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From Traits to Speed Control: Engineering Insights from a Driving-Simulator Hazard Scenario

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Abstract:

Selecting an appropriate speed when approaching roadway hazards is crucial to safety, and psychological factors can significantly influence this choice. This study aimed to investigate the direct and indirect effects of certain latent psychological variables on drivers' speed deviation before and after hazard exposure, as well as the interrelationships among these variables. Data were collected from 197 licensed drivers using a driving simulator alongside two validated questionnaires—the Aggressive Driving Questionnaire and the Driver Behavior Questionnaire (DBQ)—and analyzed through Partial Least Squares Structural Equation Modeling (PLS-SEM). Results indicated that eight of nine hypotheses were statistically significant; specifically, hostile behavior showed a strong positive association with risky driving and self-willed violations, which, in turn, were positively associated with inexperience errors. Self-willed violations were also linked to higher average speeds, although drivers reduced their speed when directly confronted with hazards. Conversely, inexperience-related errors were associated with increases in unsafe speed when encountering hazards. Subjective norms had no significant effect on speed deviation. The highest path coefficient (0.86) was observed between self-willed violations and inexperience errors. These findings emphasize the important roles of emotional traits, deliberate risky behaviors, and skill deficits in speed regulation, suggesting that targeted training and interventions in emotion regulation could improve speed choices under hazardous driving conditions.

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1. Introduction

For decades, speed has been acknowledged as a pivotal element in road safety, with high speeds substantially increasing the likelihood of traffic accidents worldwide. Empirical evidence suggests that human behavior plays a central role in over 85% of all traffic crashes [1], and among the most hazardous behaviors is exceeding the recommended speed limit. Evidence indicates that even a slight increase of 1 km/h in average traffic speed can lead to a 3% uptick in the frequency of crashes and a 4 to 5% increase in fatal accidents [2, 3]. Understanding driver behavior has therefore become a major focus in traffic safety research. One of the most widely used tools in this field is the Driver Behaviour Questionnaire (DBQ), developed by Reason in 1990, which includes 50 items covering different types of driving violations and errors. The DBQ has achieved considerable recognition since the foundational work of Reason et al. (1990) and Shi et al. (2010), leading to the development of numerous versions to assess the relationship between driver behavior and accident involvement [4, 5]. For instance, Winter and Dodou reviewed 174 studies that utilized the DBQ in various traffic safety contexts [6]. Several other psychometric tools have also been integrated into research on driving behavior. For example, Linkov et al. [7] used driving simulator data from scenarios with varying speed limits, combining it with the Zimbardo Time Perspective Inventory and the NEO-FFI to examine the relationship between driving speed and personality traits, such as conscientiousness. Similarly, Steinbakk employed the UPPS Impulsivity Scale to examine how impulsivity-related traits influence speed selection among workplace drivers [8]. Driving style has also been used as a basis for driver classification. Eboli, through a field driving experiment, categorized participants into safe, unsafe, and potentially dangerous groups based on their mean speed and the 50th- and 85th-percentile operating speeds [9]. Sensation-seeking, characterized by the pursuit of novel and thrilling experiences, has been associated with driving speed. Individuals with high

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sensation-seeking tendencies are often less affected by roadway characteristics when determining their speed. [10, 11]. Individual personality traits play a substantial role in shaping driving behavior. As noted by Summala (1974), drivers enter traffic for various reasons, many of which are influenced by underlying personality factors. To investigate this relationship, self-report questionnaires have frequently been used to assess the association between personality characteristics and specific driving behaviors [12-15]. Linkov et al. [7] found a significant relationship between conscientiousness and driving speed, consistent with earlier findings. Similarly, Zicat et al. [16] employed driving speed metrics in a simulator to assess driver competence and found a strong correlation between anxious and angry personality traits and higher driving speeds among young drivers. Other studies have shown that drivers' personal characteristics and habits significantly affect their responses to hazardous driving conditions [17].

