IATSS Research 48 (2024) 427–439

Contents lists available at ScienceDirect

IATSS Research

journal homepage: www.sciencedirect.com/journal/iatss-research

Research Article

Understanding the influence of environmental factors on driver speed: A structural equation modeling analysis

Abbas Sheykhfard [a,*], Farshidreza Haghighi [a], Soheila Saeidi [b], Mohammad SafariTaherkhani [c], Subasish Das [d]

[a] Department of Civil Engineering, Babol Noshirvani University of Technology Shariati Ave., Babol, Mazandaran, Iran
[b] Department of Civil, Environmental and Geomatics Engineering, College of Engineering and computer Science, Florida Atlantic University, 777 Glades Road, Boca Raton, FL 33431, USA
[c] Center for Advanced Transportation Technology (CATT) Department of Civil and Environmental Engineering University of Maryland, College Park, MD 20740, USA
[d] Ingram School of Engineering, Texas State University, 601 University Drive, San Marcos, TX 78666, USA

ARTICLE INFO

Keywords:
Driver behavior
Speed
Roadway and contextual factors
Structural equation modeling

ABSTRACT

This study examined the influential roadway and contextual factors affecting drivers' speed selection through a comprehensive investigation employing structural equation modeling. Roadway and contextual variables including road curvature, presence of roundabouts, adverse weather conditions, and access were investigated using infrared speed sensors. The analysis revealed that specific roadway and contextual factors such as field variables, uphill and downhill road inclines, particular road curvature, and rainy weather significantly influence drivers' chosen speeds, while factors such as road access, nighttime conditions, larger road curvature, and signage exhibit a lesser impact. Notably, the study also found a positive correlation between road curvature radius and driver-chosen speed. The study's implications for transportation infrastructure planning and road safety interventions are underscored, with potential applications in road design, signage improvement, and weather-responsive measures to regulate driver speed choices in specific roadway and contextual conditions.

1. Introduction

Driver behavior on the road is influenced by a complex interplay of factors, including personal characteristics and a wide range of roadway and contextual factors [1]. The design and layout of road infrastructure, encompassing variables such as lane width, curve radius, sight distance, and signage, are integral in shaping the driving experience and influencing drivers' speed choices [2,3]. Additionally, factors such as road misalignment, inadequate signage, substandard road markings, poor illumination, and geometric design deficiencies play a critical role in affecting drivers' speed selections and consequently impacting road safety. Notably, the influence of these roadway and contextual elements on driver behavior has far-reaching implications for public safety.

Over the years, traffic engineers and planners have focused on addressing factors like congestion and geometric design that significantly impact the frequency and severity of road crashes. However, a notable research gap exists in thoroughly analyzing the specific roadway and contextual factors that influence drivers' speed selections under varied conditions. Such an analysis is imperative to inform targeted road safety interventions and infrastructure planning, aiming to mitigate the frequency and severity of traffic accidents. Furthermore, existing research studies have highlighted the critical role of speeding as a risk factor in traffic crash injuries [1,2]. However, a detailed exploration into the specific influencers affecting drivers' speed selection is essential for understanding road safety dynamics, thus allowing for more effective speed control measures and targeted infrastructure improvements to enhance road safety.

The existing literature shows the need for an in-depth study to analyze the influence of driver's speed selection and address the research gap. This study aimed to investigate the impact of various roadway and contextual factors on drivers' speed choices in a specific road segment. These factors include road geometry and infrastructure, traffic characteristics, environmental conditions, and driver-related factors. By employing advanced data analysis techniques and leveraging infrared speed sensors, this research aimed to provide nuanced insights into the factors that significantly shape drivers' speed selections, ultimately

* Corresponding author.
E-mail addresses: A.Sheykhfard@nit.ac.ir (A. Sheykhfard), Haghighi@nit.ac.ir (F. Haghighi), ssaeidi2022@fau.edu (S. Saeidi), msafari@umd.edu (M. SafariTaherkhani), subasish@txstate.edu (S. Das).

https://doi.org/10.1016/j.iatssr.2024.08.001
Received 4 March 2024; Received in revised form 3 July 2024; Accepted 1 August 2024

contributing to the advancement of road safety measures and infrastructure planning.

1.1. Factors influencing driver speed

Driver speed is influenced by various factors such as roadway characteristics, environmental conditions, contextual factors, and individual attributes. This section provides a comprehensive overview of key elements that can either reduce or increase speed, based on an extensive review of current literature from various global contexts.

- Roadway Characteristics

The physical layout of the road significantly impacts speed choice. Stamatiadis et al. (2018) found that straighter roads and good sight distances tend to encourage higher speeds [4], while curves, hills, and limited visibility generally reduce speed. This is corroborated by Himes et al. (2011), who demonstrated that increasing sight distance is associated with higher average speeds and reduced speed deviation [5]. Lee et al. (2008) further emphasized the significance of road factors in influencing speed choice and crash frequency on South Korean highways [6].

Lane width affects speed, with wider lanes associated with higher speeds. Fitzpatrick et al. (2000) quantified this relationship, showing that for every foot increase in lane width, speeds increased by approximately 2.9 mph [7]. The number of lanes on a road is another factor, with Ng and Small (2012) reporting that multilane highways typically see average speeds 5–10 mph higher than two-lane roads with similar speed limits [8].

