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Research Article

A Behavioral Model of Drivers' Mean Speed Influenced by Weather Conditions, Road Geometry, and Driver Characteristics Using a Driving Simulator Study

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Driving above the speed limit is one of the factors that significantly affect safety. Many studies examined the factors affecting the speed of vehicles in the simulated environment. The present study aimed to analyze drivers' characteristics, time and weather conditions, and geometric features' effect on mean speed in simulated conditions simultaneously. In this regard, the simulator experiment data of 70 drivers were collected in a two-lane rural highway at six different times, and weather scenarios and their socioeconomic characteristics were collected by a questionnaire. Structural equation modeling (SEM) was used to capture the complex relationships among related variables. Eleven variables were grouped into four latent variables in the structural model. Latent variables including "Novice Drivers," "Experienced Drivers," "Sight Distance," and "Geometric Design" were defined and found significant on their mean speed. The results showed that "Novice Drivers" have a positive correlation with the mean speed. Meanwhile, "Experienced Drivers," who drive 12% slower than the novice group, negatively affect the mean speed with a standard regression weight of −0.08. This relation means that young and novice drivers are more inclined to choose higher speeds. Among variables, the latent variable "Sight Distance" has the most significant effect on the mean speed. This model shows that foggy weather conditions strongly affect the speed selection behavior and reduce the mean speed by 40%. Nighttime also reduces mean speed due to poor visibility conditions. Furthermore, "Geometric design" as the latent variable indicates the presence of curves on the simulated road, and it can be concluded that the existence of a curve on the road encourages drivers to slow down, even young drivers. It is noteworthy that the parts of the simulated road with a horizontal curve act as a speed reduction tool for drivers.

1. Introduction

Driving above the speed limit is one of the most critical issues in safety studies, increasing collision risk. Besides, it plays a significant role in the cost and severity of accidents. World Health Organization reported that an increase in mean speed is directly related to the likelihood of a crash occurring and its consequences; for example, a rise of 1 km/h in mean vehicle speed increases 3% and 4-5% in the incidence and fatality of crashes, respectively [1]. Thus, researchers have a great deal of interest in evaluating the factors affecting the drivers' speed. A wide variety of factors have been studied concerning drivers' speed choice and mainly divided into environmental characteristics, drivers' behavior and characteristics, and weather and time condition. Some studies evaluated the effects of geometric and roadside features on vehicles' speed using a driving simulator [2–7]. In this regard, Bella [2] considered the effect of three different roadside conditions and two cross-sections on drivers' speed in a two-lane highway. The collected data for 36 drivers indicated that roadside configuration influences lateral position without any role for driving speed. Goralzik and Vollrath [3] defined different scenarios based on the differences in roadway curvature, lane width, speed limit, and passengers' number in the car to evaluate drivers' speed choice. The findings indicated that speed limitation and road geometry have the most substantial effects on drivers' speed choice. Furthermore, Sadia et al. [4] investigated the effect of different environmental and road characteristics (such as horizontal and vertical curves and

speed limit signage), driver characteristics (sociodemographic and latent features), and risk/benefit factors (enforcement, crash risk, and time-saving benefits) by using structural equation modeling (SEM). These three models revealed that gender, age, and driving frequency determine drivers' perceptions and attitudes that influence speed selection. Situational factors such as traffic speed, enforcement, and time-saving benefits are also related to speed selection and infrastructure characteristics. Figure 1 displays the SEM for analyzing the driver level.

Hussain et al. [6] examined the impact of the geometric field of view (GFOV) on driving behavior, including speed perception and lateral position. In this regard, two different GFOV angles (60 and 135 degrees) were tested for four different speeds (50, 70, 80, and 100 kmph) on 41 participants having a valid driving license. Thus, using an incorrect GFOV in driving simulators can generate bias in speed perception. Furthermore, drivers underestimated their traveling speed while driving in the 60 degrees of GFOV. The effectiveness of fog warning systems on driving performance and traffic safety in the heavy fog was considered by Chang et al. [5]. The experimental findings revealed that the participants would reduce their speed when proceeding to a fog zone. Additionally, the effects of drivers' individual characteristics compared with warning messages were not significant when adjusting the driving speed due to risk perception [5]. Babić and Brijs [7] also investigated how two low-cost road marking measures, alone or combined with a vertical warning sign, affect driver behavior before and along dangerous horizontal curves on a two-way rural road.

In some other studies [8–17], the effect of weather and time conditions and drivers' characteristics was evaluated on vehicles' speed. On this subject, Mueller and Trick [10] found that experienced drivers reduce their speed more than inexperienced drivers in foggy conditions. However, their driving experience had no significant effect on the mean speed. Besides, Chakrabartya and Gupta [11] concluded that experienced drivers not only do they drive faster but also they have the most frequent violation. Also, in foggy weather conditions, the frequency of experienced drivers' accidents is higher than that for inexperienced drivers. Furthermore, Li et al. [13] observed that the foggy condition and driving experience affect the mean speed while gender does not affect it. Moreover, professional drivers drive more slowly than less skilled drivers. Zolali and Mirbaha [15] also evaluated the effects of adverse weather conditions on drivers' speed choice behavior in a two-lane rural highway. The findings showed that light and heavy fog, driving experience, and the rate of accident involvement were negative factors for speeding. In Sweden, Jägerbrand and Sjöbergh [14] examined whether the vehicle speed on roads is higher in daylight and under road lighting than that of in darkness and also determined the combined effects of light conditions, posted speed limit, and weather conditions (clear weather, rain, and snow) on driving speed. The results showed that the analysis of vehicle speed and speed differences between daylight, twilight, and darkness, with/without road lighting did not reveal any differences attributable to light conditions. Huang et al. [16] aimed to study the drivers' behavioral pattern at different behavioral stages under different fog conditions and speed limits. The findings revealed that as the fog density increased, the length of vehicle fleet decreased significantly, and drivers tended to keep a more stable car-following distance. In addition, lowering speed limit can significantly decline the vehicle fleet rear-end collisions under foggy conditions. Wang et al. [17] also used a driving simulator to investigate a reasonable speed limit and ensure traffic safety in a dynamic low-visibility environment with fog. The results showed that there are significant differences in the recognition times of drivers under different visibilities and speed conditions. For investigating the effect of time on operational speed in two-lane highways using a driving simulator, Bella et al. [18] evaluated four different models for tangents and curves in day and nighttime conditions. The results showed that drivers' speed in curves is not significantly different during the night and day, while it is different during the night and day in the tangents. Bassani et al. [19] also investigated the impact of geometric and lighting elements on drivers' speed in urban arterial. The results showed that average speed is significantly affected by lighting conditions.

The results of previous studies indicated that geometric and roadside features [2–7], besides time, weather conditions, and drivers' characteristics [8–18, 20, 21], affect the speed choice of drivers. However, to the best of our knowledge, no study evaluates the combination effect of drivers' characteristics (latent variables), geometric features, and different weather conditions on speed choice behavior simultaneously. The rest of the paper includes the study method, which consists of the information about participants, driving simulator, driving scenario, procedure, and the modeling approach (Section 2). The data description follows this in Section 3 and the results of modeling in Section 4. Finally, the conclusion is presented in Section 5.

