behavior.

Environmental condition also showed no significant effect on behavioral intention (D'Arco et al., 2025). Factors such as traffic congestion, poor road quality, or road geometry were not predictive of the intention to violate. This may be due to the situational and reactive nature of environment-related violations, which often occur spontaneously rather than as planned behavior. Habit did not significantly influence either behavioral intention or use behavior. This might be because habitual driving behavior tends to occur unconsciously and may not be fully internalized as a deliberate intention. Moreover, habits are more likely to influence behavior in stable, repetitive contexts, while many traffic violations are responsive to dynamic traffic conditions.

Legal knowledge and awareness were also found to be non-significant predictors of intention. This supports the notion that possessing knowledge of traffic laws does not automatically translate into compliance, especially in contexts where legal enforcement is weak or inconsistent. Subjective norms did not significantly influence behavioral intention either. One possible explanation is that in the local cultural context, social norms may actually tolerate or even normalize traffic violations. If deviant behavior is perceived as "common practice" within one's peer group, there may be little to no perceived social pressure to comply with the law.

Taken together, the final model indicates that traffic violation intention among East Javanese drivers is predominantly influenced by internal cognitive factors: namely, attitude toward behavior, perceived behavioral control, and risk perception (indirectly through attitude). In contrast, external or social factors such as peer pressure, habits, legal awareness, and environmental constraints did not show a significant impact. This finding highlights a critical insight: in developing societies with under-optimized legal systems, behavioral intention and actual violations are more strongly shaped by personal evaluations of risk and benefit than by formal rules or social pressure. Consequently, behavior change strategies should focus on reconstructing individual perceptions and increasing subjective risk awareness. Experience-based education and technology-enhanced enforcement (e.g., automated ticketing systems) may offer more effective pathways to reduce violations than relying solely on legal dissemination or peer influence.

The non-significant role of subjective norms, habit, and emotional and environmental conditions merits critical attention. Similar patterns have been observed in several Southeast Asian studies where permissive cultural norms or inconsistent enforcement weaken the role of social pressure on compliance (e.g., studies in Vietnam, Japan, Thailand) (Ng & Phung, 2021; Seefong et al., 2024;

Katanararoj et al., 2024; Hai et al., 2024). Specifically, normalization of minor rule-breaking may reduce perceived social sanctions, thereby attenuating the influence of subjective norms. These findings indicate that conventional strategies relying solely on social pressure are insufficient in contexts with permissive norms and weak enforcement. More effective interventions should emphasize cognitive restructuring (changing attitudes) and enhancing the salience of perceived risk (e.g., through simulations and vivid storytelling). Technology-assisted enforcement (such as automated ticketing) can strengthen perceived behavioral control by increasing the certainty of sanctions, yet such measures should complement, rather than replace, education and community engagement.

4. Conclusion

This study identified psychological, social, and environmental factors influencing traffic violation behavior among road users in East Java using PLS-SEM based on the extended TPB. The results showed that attitude toward the behavior (β= 0.339; t= 2.433; R^2 intention= 0.425), perceived behavioral control (β= 0.317; t= 2.222), and risk perception through attitude (β= -0.261; t= 2.947) significantly affected behavioral intention, while behavioral intention strongly predicted actual violation behavior (β= 0.739; t= 9.723; R^2 behavior= 0.546). In contrast, subjective norms, habit, emotional condition, environmental factors, and legal knowledge were not significant. These findings highlight that traffic violations in East Java are more strongly driven by internal cognitive evaluations than by external or contextual pressures, indicating the need for interventions that reshape driver attitudes, strengthen risk perception, and improve enforcement mechanisms. Importantly, the measuring instruments used in this study were confirmed to be valid and reliable. All constructs met the thresholds for convergent validity (outer loadings >0.70; AVE= 0.650–0.758) and internal consistency (Cronbach's alpha= 0.873–0.918; composite reliability= 0.901–0.935). Discriminant validity was also supported (HTMT<0.90), ensuring that the conclusions drawn are based on robust and trustworthy measurements.

This study extends TPB by integrating risk perception as an antecedent to attitude, offering both theoretical and practical contributions to understanding traffic violations in a developing-country context. Policy measures should prioritize attitude change and risk-awareness interventions, supported by targeted enforcement technologies. Limitations include modest sample size (N= 100), online distribution bias, and cross-sectional design; future research should use larger representative samples, longitudinal designs, and objective behavioral measures (e.g., telematics data or official violation records).

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