Road surface condition impacts speed as well. Hamdar et al. (2016) found that drivers reduce speed by an average of 7% on roads with visible deterioration [9]. Curve geometry plays a crucial role, as highlighted by Xu et al. (2022), who found that curve radius significantly influenced drivers' perceived speed on freeway curves [10]. Vos et al. (2021) further scrutinized the impact of curve cues on speed choice in right-turning curves [11].

Road markings and design elements also affect speed. Griffin et al. (1995) concluded that horizontal road markings can influence drivers' behavior and speed [12]. Tola and Gebissa (2019) emphasized the importance of road alignment in speed selection in Ethiopia [13].

- Environmental Conditions

Weather conditions significantly influence speed choice. Rakha et al. (2007) quantified this effect, finding that [14] light rain reduces speeds by 2–4% and heavy rain causes reductions of 5–10%. Ghasemzadeh et al. (2018) [15] and Nasim Khan et al. (2020) [16] further examined the impact of weather on drivers' speed choices, particularly in adverse conditions. Lee et al. (2017) found that weather conditions, along with speed limits and road geometry, influence driver's speed choice in Malaysia [17].

Lighting conditions affect speed as well. Jägerbrand and Sjöbergh (2016) observed an average speed reduction of 3 km/h during nighttime hours on roads without street lighting [18]. Anarakooli and Hosseinlou (2016) evaluated the impact of lighting conditions on factors affecting crash severity and driver's chosen speed [19].

Traffic volume is another crucial factor. Kockelman (1998) found a negative correlation between traffic density and average speed [20]. Imprialou et al. (2016) further demonstrated the relationship between speed, crashes, and traffic volume, with higher traffic volumes typically leading to lower speeds due to increased vehicle interactions [21].

- Contextual Factors

Speed limits significantly impact driver behavior. Goldenbeld and van Schagen (2007) found that changing speed limits resulted in speed changes of about 25% of the difference between the old and new limits [22]. Hmazeie et al. (2017) examined how speed limits affect driver speed selection and associated crash risk [23], while Anastasopoulos and Mannering (2016) found that drivers' speed was influenced by both road geometric conditions and the imposed speed limit [24]. Goralzik et al. (2017) showed that speed limits, along with road geometry, significantly influence speed choice [25].

Enforcement measures can effectively reduce speeds. A meta-analysis by Wilson et al. (2010) showed that speed cameras reduced average speeds by 1–15% and the percentage of vehicles exceeding the speed limit by 14–65% [26].

The surrounding environment also affects speed choices. Gargoum and El-Basyouny (2016) found that drivers tend to reduce speed in residential areas compared to commercial or rural areas [27]. Kim et al. (2011) indicated a direct impact of access on driver speed and crashes in Hawaii [28], suggesting that drivers adjust their speed based on the surrounding land use and access points.

- Individual Factors

Driver characteristics play a crucial role in speed selection. Oltedal and Rundmo (2006) found that younger drivers and males tend to drive faster [29]. Liu et al. (2020) emphasized the influence of driving ability and risk perception on speed selection behavior [30]. Sadia et al. (2018) investigated how driver characteristics, along with environmental and road factors, influence speed selection [31].

The nature of the trip affects speed as well. Peer (2011) found that drivers on work-related trips tend to drive faster than those on leisure trips [32]. The type of vehicle can also influence speed, with Horswill and Coster (2002) noting that drivers of high-performance vehicles tend to drive faster [33].

Javid et al. (2021,2022) highlighted the role of personal norms, traffic enforcements, and speeding propensity in speed choice [34,35]. Zolali et al. (2021) considered a comprehensive set of factors, including drivers' characteristics, time conditions, and geometric features in influencing speed choice, providing a holistic view of the speed selection process [36].

1.2. Research gap and rationale for study focus on rural areas

While existing studies have explored various factors influencing speed selection in urban areas, there was a need for a more focused investigation into the specific variables that impact drivers' speed choices within rural areas. Rural roads present unique challenges and environmental contexts that may influence driver behavior differently from urban settings. Furthermore, the review suggested that while many studies have examined the influence of psychological variables on drivers' speed selection, the focus on the impact of roadway and contextual factors on speed choice in rural regions was relatively limited. This gap in research highlighted the importance of examining how specific rural road characteristics, environmental conditions, and infrastructural elements affect drivers' speed decisions in these less-studied areas. Therefore, our research aimed to fill this gap by conducting a detailed and specific analysis of factors such as road geometry, access points, lighting conditions, weather, traffic signs, and intersections in our geographic area to better understand their influence on driver speed choices. By addressing this research gap, our study contributes to the development of targeted and region-specific interventions to promote safer driving behaviors based on a thorough understanding of the factors influencing speed choice. This could ultimately lead to more effective measures for controlling drivers and preventing vehicles from moving at illegal speeds in our specific geographic context.

2. Methodology

2.1. Study area

The study area for this research encompasses a rural bypass route connecting three cities in Mazandaran province: Babol, Amol, and Qaemshahr (Fig. 1). This 16-km rural highway, depicted in Fig. 1, traverses predominantly agricultural and undeveloped land. The road features four lanes - two in each direction - separated by a median, designed to facilitate smoother traffic flow between these urban centers while bypassing densely populated areas. Despite its rural setting, the highway incorporates modern design elements, including 8 horizontal curves to navigate the terrain and a maximum longitudinal slope of 3%. The road's design accommodates a speed limit of 110 km per hour, which is typical for rural highways connecting urban areas in this region. This setting provides an ideal environment to study driver behavior and speed selection in a rural context, where the road characteristics differ significantly from those in urban or suburban areas.