2. Method

2.1. Required Sample Size. To extend the present study results to the community from which the samples were taken, researchers should use appropriate statistical samples. For this purpose, researchers used Cochran's formula in this study (formula (1)). In this formula, n is the sample size, N is the population under study, Z is the test statistic value, p is the portion of the population with the specific factor, and q is the portion of the population that does not have the specific factor. Z is the standard deviation of the standard unit, which at 95% confidence level equals 1.96 and at 90% confidence level equals 1.64. d is the permissible error value or percentage of error (which is usually between 0.01 and 0.1 and is used to estimate the sample mean's proximity to the population mean) [22]:

$$n = \frac{\left(z^2 pq/d^2\right)}{1 + (1/N)\left(\left(z^2 pq/d^2\right) - 1\right)}. \quad (1)$$

Given that the researchers' goal was to select sample individuals based on age, the samples must meet specific requirements (having a driver's license and driving).

Therefore, the community's minimum and maximum possible ages were considered to be 21 and 60 years, respectively. Considering all the conditions in this study and the target population (1036349 people) in the city of Tabriz, the total number of samples with a confidence level of 90% was 67 people. Because the researchers aimed to generalize the results of this study to the entire population, participants' selection was based on age distribution in the community; for example, the number of target population in the city of Tabriz was equal to 1036349. Cochran's formula estimated the number of sample people is equal to 67. The population distribution in the age group of 21 to 28 years was equal to 331951, equivalent to 32% of the target population. Therefore, researchers selected 32% of the total samples required (32% of 67 was about 21 participants) from people aged 21 to 28 years. This process was performed for all age groups, which can be seen in Table 1.

2.2. Participant. A total of 75 participants (47 men and 28 women) were included in the present study. After removing 5 participants due to dizziness or tiredness during the experiment, the final number of 70 participants was used for modeling. The participants' age was from 21 to 60 years, in which most of them were in the age group of 21–28 years (30%). Regarding the driving experience of the participants, 48% were in the range of 2–9 years. Figure 2 shows the descriptive statistics of the sample population's characteristics.

2.3. Apparatus. Driving tests were conducted in an unfixed-platform driving simulator built for safety studies in Tabriz city (Figure 3). The driving simulator was like a typical car in terms of the steering system, shock absorbers, pedals, and a manual gear lever. Some speakers were embedded in a cabin in order to induce environmental situations inside the driving simulator. A recording system collected all the driving performance factors like position, speed, average speed, and other vehicle positions in 0.06 seconds. The simulator had three wide screens with a 120 degrees front field of view and a left, middle, and right rear-view mirror to project the driver's road scenario.

2.4. Driving Scenarios. A two-lane rural road with a 9-kilometer length (1.5 kilometers for each scenario) was simulated in the present study. Each scenario with different geometric features was considered to examine the drivers' behavior. The simulated road was theoretically divided into five segments based on their geometric feature, including a tangent length, horizontal curve, and the combination of vertical and horizontal curve. Table 2 shows each segment's distance and feature. Also, the posted speed limit was 90 kilometers per hour, in which the cross section width was 7 meters. The road plan for each scenario (1.5 km) and the road segments are illustrated in Figure 4.

For evaluating the effect of different weather and time conditions on drivers' behavior, scenarios were divided into different weather and time conditions. Table 3 displays different weather and time conditions in each scenario. The foggy condition was divided into light and heavy fog, in which the visibility distance was the main difference between them. Thus, the visibility distance was 250 meters in light fog conditions. The driver was not able to see the road at 251 meters. Also, in the heavy foggy conditions, the visibility distance was 50 meters. The driver was unable to see the distance of 51 meters (even in the blurred). The visibility distances were consistent with previous studies such as Yan et al. [12] and Li et al. [13], which used 50 and 250 meters for light and heavy fog conditions, respectively. Traffic flow in the scenarios was 1000 vehicles per hour, in which the driver was able to choose speeds at or near the free-flow speed.

2.5. Procedure. First, participants filled a questionnaire that included personal information (such as age, gender, and education) and their driving background (such as license, driving experience, and accident rate). Then, participants were taught how to use the driving simulator and drive to get familiar with controlling the simulator and simulated environment. The participants were also asked to drive a 3-kilometer two-lane simulated highway with full visibility conditions that could easily detect the road features like tangents, curves, and signs. Finally, participants drove with no guidance and were asked to show their actual and normal driving behavior. The sequence of the scenarios was the same for all the participants. They had to drive in 6 scenarios to omit any bias.

2.6. Modeling Approach. This study investigates the effects of drivers' latent and individual characteristics, geometric features, and weather conditions in two lighting events (day and nighttime) simultaneously. Therefore, the structural equation model was used to evaluate the effect of variables on participants' mean speed choice behavior. The structural equation model has several advantages, which are included as the simultaneous use of a given parameter as both a predicted and an explanatory variable, use of latent variables, which are a representative variable that cannot be directly measured or observed, and dealing with time-series data [23]. The structural equation model is a multivariate regression model, allowing the researchers to simultaneously measure a set of relationships between observable and latent variables [24]. Furthermore, it consists of two parts of measurement and structural models, determining which observable variables measure latent variables and which variables are related to each other [25]. Besides, previous studies have shown that SEM provides better performance for the combined effects of different factors on drivers' speed choice [4]. Thus, in the present study, the structural equation model was used to determine the relationships between variables and the ones affecting a drivers' mean speed. Exploratory factor analysis is used as a statistical method to identify latent variables [26]. In this method, the internal correlation of variables is examined. The variables related to each of the latent variables are classified into specific categories. In this method, the observed variables are considered dependent variables [27].

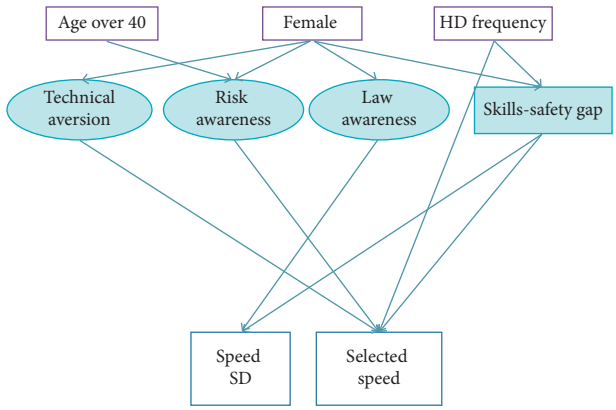


Figure 1: Structural equation model for analyzing driver-level model [4].

Table 1: Required sample size estimation based on age and gender distribution.