Aggressive driving has received significant attention as a predictor of risky road behavior. Drivers have been categorized by their level of aggressiveness, typically characterized by high speeds and abrupt acceleration or deceleration [18]. Numerous studies have examined how aggressive driving—whether hostile or instrumental—relates to personality traits such as anger, and how these factors contribute to dangerous driving behavior through frameworks like the Theory of Planned Behavior [19-21]. According to these findings, individuals with strong aggressive tendencies and high-risk attitudes are more likely to engage in hazardous driving. Regulatory bodies have also defined aggressive driving to improve traffic safety interventions. For example, the Pennsylvania Department of Transportation describes it as operating a vehicle in a way that endangers people or property. The U.S. National Highway Traffic Safety Administration (NHTSA) includes behaviors such as speeding, improper lane changes, failure to signal, tailgating, and misuse of emergency lanes or road shoulders as examples of aggressive driving [9]. Speeding remains a global concern and is a major topic in accident prevention research. Cabral, Mendonça, and Cabral developed a multisensory system to help young drivers maintain a consistent and controlled speed, aiming to reduce crash risks associated with speeding [22]. In contrast, Chevalier focused on elderly drivers and examined whether reductions in speeding among older adults reflect self-restrictive behaviors due to declining cognitive and visual abilities [23]. Crucially, risk perception plays a pivotal role in shaping driving behavior. Ulleberg and Rundmo [24] found that individuals with a higher perception of risk are less likely to engage in dangerous driving. A positive attitude toward speeding and low risk perception may explain higher speed preferences, particularly in work zones. Furthermore, a driver's habitual driving style often predicts their behavior in upcoming traffic scenarios.

Various variables suggest that personality traits impact driving behavior in both a direct and indirect manner [7, 8, 25]. Javanbakht and Meibarha (2024) demonstrated that personality traits influence individuals' mean speed on routes with potential hazards [26]. In a related study, they introduced a safe driving index, derived from changes in several behavioral variables, one of which was the difference in drivers' speed before and after encountering a road hazard [27]. Supporting the relevance of behavioral variability, Majun Fei et al. demonstrated that frequent speed changes serve as a critical marker of unsafe driving, emphasizing the value of detailed behavioral indicators in traffic safety evaluations [28]. Nonetheless, it remains unclear whether the proposed relationship between personality traits and driving outcomes is contingent on specific contextual factors. Hence, this study investigates the direct and indirect effects of personality traits on drivers' speed regulation in hazardous scenarios.

The proposed research model is illustrated in Figure 1. Section 2.2 offers a detailed explanation of each variable included in the model.

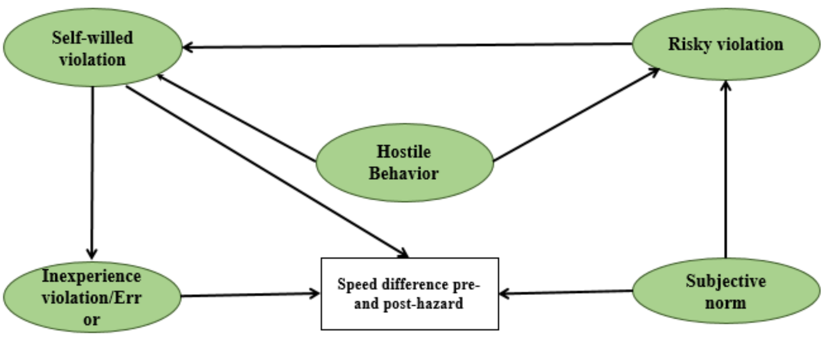

Figure 1. Suggested model

2. Methodology

The primary focus of this study is to investigate how psychological factors affect drivers' behavior in response to road hazards. In this research, driver behavior is assessed by the change in driving speed before and after encountering a hazard, a parameter shown to be relevant for evaluating safe driving performance. To this end, a simulated driving route was developed, during which participants' speed variations in response to a predefined hazard were recorded. Psychological traits were also assessed using a standardized questionnaire. Using the proposed analytical model, both the direct and indirect effects of these traits on drivers' speed adjustment around hazardous situations were examined. The following subsections describe the analytical tools employed in this research.