2.2. Data collection and variables

In the recent study, we configured environmental sensors using the Internet of Things (IoT) to collect vehicle speed data. The system consists of passive infrared sensors (PIR), a minicomputer, and an interface for processing sensor data (Fig. 2). PIR sensors are installed in pairs at different points along a route. When a vehicle passes each sensor, the time of detection is recorded, and the distance between sensors is used to calculate the vehicle's speed. These sensors operate wirelessly to avoid interfering with moving vehicles. The study verified the accuracy and reliability of the speed sensors through calibration, comparing data from the vehicle's speedometer with the sensor readings. The results indicated no significant difference, confirming the system's effectiveness in continuous speed monitoring for road safety planning and accident prevention.

In this study, the accuracy and reliability of the speed sensors used were determined through calibration. A specific point along a straight path was chosen to verify the device's correct operation. Two sets of data were collected: one from the vehicle's speedometer (where the driver passed the sensor at predetermined speeds) and the other from the sensor after the vehicle passed. These data were then entered into SPSS software, capturing speeds from 50 vehicles.

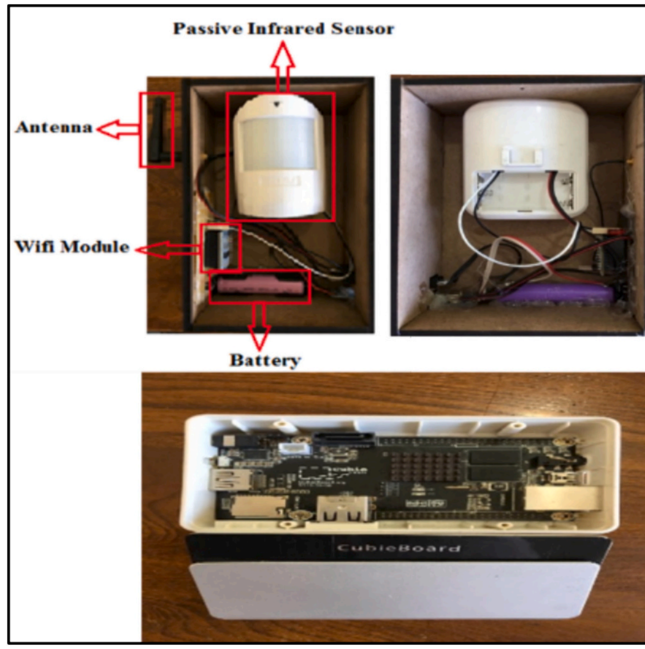


Fig. 2. RIP speed recorder.

Using a paired sample *t*-test at a 95% confidence level, the study examined the significance of data variations. If the significance level is less than the error value, it indicates a difference between the averages of the two populations concerning the examined variable.

In this study, a control point unaffected by roadway and contextual

Fig. 1. The southern bypass of Babol city.

factors was selected. Speeds were recorded at four points spaced 30 m apart using a speed recording sensor. Ten roadway and contextual factors potentially influencing drivers' speed choices were identified, including speed limit signs, entrance curve radius (600 m), nighttime traffic, uphill and downhill flow, movement through a curve (radius 950 m), presence of a roundabout, traffic signs, and adverse weather conditions. Speed readings were collected 30 m before and after these factors, totaling approximately 10,000 readings.

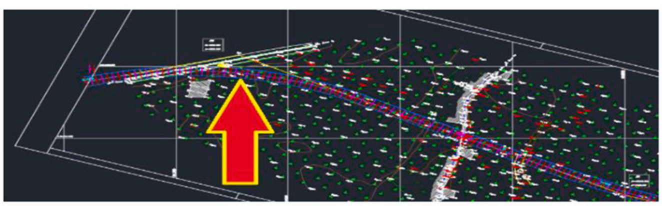
The study treated the control point as the dependent variable and the ten roadway and contextual factors as independent variables. Partial Least Squares Structural Equation Modeling (PLS-SEM) was employed. Speed data for each latent variable were selected as observed variables in the software. The measurement model captured relationships between speeds and the eleven studied variables, while the structural model explored the connections between the ten roadway and contextual factors and the control point. Detailed route maps and the study model are depicted in Fig. 3, Table 1.

2.3. Methods

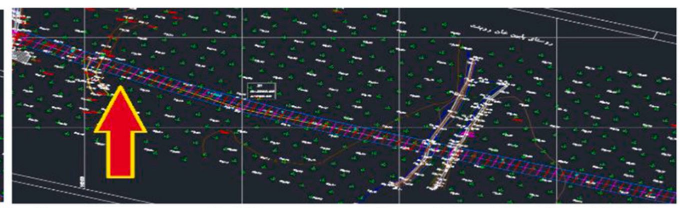
2.3.1. SEM

A Structural Equation Model is a statistical modeling technique used to analyze the relationships between observed and latent variables. It is a powerful tool for understanding complex relationships within a dataset.