Age group	Number of population in the age group	Number of required samples at 90% confidence
Between 21 and 28 years	331951	21
Between 29 and 36 years	238398	15
Between 37 and 44 years	191204	12
Between 45 and 52 years	193180	13
Between 53 and 60 years	81616	6
Overall	1036349	67

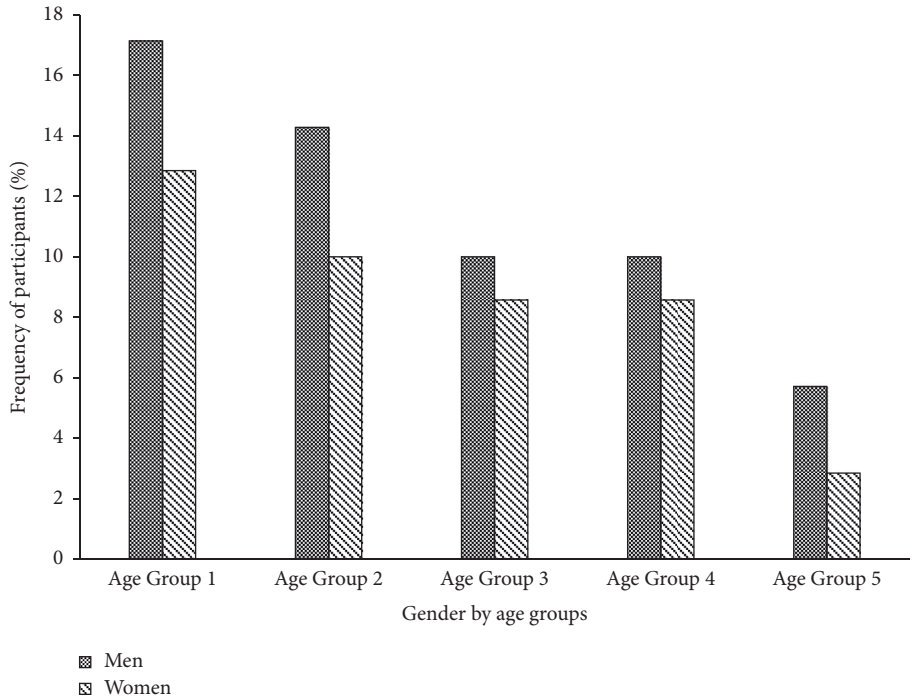
3. Results

3.1. Descriptive Analysis of Data. Table 4 shows all the variables considered in this study. For each categorical variable, binary variables were also considered for modeling; for example, the age variable (which is a categorical variable) was considered as five binary variables due to the related age groups. One stands for the youngest age group in these categories, and five stands for the oldest participants. This procedure is applied to other variables such as "Education Level," "Driving Experience," and "Job." Of all the variables, descriptive statistics for several variables are shown in Figure 5.

3.2. Structural Equation Modeling Results. Exploratory factor analysis was used to select variables that were more relevant and correlated with the latent variable. Observed variables' correlation was examined, and variables with a correlation of greater than 0.3, which is regarded as a variable unrelated to any other variable, were omitted. Also, variables with a load factor of less than 0.5 were excluded from the corresponding factor [27]. Table 5 indicates the results of exploratory factor analysis. Based on Table 5, two latent variables can be considered. Considering the value of 0.715 for the KMO (Kaiser–Meyer–Olkin), the sample number is adequate for this analysis [28].

Table 6 shows the total variance explained by the components which are extracted from the exploratory factor analysis. From Table 6, it can be said that the first component accounts for about 37% and the second component accounts for about 34% of the variance.

In the present study, the structural equation model (SEM) was used to investigate several latent variables' simultaneous effects on participants' speed choice behavior. In this regard, the measurement models included personal characteristics, weather conditions, and geometric features of the simulated road (Table 2). Figure 6 displays the graphical representation of the model. Considering the number of latent variables in the model (4 latent variables) and the required sample size rule (the required samples for calibrating SEM should be at least equal to the number of latent variables multiplies by 8 plus 30) [29]), the minimum sample size for this study is calculated. The minimum number of samples required for the present study is equal to 62, in which the number of participants (70 participants) was greater than the minimum required sample size. In this model, all significant variables, their relations, and the extent of their influence coefficients are well displayed. The calibrated SEM model has three different parts, which combined to evaluate the speed selection behavior. Therefore, the selected mean speed by drivers was the basis of the study (dependent variable). The dependent variable is converted to a binary variable (values 0 and 1) with value 1 for speeds higher than overall mean speeds and zero otherwise. As mentioned, the SEM model has three parts: the first part refers to the drivers' characteristics which include some observed variables such as age, gender, driving experience, and so forth, the second part evaluates the weather conditions and their effect on the dependent variable, and the third part shows the effect of road's geometric features on the mean speed. The final structure of the SEM model is shown in Figure 6. Each part will be described following in this section.



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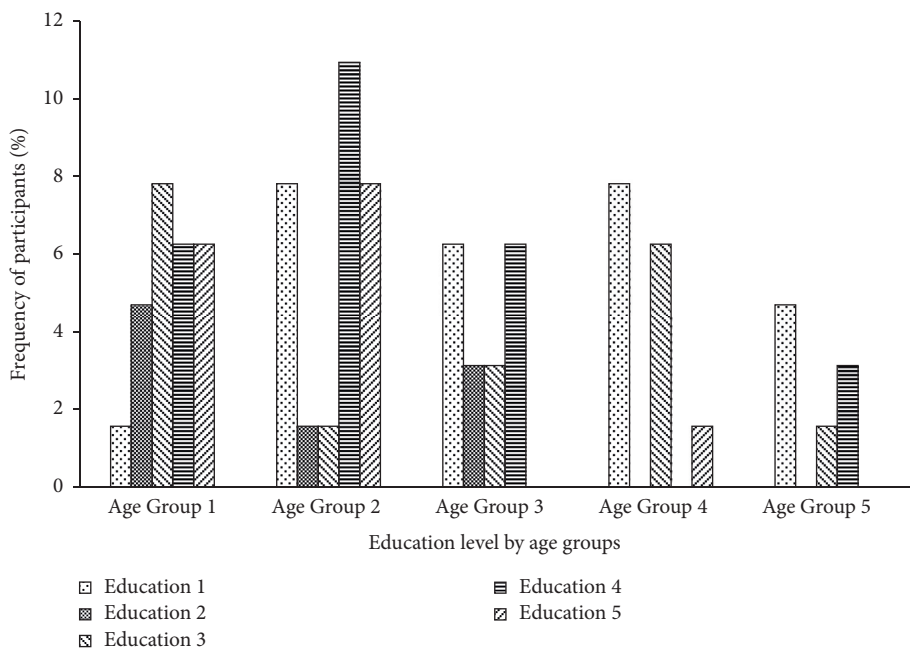

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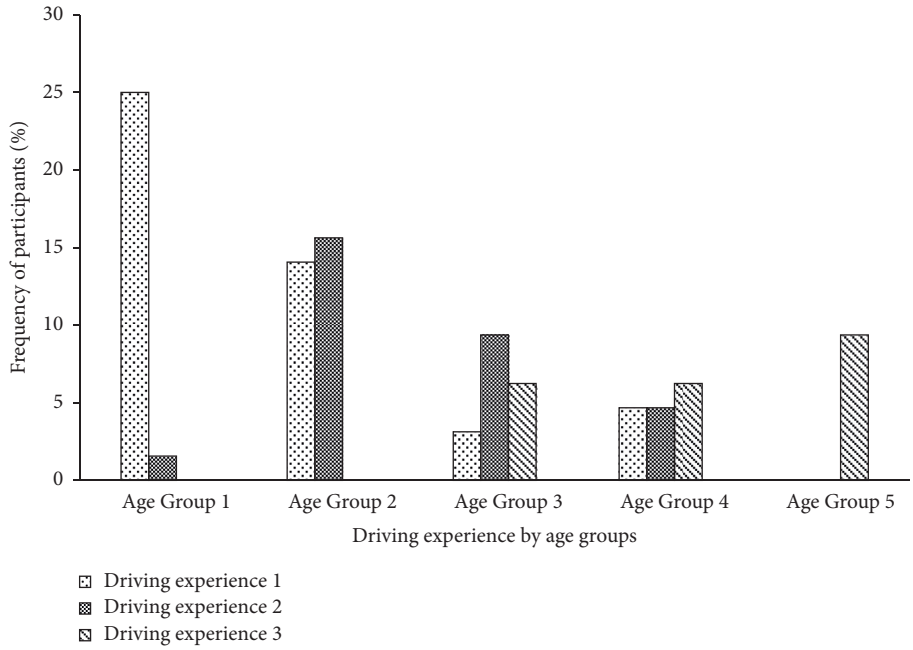