2.1. Data collection

In this study, a total of 197 individuals (130 males and 67 females) were recruited from the city of Tehran. Participant recruitment was carried out through an advertisement distributed both online and in public areas. From the pool of respondents who expressed interest, 197 participants were randomly selected. Descriptive statistics about the sample are presented in Table 1. In Table 1, “Driving history” denotes the number of years of driving experience since obtaining a license and differs from the elapsed time since the license was issued. It is worth noting that the participants' age group was selected based on previous studies in Iran [26, 27].

Table 1. Summary statistics of the sample

	Frequency	Percentage	Cumulative Percent
Gender			
Female	67	34.0	34.0
Male	130	66.0	100.0
Age			
20<X<25	34	17.25	17.25
26<X<30	46	23.35	40.6
31<X<35	47	23.85	64.45
36<X<40	28	14.21	78.63
X>40	42	21.32	100.0
Education			
illiterate	5	2.53	2.53
High school diploma	74	37.56	40.09
university	119	60.4	100.0
Driving history			
x<1	14	7.12	7.12
1<X<2	6	3.04	10.16
3<X<5	33	16.75	26.91
6<X<10	57	28.93	55.84
X>10	87	44.16	100.0

2.1.1. Questionnaire

In this study, data were collected using the Aggressive Driving Questionnaire [29] and Shai’s Driving Behavior Questionnaire [5]. From the Aggressive Driving Questionnaire, the factors of Subjective Norm, and Hostile Behavior were incorporated, while the model also included Risky Violations, Self-Willed Violations, and Inexperience Violations/Errors derived from Shai’s questionnaire. A detailed overview of the selected factors and their corresponding items is provided in Table 2.

Table 2. Constructs and measurement items with sources

Construct	Items	Sources adapted
Subjective norm	SN1: How compelled do you feel to maintain appropriate driving behavior when family members are present? SN2: To what extent are you motivated to observe proper driving conduct in the company of friends? SN3: How obligated do you feel to drive properly when strangers are around?	Ajzen and Fishbein [30]
Hostile Behavior	HB1: To what degree do you disregard posted speed limits on roads? HB2: How fast do you typically drive to ensure timely arrival?	Ajzen and Fishbein [30]
Risky violation	RV1: Do you accelerate to avoid a yellow traffic light turning red? RV2: Do you overtake vehicles from the right side? RV3: Do you drive in the opposite direction on a one-way lane? RV4: When turning right, do you fail to yield to bicycles?	Shi et al. [5]
Self-willed violation	SV1: Do you neglect to use turn signals when required? SV2: Do you drive across two lanes simultaneously? SV3: Do you drive while distracted? SV4: Do you maintain an unsafe following distance behind the vehicle ahead?	Shi et al. [5]
Inexperienced violation/error	(IV-IE)1: Do you enter incorrect lanes while driving? (IV-IE)2: Do you fail to recognize yield signs? (IV-IE)3: Do you misinterpret road signs? (IV-IE)4: Do you make left turns where they are prohibited?	Shi et al. [5]

2.1.2. Apparatus

This research employed a driving simulator developed by K.N. Toosi University of Technology, which is recognized as a leading center for driving simulator production in Iran. (Figure 2). To date, several published studies have employed this simulator for research purposes [26, 27, 31-33]. The selected route for the simulation is the intercity road between Sabzevar and Neyshabur in Khorasan Province, Iran, which is shown in Figure 3. The entire route measures 107 km, from which a segment was chosen for simulation. The simulated environment includes a two-lane highway with an asphalt shoulder. Each lane has a width of 3.75 meters, and the total length of the simulated road is 2.5 kilometers. The designated speed limit for this route is 80 km/h. Additionally, all visual and structural elements of the simulated route—including traffic signs and markings—were designed to replicate real-world road conditions closely. A hazardous scenario was simulated by introducing a parked vehicle that suddenly entered the traffic lane. Figure 4 illustrates the layout of the simulated route.