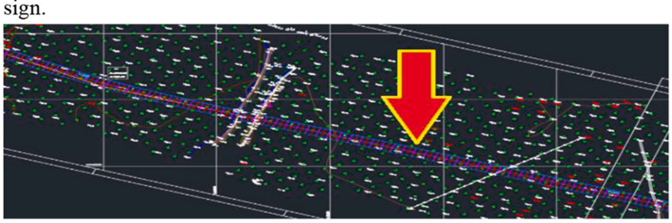
By combining both measurement and structural components, SEM enables researchers to not only assess the direct effects between variables but also capture the underlying, unobserved constructs that drive these relationships. The measurement model, as denoted by the equation $\eta = \Lambda\xi + \delta$, serves as the foundation of SEM. Here, observed variables (η) are linked to latent variables (ξ) through factor loadings (Λ), representing the strength of the relationship between the observed variables and the underlying constructs. The presence of measurement errors (δ) acknowledges that observed variables are imperfect indicators of their respective latent constructs, accounting for any random



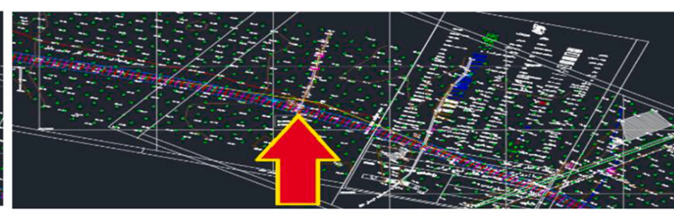
a) Kilometer one, the study variable: Entrance curve of the route (Curve No. 1).



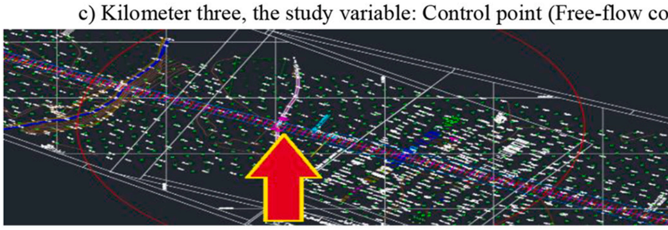
b) Kilometer two, the study variable: Speed Limit sign.



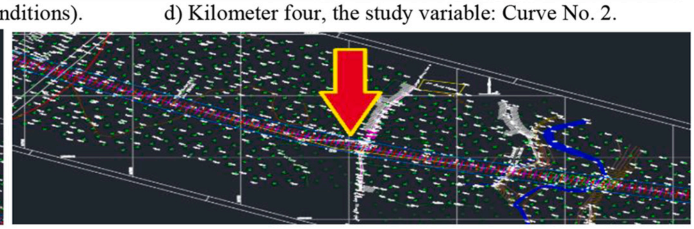
c) Kilometer three, the study variable: Control point (Free-flow conditions).



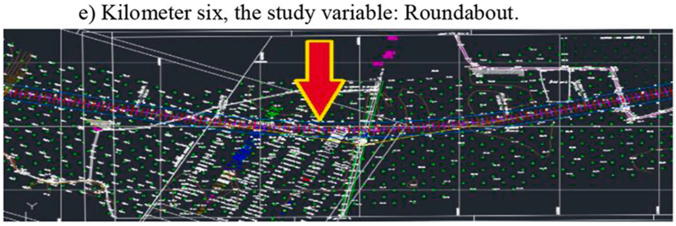
d) Kilometer four, the study variable: Curve No. 2.



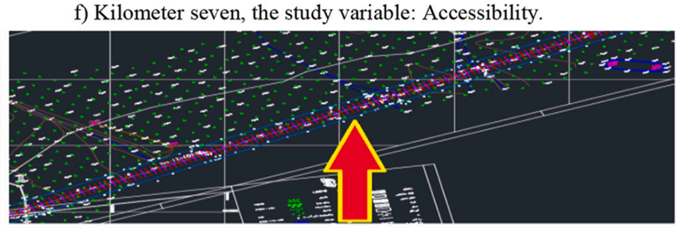
e) Kilometer six, the study variable: Roundabout.



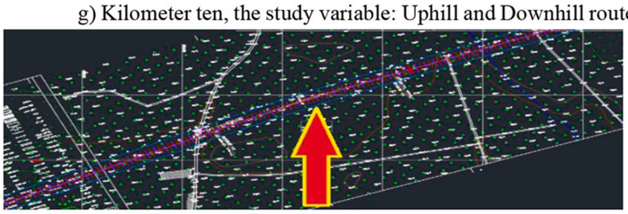
f) Kilometer seven, the study variable: Accessibility.



g) Kilometer ten, the study variable: Uphill and Downhill route.



h) Kilometer twelve, the study variable: Rainy weather - Night.



i) Kilometer fourteen, the study variable: Traffic signs.

Fig. 3. 3a) Kilometer one, the study variable: Entrance curve of the route (Curve No. 1). Fig. 3b) Kilometer two, the study variable: Speed Limit sign. 3c) Kilometer three, the study variable: Control point (Free-flow conditions). Fig. 3d) Kilometer four, the study variable: Curve No. 2. 3e) Kilometer six, the study variable: Roundabout. Fig. 3f) Kilometer seven, the study variable: Accessibility. 3g) Kilometer ten, the study variable: Uphill and Downhill route. Fig. 3h) Kilometer twelve, the study variable: Rainy weather - Night. 3i) Kilometer fourteen, the study variable: Traffic signs.

Table 1
Variables investigated in this study.