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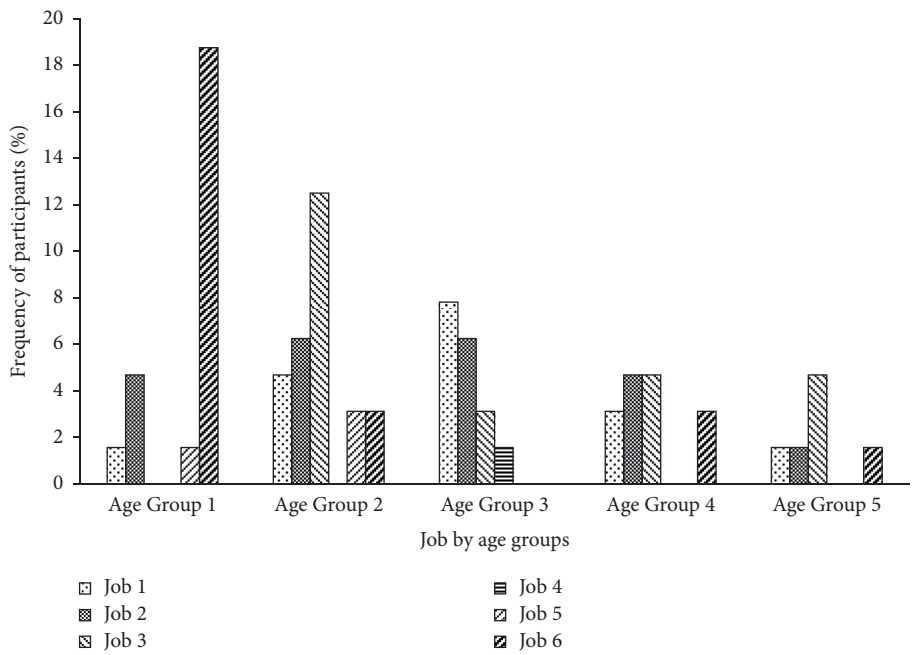


(d)

Figure 2: Detailed information of drivers' characteristics.

Table 7 shows the goodness-of-fit statistics of the SEM model that is presented in this paper. As shown in Table 7, the models displayed values greater than 0.9 on GFI and AGFI, a value smaller than 0.08 on RMSEA, a PNFI above 0.5, and a CMIN/DF smaller than 3 indicate a good model's fitness [25, 30, 31].

The validity and reliability of the SEM model structure have been evaluated. For this purpose, Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE), used to evaluate the model, are presented in Table 8. CR values and Cronbach's alpha values are above 0.7, demonstrating the internal consistency reliability [32]. Also, the AVE value is above 0.5, representing the existence of convergent validity [33, 34].

Moreover, to test the discriminant validity, the Heterotrait-Monotrait Ratio (HTMT) value was calculated. The calculated value for the "Experienced driver" and "Novice driver" measurement models was equal to 0.35, which is below the threshold of 0.9, representing the strong evidence for the validity of discriminant [35].

Table 2: Road segments' description including the location and the geometric features.

Segment	Distance	Feature	Radius (meters)
Segment 1	0 + 100 to 0 + 312	Horizontal curve	300
Segment 2	0 + 312 to 0 + 700	Tangent	∞
Segment 3	0 + 700 to 0 + 912	Horizontal and vertical curve	300
Segment 4	0 + 912 to 1 + 200	Tangent	∞
Segment 5	1 + 200 to 1 + 412	Horizontal curve	300

Figure 3: Driving simulator cabin.

Table 3: Images related to the simulated environment for each scenario.

Scenario	Weather	Time	
1	Clear	Day	
2	Clear	Night	
3	Light fog	Day	
4	Light fog	Night	

Table 3: Continued.

Scenario	Weather	Time	
5	Heavy fog	Day	
6	Heavy fog	Night	

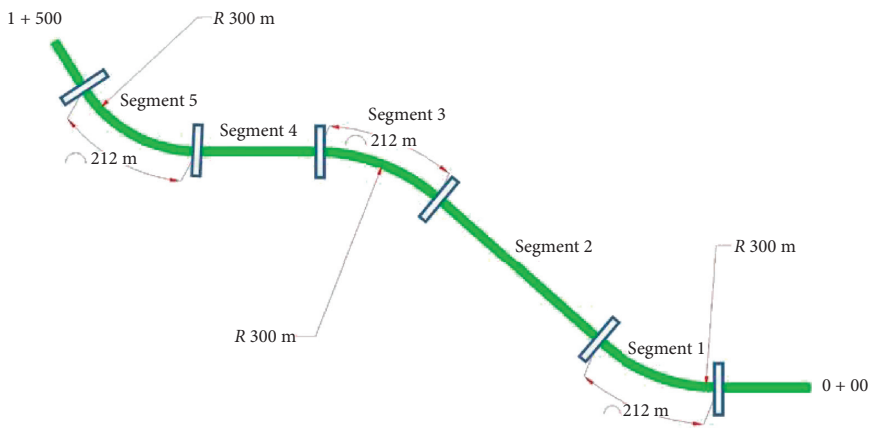


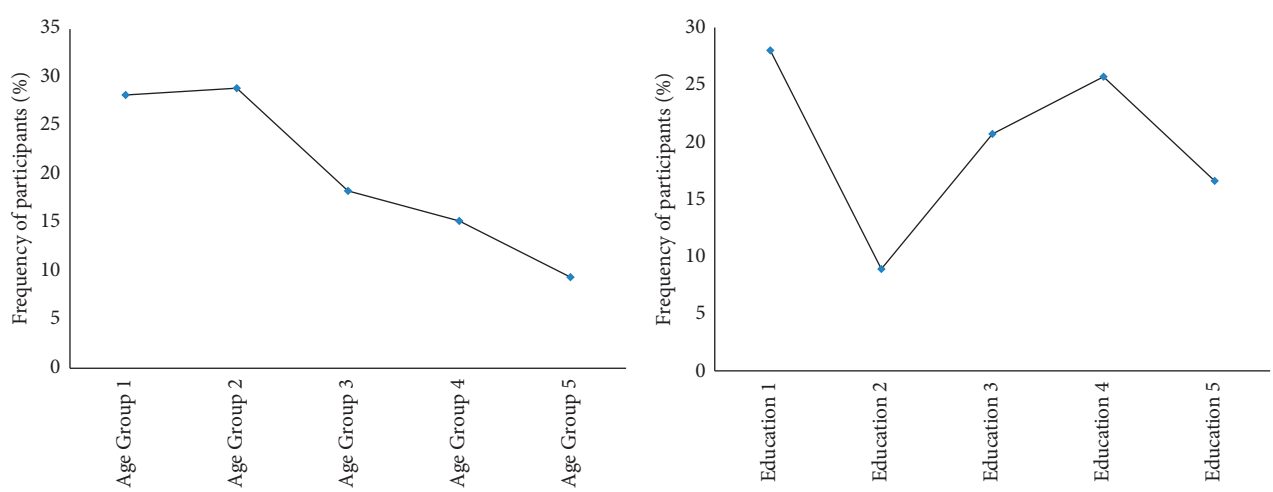
Figure 4: Plan view of the simulated road in the driving simulator with divisions related to each segment.