Figure 2. Driving simulator

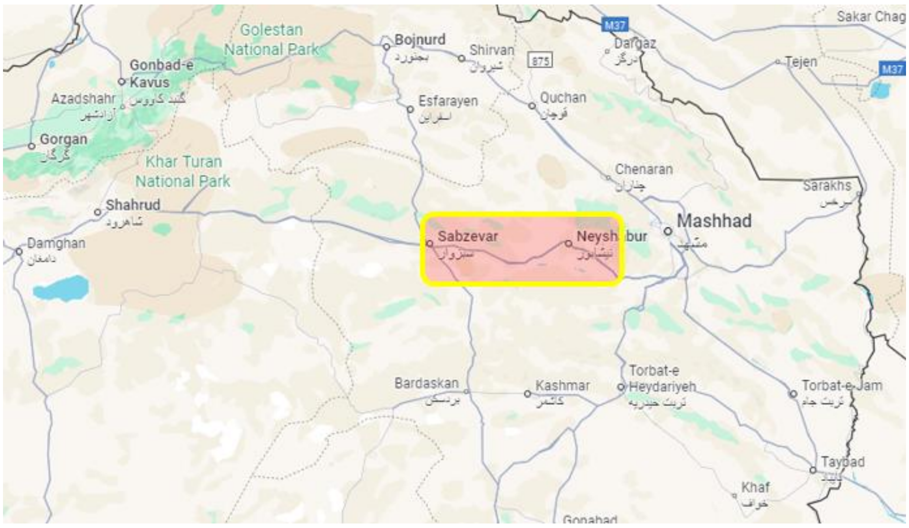

Figure 3. The intercity route used in the simulation

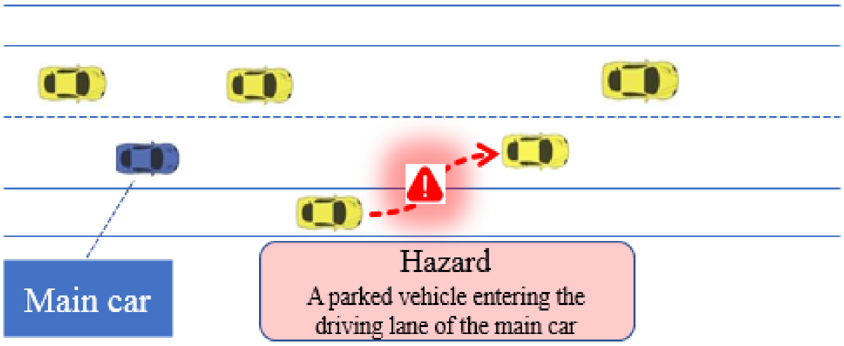

Figure 4. Details of the simulated route

Data collection followed a standardized protocol. Participants first received instructions for using the simulator and then participated in a two-minute trial session to familiarize themselves with the environment. Once comfortable, they proceeded to the main driving task. It is important to note that some participants reported dizziness during the simulation, and a few terminated the session early. Consequently, their data were excluded from the final analysis.

2.2. Hypotheses

2.2.1. Speed Difference Pre- and Post-Hazard (Sb-Sa)

The dependent variable in the model is the difference in driving speed before and after the occurrence of a hazard. Based on the data obtained from the driving simulator, a time window of 5 seconds before and 5 seconds after the hazard was extracted for each participant in every scenario. The speed before the obstacle is denoted as Sb, and the speed after the obstacle is denoted as Sa. Table 3 presents the results obtained from the driving simulator output. In this table, participants are categorized into two groups based on the difference between Sa and Sb. Group 1 includes individuals whose speed after the hazard (Sa) is higher than their speed before the hazard (Sb), while Group 2 consists of those whose Sa is lower than Sb. The results indicate that Group 1 experienced a higher rate of hazard encounters (66.3%) compared to Group 2 (12.96%). Since the data were not normally distributed, a non-parametric method was used to assess the significance of differences between groups. The Kruskal–Wallis test revealed a statistically significant difference between the two groups for hazard encounters, as shown in Table 4.

Table 3. Description of the accident with the hazard

Group	Sb-Sa	number of participants	Number of accidents	Percent
1	<۰	89	59	66.3
2	>۰	108	14	12.96
Sum		197	73	

Table 4. Kruskal–Wallis Analysis of Hazard Encounter Rates Across Driver Groups

Sb-Sa		N	Mean Rank	Test Statistics	
Collision with Hazard	<۰	89	128.40	Chi-Square	61.372
	>۰	108	74.77	df	1
Total		197		sig	0.000

2.2.2. Subjective norm (SN)

Subjective norm refers to an individual's perceived social expectations that influence their behavior. It reflects the influence exerted by the social environment, in which certain behaviors are either encouraged or discouraged by perceived rewards or punishments. In essence, subjective norms are shaped by a person's beliefs about how significant others view a given behavior, weighted by the value the individual places on their opinions [30].