Variables	Cited in previous research
Speed limit - Traffic density	Hamzeie et al. [13]
Speed limit	Lee et al. [5]
Driver's age and gender, lane width, shoulder width, and visibility distance	Anastasopoulos and Mannering [15]
Weather conditions	Hassan et al. [37]
Accessibility	Kim et al. [6]
Radius and length of horizontal curve, available sight distance	Himes et al. [7]
Weather conditions, speed limit	Ghasemzadeh et al. [16]
Factors related to road geometry, horizontal alignment, and sight distance	Tola et al. [9]
Traffic volume, road surface, weather conditions, traffic composition, shoulder	Papadimitriou et al. [8]
Speed limit, road geometry (curve), presence of a passenger, and driver characteristics	Goralzik et al. [10]
Traffic volume, lane width, number of lanes, horizontal alignment, shoulder width, median width	Abdel-Aty and Radwan. [38]
Traffic volume, lane and shoulder width	Hadi et al. [39]
Influence of roadside infrastructure	Van Der Horst and De Ridder [40]
Speed cameras with and without warning signs	Wilmots et al. [41]
Traffic signs	Griffin et al. [11]
Lighting conditions (day/night) - Access	Bandyopadhyaya and Mitra [42]
Weather conditions - Lighting conditions	Celik and Oktay [43]
Lighting conditions	Anarkoli and Hosseinlu [12]

variability or measurement imprecision. On the other hand, the structural model, $\xi = B\xi + \zeta$, encapsulates the causal relationships between the latent variables (ξ). This set of equations allows us to understand how these unobserved constructs influence each other directly (via the structural coefficients represented by B) and how external factors contribute to any unexplained variance or disturbances (ζ). By formulating these relationships in a matrix-based representation and employing specialized statistical software, the parameters of the model can be estimated. This estimation process involves finding values for Λ, B, and potentially other parameters, such as the variance and covariance of the disturbances (δ and ζ), that best fit the observed data.

2.3.2. Multiple linear regression

Multiple linear regression is a statistical method used to model the relationship between two or more independent variables (often denoted as $x_1, x_2, \ldots, x_p$) and a dependent variable (y). It extends the concept of simple linear regression, which models the relationship between one independent variable and the dependent variable.

In multiple linear regression, the relationship between the variables is expressed by the following equation:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_p x_p + \varepsilon$$

Where:

- y is the dependent variable.
- x_1 ,x_2, …, and x_p are the independent variables.
- β_0, β_1, β_2, …, and β_p are the coefficients that represent the effect of each independent variable on the dependent variable.
- ε represents the error term, which captures the variability in y that cannot be explained by the independent variables.

The goal of multiple linear regression is to estimate the coefficients ($\beta 0$, $\beta 1$, …, βp) that minimize the sum of squared differences between the observed and predicted values of the dependent variable.

3. Results and discussion

3.1. Descriptive statistics

The required sample size for statistical sampling for each point has been selected as 200 in this study. The descriptive statistics of the variables are shown in Table 2. Additionally, the descriptive statistics for control point are shown in Table 3.

3.2. Model

3.2.1. Evaluation of the normality of the variables

The Structural Equation Modeling software (Smart PLS) is used to test the hypotheses and fit the conceptual model of the study. Although, as explained in the previous chapter, the PLS-SEM statistical method does not require data to be normally distributed, this section examines the normal distribution of data for use in subsequent tests.

Based on Table 4, the skewness and kurtosis coefficients for most of the research variables are in the range (−2,2). However, since the results of the Kolmogorov-Smirnov test for some of the research variables are less than 0.05, the assumption of data normality for these variables is not confirmed.

Table 2
Descriptive statistics of the variables in the study.

Variable Name		Count	Minimum Value (km/h)	Maximum Value (km/h)	Mean (km/h)	Standard Deviation
Speed limit sign	Sp3	200	49	126	84.87	15.081
	Sp4	200	46	121	86.02	13.275
Horizontal Curve No.1	Sp5	200	45	105	64.46	12.679
	Sp6	200	42	116	66.72	15.289
Night	Sp7	200	45	128	83.7	18.387
	Sp8	200	44	134	82.72	18.991
Uphill	Sp9	200	43	133	85.93	19.383
	Sp10	200	48	130	81.02	19.314
Downhill	Sp11	200	47	135	84.08	22.923
	Sp12	200	43	130	81.88	22.783
Accessibility	Sp13	200	45	129	88.1	17.211
	Sp14	200	47	129	87.55	19.471
Horizontal Curve No.2	Sp15	200	46	128	85.12	18.887
	Sp16	200	46	135	83.76	17.401
Roundabout	Sp17	200	44	130	61.96	17.759
	Sp18	200	43	121	68.79	20.400
Traffic Signs	Sp19	200	49	131	89.16	16.505
	Sp20	200	45	130	88.27	21.534
Rainy Weather	Sp21	200	47	134	86.97	21.445
	Sp22	200	46	129	83.8	19.946

Table 3
Descriptive statistics for control point.

Variable Name		Count	Minimum Value	Maximum Value	Mean	Standard Deviation
Control Point	Sp1	200	49	131	90.36	18.823
	Sp2	200	52	131	89.67	18.559

Table 4
Normality test results for Variables and Control Point.