Table 4: Definition of variables.

Variable	Symbol	Definition	Binary value	Frequency (%)	Mean	Standard deviation
Age of participants	Age Group 1	Between 21 and 28	1	30	0.282	0.4501
	Age Group 2	Between 29 and 36	1	24	0.289	0.4536
	Age Group 3	Between 37 and 44	1	19	0.183	0.3869
	Age Group 4	Between 45 and 52	1	19	0.152	0.3587
	Age Group 5	Between 53 and 60	1	8	0.094	0.2915
Gender	Gender	Male	1	57	0.578	0.4905
		Female	0	43		
Marital status	Marital status	Single	1	32	0.320	0.4666
		Married	0	68		
Education level	Education 1	Diploma and lower	1	28	0.280	0.4491
	Education 2	Associate degree	1	8.9	0.089	0.2855
	Education 3	Bachelor	1	20.7	0.207	0.4055
	Education 4	Masters	1	25.7	0.257	0.4370
	Education 5	Ph.D. and higher	1	16.6	0.166	0.3725
Average duration of daily driving hours	Hour Daily 1	Under one hour	1	30.2	0.302	0.4591
	Hour Daily 2	Between 2 and 4 hours	1	59.9	0.599	0.4902
	Hour Daily 3	More than 5 hours	1	9.9	0.099	0.2994

Table 4: Continued.

Variable	Symbol	Definition	Binary value	Frequency (%)	Mean	Standard deviation
Driving experience	Driving Experience 1	Between 2 and 9 years	1	47.8	0.478	0.4996
	Driving Experience 2	Between 10 and 17 years	1	30.8	0.308	0.4620
	Driving Experience 3	More than 18 years	1	21.4	0.214	0.4100
Average annual kilometer for each participant	AAK 1	Between 0 and 500 km per year	1	17.3	0.173	0.3780
	AAK 2	Between 500 and 1500 km per year	1	20.1	0.201	0.4005
	AAK 3	Between 1500 and 3000 km per year	1	32.3	0.323	0.4678
	AAK 4	Between 3000 and 5000 km per year	1	13.5	0.135	0.3415
	AAK 5	More than 5000 km per year	1	16.9	0.169	0.3748
Job title of participants	Job 1	Housewife	1	18.2	0.182	0.3856
	Job 2	Self-employed	1	24.3	0.243	0.4291
	Job 3	Employee	1	24.2	0.242	0.4285
	Job 4	Professor	1	1.6	0.016	0.1247
	Job 5	Doctor	1	4.7	0.032	0.1749
	Job 6	Student	1	27	0.270	0.4441
Sight Distance	Day and clear weather	Day condition in clear weather	1	16.6	0.166	0.3728
	Night and clear weather	Night condition in clear weather	1	16.6	0.167	0.3728
	Day and light fog	Day condition in foggy weather with a vision distance of 250 m	1	16.6	0.167	0.3728
	Day and heavy fog	Day condition in foggy weather with a vision distance of 50 m	1	16.6	0.167	0.3728
	Night and light fog	Night condition in foggy weather with a vision distance of 250 m	1	16.6	0.167	0.3728
	Night and heavy fog	Night condition in foggy weather with a vision distance of 50 m	1	16.6	0.167	0.3728
Geometric Design	Segment 1	Horizontal curve	1	20	0.2	0.4
	Segment 2	Tangent	1	20	0.2	0.4
	Segment 3	Horizontal and vertical curve	1	20	0.2	0.4
	Segment 4	Tangent	1	20	0.2	0.4
	Segment 5	Horizontal curve	1	20	0.2	0.4



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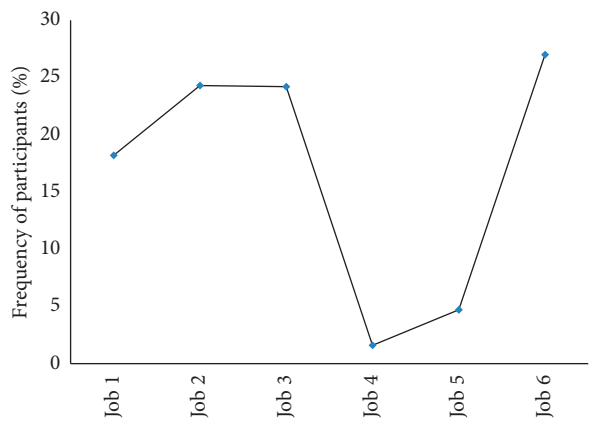

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Figure 5: Descriptive statistics related to variables.

Table 5: The results of exploratory factor analysis.

Latent variable	Indicators	Factor loading
Experienced Drivers	Driving Experience 3	0.782
	Gender	0.704
	Age Group 5	0.722
Novice Drivers	Driving Experience 1	0.675
	Marital Status	0.858
	Age Group 1	0.855

Table 6: Total variance explained.

Component	Initial eigenvalues			Extraction sums of squared loadings			Rotation sums of squared loadings		
	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %
1	2.676	44.596	44.596	2.676	44.596	44.596	2.210	36.825	36.825
2	1.358	22.632	67.228	1.358	22.632	67.228	1.824	34.403	71.228

3.2.1. Drivers' Characteristics. The first part of this model describes the drivers' characteristics on the mean speed at two different levels. The first level consists of three observed variables: "Age Group 5," "Gender Male," and "Driving Experience 3," which define a latent variable called "Experienced Drivers." The latent variable nature refers to drivers who perform more driving tasks than others and drive more often than others due to their age and profession.

The detailed structure of this latent variable in the whole model and contribution of observed variables in the latent variable structure is shown in Figure 6. The latent variable "Experienced Drivers" affects the mean speed with a coefficient of −0.08. The negative sign indicates that more experienced drivers tend to drive slower and slow down more than others. Table 9 shows the SEM results for the latent variable "Experienced Drivers." All variables are significant at the 0.05 level ($P < 0.05$).

As shown in Table 9, among the variables present in the latent variable set, the variable "Driving Experience 3" has the most impact on the latent variable (SRW = 0.840). This can be observed in the speed statistics for these variables. The speed statistics for the observed variables in the latent variable set are extracted. The results show that the drivers classified in the "Driving Experience 3" variable have the lowest speed than others (Figure 7).

The other level represents young drivers who are experiencing their early years of driving, known as "Novice Drivers." This latent variable is defined by three other observed variables: "Marital Status-Single," "Age Group 1," and "Driving Experience 1." The final structure of this latent variable and its observed variables is presented in Figure 6. The standard regression weight of this latent variable is 0.092. This latent variable's coefficient sign is positive and indicates that it is directly related to the dependent variable. This model shows that being single and having lower years of driving experience is a factor that motivates drivers to choose speeds above the mean speed. Table 10 shows the results of the model for "Novice Drivers."