For example, a person may believe that wearing a seatbelt while driving is important because their parents or friends advocate for it. Based on this understanding, the following hypothesis is proposed:

Hypothesis 1: There exists an inverse association between subjective norm and risky violation behavior.

Hypothesis 2: Subjective norm is positively associated with the change in driving speed observed before and after encountering a hazard.

2.2.3. Hostile Behavior (HB)

Hostile behavior refers to actions that aim to provide emotional relief to the individual without necessarily addressing or resolving the underlying issue. The primary intent of such behavior is often to inflict harm on the person or object perceived as the source of frustration. In the context of driving, this type of behavior—especially under stressful or extreme conditions—can manifest as road rage. However, the distinction between hostile and goal-directed (instrumental) driving behaviors is not always clear-cut. For example, honking at a pedestrian or another driver may be interpreted as either hostile or instrumental, depending on the context [34]. Guided by this perspective, the two hypotheses outlined below are presented:

Hypothesis 3: Hostile behavior is positively associated with risky violations .

Hypothesis 4: Hostile behavior is positively associated with self-willed violations.

Hypothesis 5: Hostile behavior is indirectly associated with speed deviation.

2.2.4. Risky violation (RV)

where abnormal behavior is consistently deliberate, involves high risk, and lacks emotional influence. In some circumstances, drivers choose to take risks for convenience or gain [5]. Accordingly, the following hypothesis is proposed:

Hypothesis 6: Risky violation positively influences Self-willed violation.

2.2.5. Self-willed violation (SV)

In cases of self-willed violations, drivers tend to avoid taking risks and are generally not influenced by their emotional state. Such violations are typically committed for convenience or comfort, and only after the driver has ensured that the situation poses no immediate danger [5]. Accordingly, the following hypothesis is proposed:

Hypothesis 7: Inexperience violation/error is positively influenced by Self-willed violation.

Hypothesis 8: Speed deviation is positively impacted by Self-willed violation

2.2.6. Inexperience violation/error (IV/IE)

Such behaviors are unintentional and typically stem from a lack of driving skills, insufficient familiarity with the traffic environment, or similar factors [5]. Therefore, the following hypothesis is proposed:

H9: The Inexperience violation/error is negatively associated with speed deviation.

3. Results

This study utilized data from 197 participants, with their descriptive statistics presented in Table 1. To analyze the proposed model, the Structural Equation Modeling (SEM) approach was employed. SEM enables examination of both the relationships between latent variables and their observed indicators (the measurement model) and the interrelationships among the latent variables themselves (the structural model). Importantly, this method also accounts for measurement errors associated with the observed variables [35]. There are two main types of SEM: (1) covariance-based SEM and (2) variance-based SEM. In this research, the Partial Least Squares (PLS) method—a variance-based approach—was selected due to its notable advantages. PLS is particularly well-suited for studies with relatively small sample sizes and does not require the assumption of data normality [36]. Furthermore, it is highly effective for analyzing complex models and under-researched domains, owing to its strong statistical power [37, 38]. Given these strengths, the use of PLS was deemed appropriate for the current study. Following the approach of [39], the measurement model was assessed first, followed by the evaluation of the structural model using SmartPLS 3.2.8 software [40], as detailed in the sections below.