Variable Name		Count	Skewness	Kurtosis	Kolmogorov-Smirnov Test Value
Control point	Sp1	200	0.188	−0.463	0.200
	Sp2	200	0.227	−0.567	0.074
Speed limit sign	Sp3	200	−0.074	−0.281	0.200
	Sp4	200	−0.427	−0.267	0.083
Horizontal Curve No.1	Sp5	200	0.866	0.593	0.000
	Sp6	200	1.163	0.962	0.000
Night	Sp7	200	0.379	−0.331	0.014
	Sp8	200	0.491	−0.481	0.000
Uphill	Sp9	200	0.065	−0.514	0.200
	Sp10	200	0.446	−0.586	0.000
Downhill	Sp11	200	0.131	−1.067	0.003
	Sp12	200	0.153	−0.99	0.000
Accessibility	Sp13	200	−0.041	−0.225	0.200
	Sp14	200	0.084	−0.636	0.200
Horizontal Curve No.2	Sp15	200	0.299	−0.361	0.200
	Sp16	200	0.741	0.596	0.000
Roundabout	Sp17	200	1.643	2.654	0.000
	Sp18	200	0.898	−0.330	0.000
Traffic Signs	Sp19	200	0.282	0.223	0.200
	Sp20	200	0.128	−0.748	0.020
Rainy Weather	Sp21	200	−0.094	−0.909	0.064
	Sp22	200	0.182	−0.617	0.200

3.2.2. Investigation of the model fit

- Evaluation of the Measurement Model

Factor loadings are calculated by measuring the correlation of indicators of a factor with that factor. If this value is equal to or greater than 0.4, it indicates that the variance between the factor and its indicators is greater than the measurement error variance of that factor, suggesting that the reliability of that measurement model is acceptable. An important point to note is that if a researcher encounters values less than 0.4 after calculating the factor loadings between a factor and its indicators, they should either modify that indicator or remove it from the research model. In this study, the factor loading coefficients of each indicator related to 11 factors have been examined. As shown in Fig. 4, the factor loadings of the indicators sp5, sp8, sp9, and sp16 were less than 0.4, which were removed from the process. The revised model was then executed in the software, and the results are presented in Fig. 5 and Table 5.

In Table 6, all factor loadings of the revised model exceed 0.4, indicating the suitability of the measurement tool used in this study. This suggests consistent results under similar conditions. Additionally, the Average Variance Extracted (AVE) value for all variables is greater than or equal to 0.5, demonstrating appropriate correlation among the study variables.

Discriminant validity indicates the extent of a factor's relationship with its own indicators in comparison to its relationship with other factors. Acceptable discriminant validity in a model implies that a factor interacts more with its own questions than with other factors. The Fornell and Larcker method suggests a matrix for examining discriminant validity, where the main diagonal of the matrix contains the square root of the AVE values for each of the 11 factors. A model has acceptable discriminant validity if the main diagonal values are greater than the values beneath them, or in other words, if the square root of the AVE for all variables is greater than the correlation values among them. This matrix is presented in Table 7.

As indicated in Table 7, in the areas highlighted with dark color (the main diagonal of the matrix), the square root of AVE for each of the latent variables in this study is greater than their correlation values, which are located in the lower and left cells of the main diagonal. Therefore, it can be stated that the constructs or latent variables in the model interact more with their own indicators than with other constructs. This indicates that the model's discriminant validity is at an appropriate level. It also shows that the data obtained for measuring each of the variables affecting speed do not overlap with each other and are independent.

3.2.3. Evaluation of the structural model

The next step after examining the fit of the measurement models is assessing the fit of the structural model. Unlike the measurement models, the structural model does not deal with observed variables but instead examines the latent factors along with the relationships between them.

- Significant t-values

To assess the fit of the structural model, several criteria are used, the first and most fundamental of which is the significant t-values. If the value of these numbers exceeds 1.96, it indicates the validity of the relationship between the factors and consequently confirms the research hypotheses at a 95% confidence level. Following this, Fig. 6 shows the model of significant coefficients, and.

Table 8 presents the results of the examination of the structural model relationship. Based on Table 8, which shows the relationships for all variables, a significant correlation at the 95% confidence level exists between the Control Point and the variables Roundabout, Uphill, Downhill, Horizontal Curve No.1, and Rainy Weather. This is because the t-value for these relationships is greater than 1.96.

- R Squares or R^2 Criterion

R^2 is a criterion used to connect the measurement section and the structural model section, which relates to the endogenous (dependent) latent factors in the model. R^2 indicates the effect of an exogenous factor on an endogenous factor, and values of 0.19, 0.33, and 0.67 are considered as benchmarks for weak, medium, and strong effects, respectively. The R^2 value for exogenous or independent factors is zero. Figure illustrates that the R^2 value for the Control Point is 0.338, which falls in the medium range and confirms the suitability of the structural model fit based on the benchmark value.

- Q^2 Criterion

The Q^2 value should be calculated for all the dependent factors in the model. This criterion determines the predictive power of the model, and if the Q^2 value for one of the endogenous factors achieves 0.02, 0.15, or 0.35, it respectively indicates a weak, medium, or strong predictive power of the related exogenous factors. The analysis shows that the Q^2 value for the Control Point is 0.26, demonstrating that the exogenous (independent) factors are appropriate in predicting the dependent factors and affirms the suitable fit of the structural model. In fact, this result indicates that the model used in this study has an adequate predictive ability for the factors influencing drivers' speed choices.