The results can be evaluated with speed statistics for novice and experienced drivers. For this purpose, drivers with all the properties described in each latent variable (drivers that have all the properties of the latent variable simultaneously) were selected. The mean speed that these drivers selected was calculated, as indicated in Figure 8. In addition, Table 11 shows the descriptive statistics related to these latent variables. Regarding the significance of speed

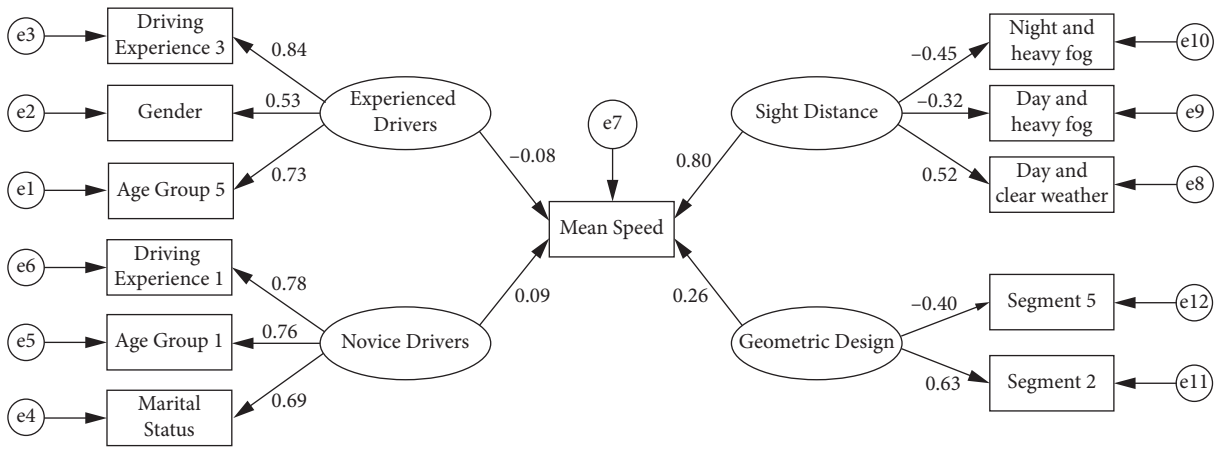

Figure 6: The graphical representation of structural equation model.

Table 7: Fit statistics for structural equation model.

Fit index	Value	Criteria of good fit
Chi-square/degree of freedom (CMIN/DF)	2.360	<3
Root mean square error of approximation (RMSEA)	0.032	≤0.08
Goodness-of-fit index (GFI)	0.966	0.9≤
Adjusted goodness-of-fit index (AGFI)	0.953	0.9≤
The parsimonious normal fit index (PNFI)	0.582	0.5<
Comparative fit index (CFI)	0.958	0.9≤
Root mean square residual (RMR)	0.008	Good models have small RMR

Table 8: Measuring each construct's reliability and validity.

Construct	Indicator item	Indicator loading	Cronbach's alpha	AVE	CR
Experienced Drivers	Driving Experience 3	0.84	0.704	0.51	0.75
	Gender	0.53			
	Age Group 5	0.73			
Novice Drivers	Driving Experience 1	0.78	0.781	0.55	0.79
	Marital Status	0.69			
	Age Group 1	0.76			

differences, the t-test analysis was used to investigate the speed differences between the two latent variables. The results show that the two variables' speeds are statistically different from each other ($P < 0.05$).

3.2.2. Weather and Time Conditions. The second part of this model is dedicated to weather conditions and the presence of visually restrictive conditions. In order to investigate the effect of weather conditions on drivers' speed choice, scenarios designed in the driving simulator have been used as observed variables to construct a latent variable. As mentioned, six scenarios were used in the driving simulator. Each of them had a specific feature in terms of weather conditions and visibility. Using the scenarios (presence or absence of lighting and fog) as observed variables, the latent variable "Sight Distance" was created. The latent variable "Sight Distance," as its name implies, represents the conditions of vision while driving. Three scenarios out of the six scenarios constitute this latent variable: "Day and clear weather," "Day and heavy fog," and "Night and heavy fog." The structure of this part is shown in Figure 6. The relationship between this latent variable and the dependent variable is a direct relationship with the regression weight of about 2.

The direct relationship between the latent variable "Sight Distance" and the dependent variable means that "Sight Distance" is an influential factor in drivers' decisions to choose speeds above the mean speed. However, it should be noted that the observed variables in this latent variable are divided into two types. The first type explains the weather conditions without visibility restrictions ("Day and clear weather"). The second indicates visually restrictive weather conditions ("Day and heavy fog" and "Night and heavy fog").

The presence of a negative sign in the observed variables and, at the same time, the presence of a positive sign between the latent variable and the dependent variable means that these observed variables have a negative effect on the selected

Table 9: SEM results for the latent variable "Experienced Drivers."

Latent variable (exogenous variable)	Observed variable	Regression weight	Standard error	Standard regression weight	P value
Experienced Drivers	Gender	0.95	0.03	0.53	0.001
	Age Group 5	1	—	0.73	—
	Driving Experience 3	1.62	0.12	0.84	0.001
	Mean speed	−0.17	0.05	−0.08	0.002

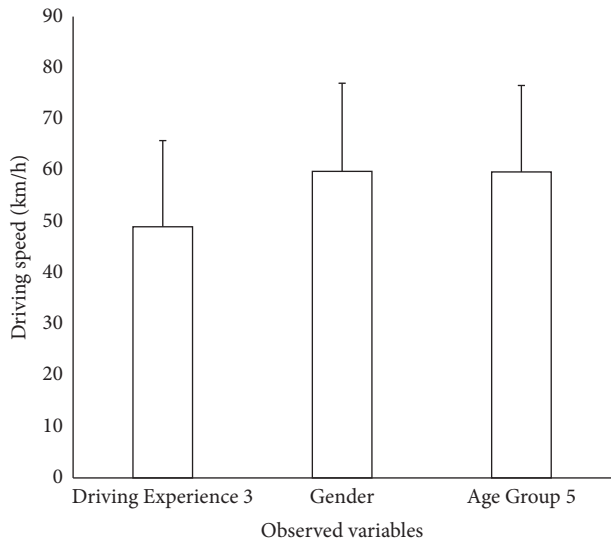

Figure 7: Speed statistics for variables involved in the latent variable "Experienced Drivers."

Table 10: SEM results for the latent variable "Novice Drivers."

Latent variable (exogenous variable)	Observed variable	Regression weight	Standard error	Standard regression weight	P value
Novice Drivers	Marital Status	1	—	0.69	—
	Age Group 1	1.25	0.05	0.76	0.001
	Driving Experience 1	1.41	0.11	0.78	0.001
	Mean speed	0.17	0.04	0.09	0.001

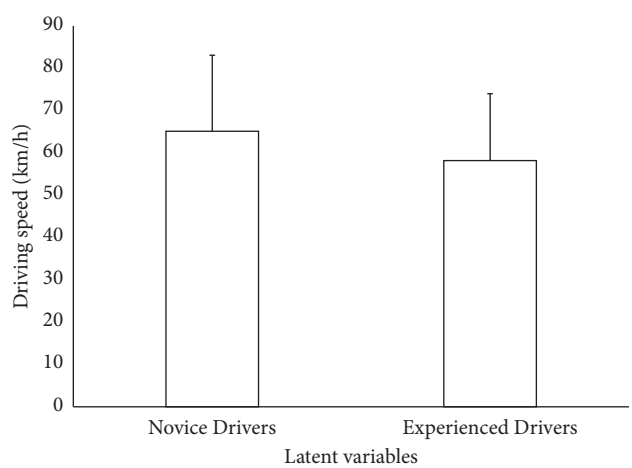

Figure 8: Speed statistics of two latent variables: "Experienced Drivers" vs "Novice Drivers."

speed. This means that drivers in these scenarios have chosen speeds lower than the mean speed. Table 12 shows the results of the model for "Sight Distance."