3.1. Measurement Model

As noted earlier, the measurement model evaluates the connections between latent variables and their corresponding observed indicators. The results of this analysis are summarized in Table 5 and Figure 5 As shown, all factor loadings are statistically significant and exceed the threshold of 0.5, as recommended by Edrisi and Ganjipour [35]. In terms of internal consistency, Cronbach's alpha values for all constructs surpass the acceptable cutoff of 0.6 [41]. Convergent validity was also assessed. According to the criteria, the Composite Reliability (CR) should be greater than 0.7 [36], and the Average Variance Extracted (AVE) should exceed 0.5 [42]. As indicated in Table 5 and Figure 6, all constructs meet these requirements. For discriminant validity, Anderson and Gerbing [39] recommends that the square root of the AVE for each latent variable should be greater than its correlations with other latent constructs. Table 6 supports this criterion, as the square roots of the AVEs (displayed on the diagonal) are higher than the inter-construct correlations (located below the diagonal). Furthermore, the Heterotrait-Monotrait (HTMT) ratios (above the diagonal) are all below the acceptable maximum threshold of 0.9 [43, 44].

Table 5. Reliability assessments of the measurement mode

Construct	Item	Factor Loading	α	CR	Rho-A	AVE
subjective norm(SN)	SN1	0.657	0.725	0.833	0.968	0.63
	SN2	0.932				
	SN3	0.768				
Hostile Behavior(HB)	HB1	0.750	0.658	0.840	0.883	0.727
	HB2	0.944				
Risky violation (RV)	RV1	0.725	0.756	0.846	0.767	0.582
	RV2	0.813				
	RV3	0.854				
	RV4	0.643				
Self-willed violation (SV)	SV1	0.744	0.714	0.822	0.721	0.536
	SV2	0.739				
	SV3	0.752				
	SV4	0.691				
Inexperience violation/error (IV/IE)	(IV/IE)1	0.812	0.704	0.818	0.749	0.536
	(IV/IE)2	0.635				
	(IV/IE)3	0.864				
	(IV/IE)4	0.680				

3.2. Structural model

To evaluate the research hypotheses, the bootstrap technique with 5,000 resamples was applied at this stage of the analysis. The outcomes of the structural model are summarized in Table 7. A hypothesis is considered supported if the corresponding path is statistically significant—specifically, when the p-value is below 0.05 and the t-value exceeds 1.96 (or is less than -1.96). The path coefficient indicates both the magnitude and direction of the influence exerted by the independent variable on the dependent variable. According to the results presented in Table 7, all hypotheses—except for Hypothesis 2—are supported. Hypothesis 2 is not statistically significant, as its t-value is below 1.96. Moreover, the negative path coefficient indicates an indirect relationship in the opposite direction of what was originally hypothesized. Among them, Hypothesis 7 exhibits the strongest effect (path coefficient = 0.570), while Hypothesis 5 shows the weakest effect with a path coefficient of -0.110.

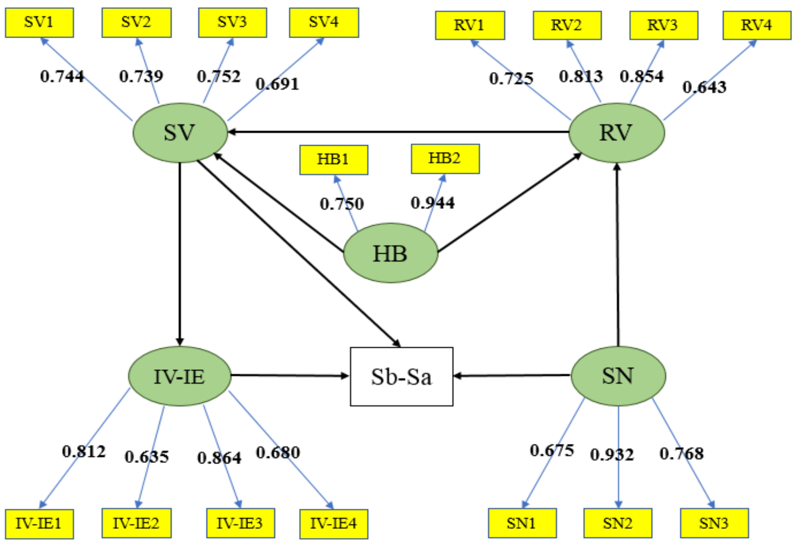

Figure 5. **Factor loadings of latent variables and observed indicators in the conceptual model**