3.2.4. Evaluation of the overall model

- GoF Criterion

The GoF (Goodness of Fit) criterion is related to the overall part of

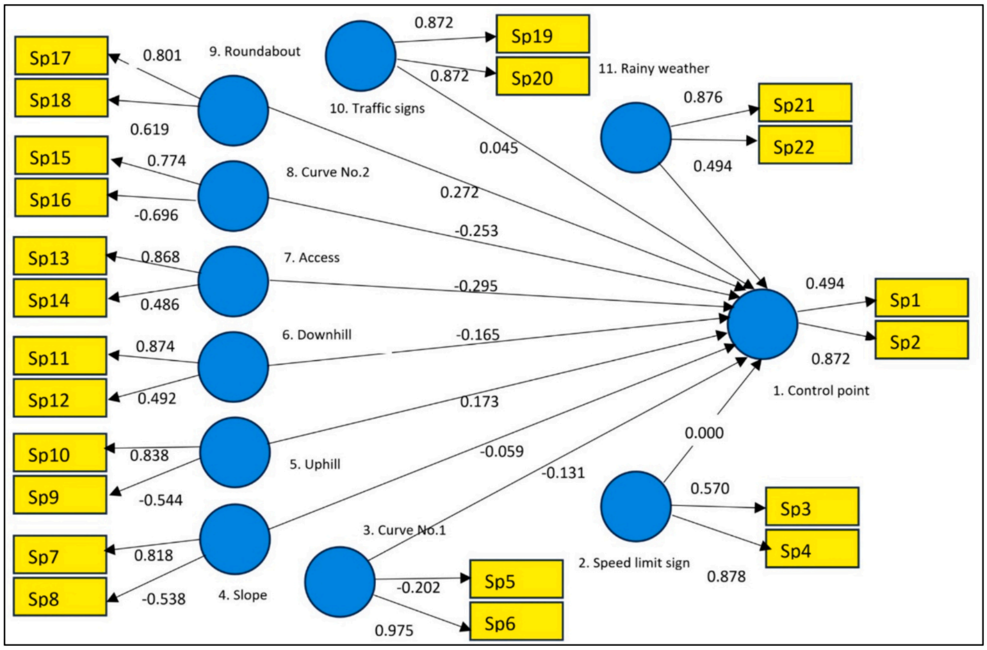


Fig. 4. Standardized coefficients model.

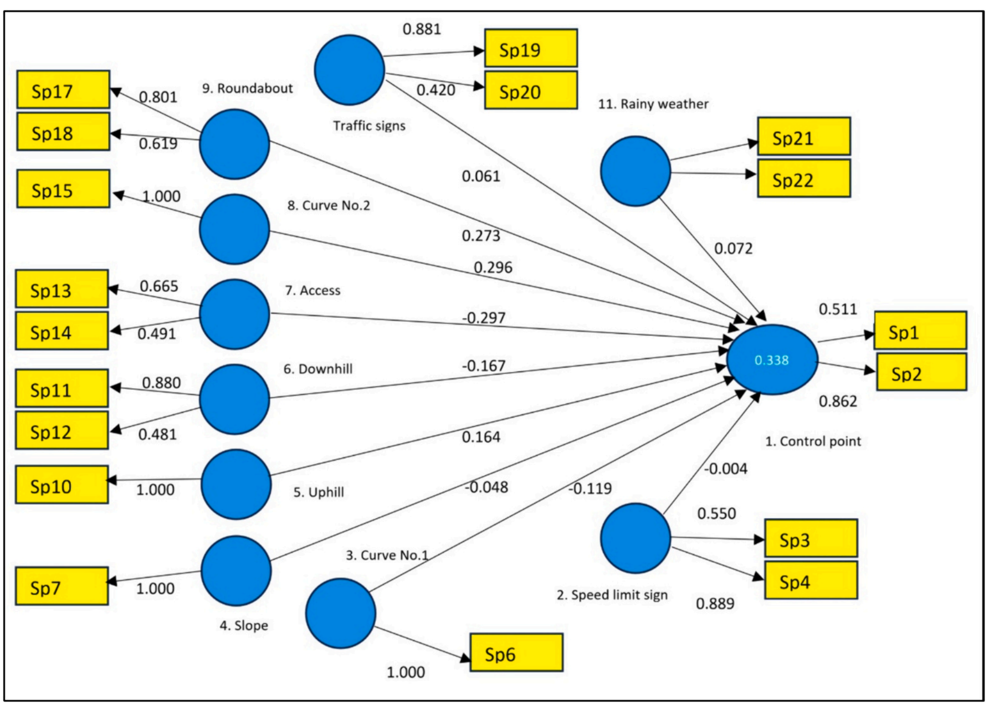


Fig. 5. Standardized coefficients for revised model.

structural models. Achieving a GoF value of 0.505 indicates a suitable fit of the model since the three values of 0.01, 0.25, and 0.36, are introduced as weak, medium, and strong values for GoF, respectively.

3.3. *Effect size measure f^2/ SEM sensitivity analysis*

This metric indicates the intensity of the relationship between the constructs in the model. Values of 0.02, 0.15, and 0.35 respectively indicate a small, medium, and large effect size of one construct on another. This measure reflects sensitivity analysis, which determines how the independent variable will change if we remove the value of one dependent variable from the model in a specific and defined condition, assuming other variables are constant.

$$f^2(x \rightarrow y) = \frac{R^2{}_y(X\ \text{included}) - R^2{}_y(X\ \text{excluded})}{1 - R^2{}_y(X\ \text{included})}$$

- Assumptions of the formula:
  - o $f^2(x \rightarrow y)$: The effect size of x on y.
  - o $R^2{}_y(X\ included)$: The value of R^2 for construct y when construct x is included in the model.

Table 5
Coefficients of factor loadings.