According to the model's statistics and results, the presence of heavy fog and lack of light are elements that affect the speed of drivers and reduce it. Statistical results from a study show that, by reducing visibility, drivers choose lower speeds. Figure 9 shows the mean speed chosen by drivers in the scenarios.

3.2.3. Geometric Design. As the third and final part of the model, the roadway's physical and geometric conditions

Table 11: Speed statistics related to the latent variables "Novice Drivers" and "Experienced Drivers."

Latent variable	Minimum (km/h)	Maximum (km/h)	Mean speed (km/h)	Standard deviation	*t*-test	
					Novice Drivers	Experienced Drivers
Novice Drivers	34	107	65	17.97	—	0.001
Experienced Drivers	31	98	58	15.8	0.001	—

Table 12: SEM results for the latent variable "Sight Distance."

Latent variable (exogenous variable)	Observed variable	Regression weight	Standard error	Standard regression weight	*P* value
Sight Distance	Day and clear weather	1	—	0.52	—
	Day and heavy fog	−0.60	0.06	−0.32	0.001
	Night and heavy fog	−0.87	0.06	−0.45	0.001
	Mean speed	2.07	0.14	0.80	0.001

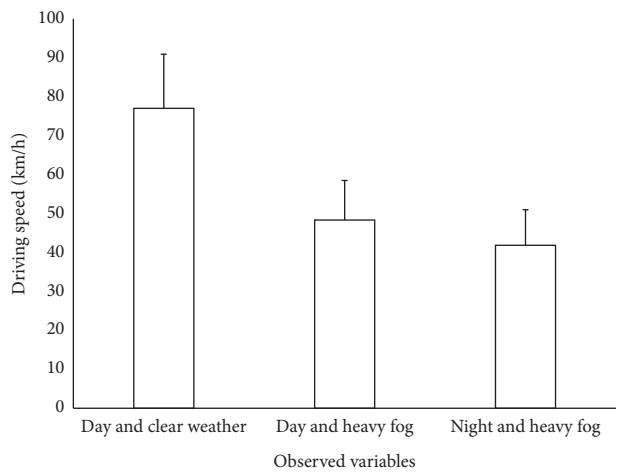

Figure 9: Speed statistics for variables involved in the latent variable "Sight Distance."

were added to the model to evaluate the effect of a curved or straight path on the driver speed selection behavior. In order to achieve the purpose of the article, the designed route was divided into five parts based on geometric features, and the mean speed of drivers in each scenario and each of the five parts was extracted. Due to the defined relations between the observed variables, "Segment 2" representing the tangent path and "Segment 5" representing the curved path, this latent variable is standing for "Geometric Design." The tangent section's length is about 300 meters, and the radius of the curved section is about 200 meters. Each section's position in this latent variable is shown in the roadmap (Figure 4). Figure 6 shows the relationship between the latent variable and the observed variables.

The latent variable "Geometric Design" has a regression weight of 0.52. Due to the positive sign in this coefficient, it is concluded that this latent variable is directly related to the mean speed. Theoretically, this coefficient means that the variable "Geometric Design" is a factor to increase drivers' speed. As shown, "Segment 2" has a positive sign with the regression weight of 1. Therefore, this observed variable is directly related to the dependent variable (due to the latent variable's positive sign). "Segment 5," on the contrary, has a regression weight with a negative sign, which means that "Segment 5," which is a curved path, has an inverse relationship with the dependent variable. As a result, having a curved section on the road causes a speed reduction. On the contrary, a tangent path can encourage drivers to choose a speed higher than the mean speed. Table 13 shows the results of the model for "Geometric Design."

In addition to the model result, the speed statistics extracted from the variables show that existing a curved section on the road can reduce the mean speed chosen by drivers. On the other hand, in tangent segments, drivers choose a wide range of speed values far from all individuals' mean speeds (Figure 10).

3.2.4. Education Level. In this study, each participant's level of education was presented in the set of variables collected. However, in making the final model, the "Education Level" variable was not significant. However, due to this variable's importance, it was decided to examine the selected speed based on the level of education in the form of a chart (Figure 11). In this study, participants were divided into five groups concerning the educational level, including "Education 1" (diploma and lower), "Education 2" (Associate degree), "Education 3" (Bachelor), "Education 4" (Masters),

Table 13: SEM results for the latent variable "Geometric Design."

Latent variable (exogenous variable)	Observed variable	Regression weight	Standard error	Standard regression weight	P value
Geometric Design	Segment 5	−0.62	0.11	−0.40	0.001
	Segment 2	1	—	0.63	—
	Mean speed	0.52	0.10	0.26	0.001

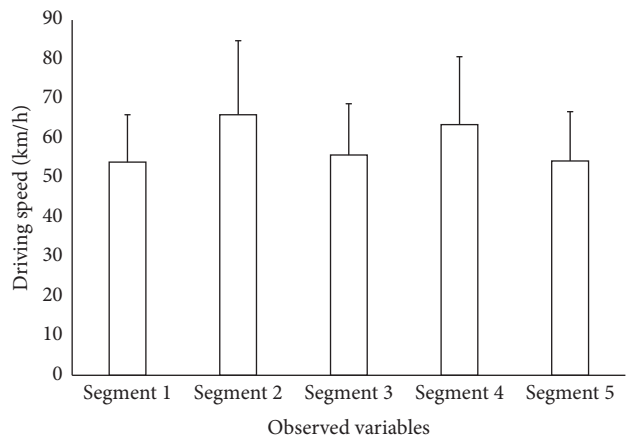

Figure 10: Speed statistics for variables involved in the latent variable "Geometric Design."

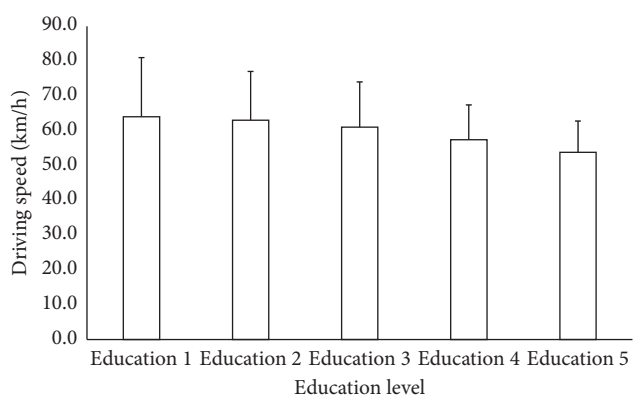

Figure 11: Speed statistics for "Education Level" variable.

and "Education 5" (Ph.D. and higher). The participants' average speed was about 60 km/h. As shown in Figure 11, participants with a higher education level chose a slower speed than other participants. The participants' average speed in group "Education 4" is equal to 57 km/h and "Education 5" is equal to 54 km/h, which are lower than the average speed of all participants.