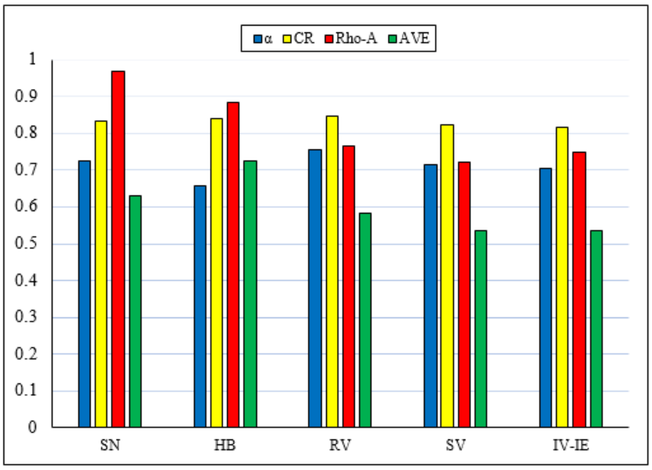

Figure 6. **Reliability and Validity Metrics: Cronbach's Alpha, AVE, RHO-o, and CR**

Table 6. **AVE, correlations and Heterotrait Monotrait (HTMT) ratio**

Variables	Sb-Sa	RV	IV-IE	HB	SV	SN
Sb-Sa	1.000	0.107	0.049	0.064	0.06	0.040
RV	0.09	0.763	0.379	0.567	0.800	0.448
IV-IE	-0.04	0.265	0.732	0.431	0.789	0.456
HB	-0.014	0.438	0.317	0.853	0.822	0.664
SV	0.046	0.606	0.570	0.607	0.732	0.458
SN	-0.32	-0.392	-0.332	-0.535	-0.535	0.794

Table 7. **Structural Model Results**

Hypothesis	Path	Path Coefficient	STD	T Statistics	P Values	Result
H1	SN -> RV	-0.221	0.030	7.287	0.000	Supported
H2	SN -> Sb-Sa	-0.075	0.040	1.871	0.062	Not Supported
H3	HB -> RV	0.320	0.024	13.168	0.000	Supported
H4	HB -> SV	0.424	0.023	18.451	0.000	Supported
H5	HB -> Sb-Sa	-0.110	0.050	2.204	0.028	Supported
H6	RV -> SV	0.420	0.026	16.018	0.000	Supported
H7	SV -> IV-IE	0.570	0.029	19.965	0.000	Supported
H8	SV -> Sb-Sa	0.154	0.055	2.797	0.005	Supported
H9	IV-IE -> Sb-Sa	-0.118	0.041	2.894	0.004	Supported

4. Discussion and Conclusions

Human factors in driving behavior encompass a broad spectrum, ranging from drivers' demographic characteristics to their personality traits and behavioral patterns. The present study aims to examine the complex relationships among latent variables associated with driving behavior, with particular focus on their direct and indirect effects on the change in speed before and after encountering a hazard. Data were collected using a combination of behavioral questionnaires and driving simulator experiments to capture both subjective reports and objective driving responses. Based on these variables, a conceptual model was carefully developed and empirically tested through nine well-formulated hypotheses, the detailed results of which are presented in Section 3.

With regard to the subjective norm (SN), drivers tend to consciously avoid engaging in risky driving when accompanied by family members or acquaintances. This phenomenon suggests that, motivated by social respect and the desire to maintain a positive image in front of their companions, drivers may deliberately restrain themselves from performing certain hazardous actions (Hypothesis 1) [19]. This finding highlights the social and psychological dimensions of driving behavior, indicating that external social pressures can significantly moderate risky driving. Further, individuals exhibiting high levels of hostile behavior (HB) are more prone to engage in dangerous and risky driving patterns (Hypothesis 3) [21]. These drivers, when confronted with road hazards, often attempt to manage or overcome these obstacles through aggressive and hazardous maneuvers, such as increasing their speed as a form of retaliation or defiance (Hypothesis 5). Previous studies have consistently demonstrated that drivers with hostile tendencies tend to be more aggressive and display overconfidence in their vehicle control capabilities under all driving conditions, which substantially raises their likelihood of participating in risky driving behavior [19]. This association between hostility and risk-taking emphasizes the importance of emotional regulation in promoting safer driving practices. Moreover, drivers characterized by hostile behavior, as well as those with a predisposition to risky violations (RV), are more likely to commit self-willed violations (SV), which are intentional rule-breaking behaviors undertaken for personal convenience or comfort. However, the data indicate that drivers with a stronger inclination toward risky behavior demonstrate self-willed violations more extensively than those whose primary behavioral trait is hostility (Hypotheses 4 and 6) [26,45]. This distinction underscores the nuanced differences between emotional aggression and deliberate rule violations in shaping driving conduct.

According to Hypothesis 7, the study confirmed that self-willed violations (SV) have a direct and positive effect on inexperience errors (IV-IE); in other words, drivers who frequently commit intentional violations are also more likely to engage in behaviors for which they lack sufficient experience or skill. This finding suggests a critical overlap between deliberate risk-taking and skill deficits, indicating that such drivers may underestimate the dangers associated with their choices. Extensive prior research has shown that individuals identified as self-willed violators generally exhibit higher average driving speeds [7, 16, 17, 19, 26]. However, consistent with Hypothesis 8, these drivers tend to reduce their speed when facing immediate hazards. As shown in Table 7, the coefficient related to the difference between speed before and after hazard exposure is positive, indicating that although these drivers usually maintain high speeds, they do not increase their speed to overcome sudden hazards. This behavior is likely because they are less influenced by emotional impulses and more calculated in their risk-taking, thereby avoiding further speed increases that could exacerbate danger. This outcome aligns well with the conceptual definition of self-willed violations [5, 26]. Finally, inexperience errors (IV-IE), arising from limited driving skills and a lack of familiarity with hazardous situations, lead drivers to make faulty decisions when encountering road hazards. Such drivers may mistakenly increase their speed in an attempt to pass the hazard quickly, unintentionally elevating their risk of collision (Hypothesis 9). This highlights the vital role that driver experience and skill acquisition play in safe hazard management on the road.

Regarding Hypothesis 2, analysis of the data in Table 7 revealed that the effect of the subjective norm (SN) on driver behavior was not statistically significant at the 95% confidence level (t-value less than 1.97). Although the effect might be considered marginally acceptable at the 90% confidence level, the path coefficient for this variable (-0.075) was problematic for two main reasons: first, its magnitude was very small compared to other coefficients, indicating a minimal impact on the dependent variable; second, the negative sign contradicted the hypothesized positive influence outlined in Hypothesis 1. Consequently, this hypothesis was not supported by the data. Given these findings, further investigation is recommended to more thoroughly examine the influence of subjective norm on drivers' speed regulation when confronted with hazards and to compare these results with those of the current study.

In light of these findings, it is advisable to strengthen drivers' understanding of the different types of road hazards, the critical importance of selecting an appropriate and safe speed when faced with such hazards, and the potential consequences of neglecting this practice. Educational efforts should go beyond addressing the physical dangers of speeding, also to highlight the psychological and situational factors that may influence speed choices in hazardous conditions. In particular, driver training centers should expand their existing curricula—which already cover comprehensive traffic regulations and road safety information—by incorporating additional, evidence-based training modules. These modules should emphasize the risks associated with excessive speed, unsafe driving attitudes, and overconfidence, as well as the wider implications of such behaviors for both individual and public safety. Practical components, such as hazard perception exercises and scenario-based driving simulations, should also be integrated to prepare drivers for real-world challenges better.

4.1. Limitations and Future Studies

Some limitations in this study should be considered in future research. First, the majority of participants (approximately 80%) were not familiar with driving simulators. This lack of experience may have influenced their driving performance and response accuracy during the tasks. In some regions, driving simulators are already used for training and licensing, and it is recommended that wider access to such simulators be provided so that participants in future studies are more familiar with this environment, thereby enhancing the validity of the collected data.

Second, although the driving simulator offered a controlled laboratory environment for data collection, it cannot fully replicate real-world driving conditions. Therefore, future studies are encouraged to use real-world driving data, such as recordings of driver behavior obtained through cameras and sensors installed in vehicles or by using rental cars, to yield more accurate and generalizable results. Nevertheless, given existing constraints, this study relied on a driving simulator as the most feasible option.

5. References

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