The correlation between education level variables was examined using the Spearman test. As shown in Table 14, the value of the Spearman correlation coefficient between the two variables "Education 2" and "Education 3" is equal to 0.45 with a significance level of 0.000. At the error level of 0.05, the null hypothesis, which indicates the absence of a uniform relationship between the two variables, is rejected. Therefore, two variables are related to each other, which means that speed selection behavior in these variables is the same. This test was performed for all variables of education level, and the results are reported in Table 14.

4. Discussion

In terms of practical factors in traffic accidents, speed and, in particular, speeds above the speed limit are the most crucial factor that can play a decisive role in the severity of accidents. Numerous factors can affect drivers' speed selection. Environmental factors such as road geometry, weather conditions, and land use or drivers' characteristics such as age, gender, and driving experience affect drivers' speed choice behavior. However, the purpose of this paper is to investigate the behavior of drivers' speed selection under the influence of factors such as geometric road conditions, weather conditions, and drivers' characteristics.

Table 14: Spearman test results for education level variables.

		Education 1	Education 2	Education 3	Education 4	Education 5
Education 1	Correlation coefficient	1				
	Sig. (2-tailed)	—				
Education 2	Correlation coefficient	0.07	1			
	Sig. (2-tailed)	0.327	—			
Education 3	Correlation coefficient	0.05	0.45	1		
	Sig. (2-tailed)	0.925	0.000	—		
Education 4	Correlation coefficient	0.01	0.13	0.17	1	
	Sig. (2-tailed)	0.834	0.110	0.113	—	
Education 5	Correlation coefficient	0.1	0.12	0.14	0.306	1
	Sig. (2-tailed)	0.895	0.135	0.126	0.000	—

Table 15: SEM results for the latent variables.

Dependent variable	Latent variable	Regression weight	Standard error	Standard regression weight	*P* value
Mean speed	Experienced Drivers	−0.17	0.05	−0.08	0.002
	Novice Drivers	0.17	0.04	0.09	0.001
	Sight Distance	2.07	0.14	0.80	0.001
	Geometric Design	0.52	0.10	0.26	0.001

The present study results showed that all three factors, including road geometric, weather conditions, and drivers' characteristics, could simultaneously affect the speed choice behavior. According to the results, age and driving experience are the most important factors that play a decisive role in drivers' decisions to choose speed. As expected, drivers who were older than other drivers recorded lower mean speeds, as noted in previous studies [10, 13, 36]. On the contrary, young and inexperienced drivers showed different behaviors. The selected speed of these drivers was higher than the average speed of driving on the simulated route. This finding is in line with previous studies that introduce young age and youth as a factor for speeding violations and choosing higher speeds [37–40].

Apart from the mentioned characteristic factors, weather conditions also affect the drivers' speed selection behavior. Weather conditions' variables, particularly, heavy fog, negatively affected the mean speed and reduced it. In this regard, previous studies have examined the effect of foggy weather conditions on speed selection and have obtained similar results [10, 41–44]. However, contrary to the discussed results, Hamdar et al. [45] concluded that fog density has little or no effect on drivers' speed selection behavior. Contrary to expectations, foggy weather conditions have the most significant impact on the mean speed among the model's factors. Neither old age nor extensive driving experience or even road geometry reduced the mean speed as much as heavy fog. Maybe this result is related to the high number of crash occurrences. Ashley et al. state that the annual number of fatalities associated with weather-related, vision-obscured vehicular crashes is noticeable [46]. In previous studies, the mean speed reduction due to foggy weather conditions was about 12% [47]. However, in the present study, heavy fog caused a reduction of about 40% in the mean speed. It is important to note that heavy fog affects the mean speed by reducing the driver's sight distance, and a reduction of about 40% in mean speed indicates a sharp reduction in drivers' sight distance. According to the results, in order to prevent accidents in foggy areas, special measures should be taken to increase the sight distance.

Due to the difference in sight distance value, driving in a tangent is different from driving in a curve. In order to investigate the effect of the presence of a curve on the mean speed, the variable of the geometric design was used in the model. The results showed that drivers choose a lower speed on the curved segments. In other words, the presence of a curve section (with a radius of 300 meters) reduces the drivers' mean speed. This result is also seen in the research of other researchers [48, 49]. In a study to investigate the selective speed in curve paths, Wang used naturalistic driving data. This study shows that the presence of an arc with a radius of fewer than 300 meters reduces the speed [50, 51]. In one study, researchers used a semiautonomous vehicle and collected speed information. The purpose of this study is to investigate the degree of adaptation of intelligent systems to road characteristics. In this study, a new concept related to speed called automated speed has been used. This study shows that automated speed decreases in arcs with a radius of less than 500–600 meters [52]. Also, the findings of previous studies indicate that the radius and length of each horizontal curve significantly influence the frequency of motorcycle crashes [53].

Numerous studies have been conducted in this field, many of which confirm the present study results. However, the result was not unexpected. The purpose of this study was to investigate these conditions simultaneously with other conditions mentioned in the study.

5. Conclusion

In the present study, the effect of drivers' behavioral characteristics, weather conditions, and geometric design on mean speed was evaluated. Speed data were collected through a driving simulator and driver profiles through a

questionnaire. The combination of variables was used to model the mean speed selection behavior of drivers in simulated conditions on a two-lane rural road. SEM was used for this study, and the model fit indices in the proposed model are on the acceptable threshold (Table 7).

Four latent variables, "Novice Drivers," "Experienced Drivers," "Sight Distance," and "Geometric Design," are defined to evaluate the speed selection behavior of drivers. These latent variables represent behavioral and individual characteristics along with geometric effects of the road and weather conditions. Table 15 provides brief information about the coefficient of latent variables with the dependent variable.

The exogenous latent variable having the highest effect on mean speed is "Sight Distance," with a value of the standard regression weight of 0.803. This means that foggy weather conditions have the highest effect on mean speed and can reduce the selected speed by drivers more than other factors like being experienced driver or driving in curved sections in a two-lane road. The mean speed selected in foggy weather conditions is about 45 km/h. In contrast, experienced drivers' mean speed is about 59 km/h, and the mean speed selected in the curved segment is 54 km/h. Thus, it is concluded that adverse weather conditions can reduce drivers' mean speed more than other factors. Also, from the indicators of the abovementioned latent variables, it can be concluded that a decrease in age and driving years leads to an increase in mean speed. In contrast, as the driving experience of drivers increases, their tendency to higher speed decreases.

According to the results, and considering that heavy fog caused a reduction of about 40% in the mean speed, it is necessary to study tools to increase drivers' sight distance. In this regard, there are several studies [54–57] which had analyzed the role of driving assistance systems for increasing the safety of drivers in foggy weather which can be more focused on object detection algorithms in different levels of fogs in order to enhance the visibility of drives in this condition. Moreover, upgrading in-vehicle (crash warning systems, direct vision enhancement systems, and imaging vehicle information systems) and roadside (road weather information systems) fog detection systems can also decrease the possibility of driver errors in fog condition driving.

Data Availability

The data are available upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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