Path Name	Factor Loadings in Initial Model	Factor Loadings in Revised Model
Sp1 → Control Point	0.494	0.511
Sp2 → Control Point	0.872	0.862
Sp3 → Speed limit sign	0.570	0.550
Sp4 → Speed limit sign	0.878	0.889
Sp5 → Horizontal Curve No.1	−0.202	–
Sp6 → Horizontal Curve No.1	0.975	1
Sp7 → Night	0.818	1
Sp8 → Night	−0.538	–
Sp9 → Uphill	−0.544	–
Sp10 → Uphill	0.838	1
Sp11 → Downhill	0.874	0.888
Sp12 → Downhill	0.492	0.481
Sp13 → Accessibility	0.868	0.865
Sp14 → Accessibility	0.486	0.491
Sp15 → Horizontal Curve No.2	0.774	1
Sp16 → Horizontal Curve No.2	−0.698	–
Sp17 → Roundabout	0.801	0.801
Sp18 → Roundabout	0.619	0.619
Sp19 → Traffic signs	0.872	0.881
Sp20 → Traffic signs	0.438	0.420
Sp21 → Rainy weather	0.876	0.875
Sp22 → Rainy weather	0.494	0.497

Table 6
Average Variance Extracted (AVE) value of research variables.

Research Variables	Average Variance Extracted
Control Point	0.5
Speed limit sign	0.54
Horizontal Curve No.1	1
Night	1
Uphill	1
Downhill	0.5
Accessibility	0.5
Horizontal Curve No.2	1
Roundabout	0.51
Traffic Signs	0.5
Rainy Weather	0.51

- o $R^2{}_y(X\ excluded)$: The value of R^2 for construct y when construct x is excluded from the model.

This measure is only calculated for endogenous constructs affected by more than one exogenous variable. Since in this study there is only one endogenous construct named 'Control Point' which is influenced by ten variables (Speed limit sign, Horizontal Curve No.1, Night, Uphill, Downhill, Access, Horizontal Curve No.2, Roundabout, Traffic Signs, and Rainy Weather) the effect size measure f^2 (Speed limit sign→ Control Point), f^2 (Horizontal Curve No.1→ Control Point), f^2 (Night→ Control Point), f^2 (Uphill → Control Point), f^2 (Downhill → Control Point), f^2 (Access → Control Point), f^2 (Horizontal Curve No.2 → Control Point), f^2 (Roundabout → Control Point), f^2 (Traffic Signs → Control Point), and f^2 (Rainy Weather → Control Point) are calculated separately for this construct. The sensitivity analysis results and the impact of the variables on the Control Point shown in Table 9. It can be concluded that the variables Roundabout, Uphill, Downhill, Horizontal Curve No.1, and Rainy Weather had the most significant impact on the Control Point, in that order. Additionally, the variables Access, Night, Horizontal Curve No.2, Traffic Signs, and Speed limit sign were ranked in the subsequent order in terms of impact. The summary of the results obtained from the SEM model used in this study is shown in Table 10.

3.4. Regression model

- Evaluation and analysis of multiple linear regression model

One of the assumptions for using a regression model is the normality of the dependent variable. If test results indicate that the data distribution is not normal, the natural logarithm of the data should be used. Since the sig (significance level) value from the Kolmogorov-Smirnov test results for the dependent variable (control point) is less than 0.05, the assumption of normality of the dependent variable is rejected at the 95% confidence level. Therefore, the natural logarithm of the dependent variable is used for performing the regression. Table 11 presents the results of the normality test for the variable Control Point.

Another assumption for the use of regression is that the errors should have a normal distribution, meaning the error variances are constant and their mean is zero. Comparing the frequency distribution chart of errors with the normal distribution chart indicates that the distribution of errors is approximately normal.

Next assumption for using regression is the independence of errors from one another, or the difference between the actual values and those predicted by the regression modeling. If there is a correlation among errors, the use of regression will not be possible. Durbin-Watson test is used to examine the independence of errors-. If the test statistic falls within the range of 1.5 to 2.5, the assumption of no correlation among errors is accepted. Based on the results, the assumption of no correlation among the errors is accepted since the Durbin-Watson statistic falls within the range of 1.5 to 2.5. The multiple correlation coefficient (R) indicates the degree of correlation between the set of independent

Table 7
Examination of Discriminant Validity of Main Components in the Research.

Variable Name	Speed limit sign	Access	Downhill	Uphill	Night	Traffic Signs	Horizontal Curve No.1	Horizontal Curve No.2	Roundabout	Control Point	Rainy Weather
Speed limit sign	0.735										
Access	0.051	0.707									
Downhill	0.098	0.012	0.707								
Uphill	-0.003	0.103	0.013	1							
Night	-0.106	-0.031	-0.025	0.074	1						
Traffic Signs	0.055	-0.044	-0.016	0.039	-0.112	0.707					
Horizontal Curve No.1	0.079	0.129	0.096	-0.032	0.088	-0.031	1				
Horizontal Curve No.2	-0.028	0.1	0.257	-0.049	0.131	-0.132	0.071	1			
Roundabout	-0.033	0.01	-0.014	0.061	-0.067	0.042	0.025	-0.043	0.714		
Control Point	-0.038	-0.101	-0.198	0.167	-0.065	0.125	-0.148	-0.094	0.029	0.707	
Rainy Weather	-0.027	0.051	-0.107	-0.042	-0.038	0.085	0.075	-0.027	0.052	0.09	0.714

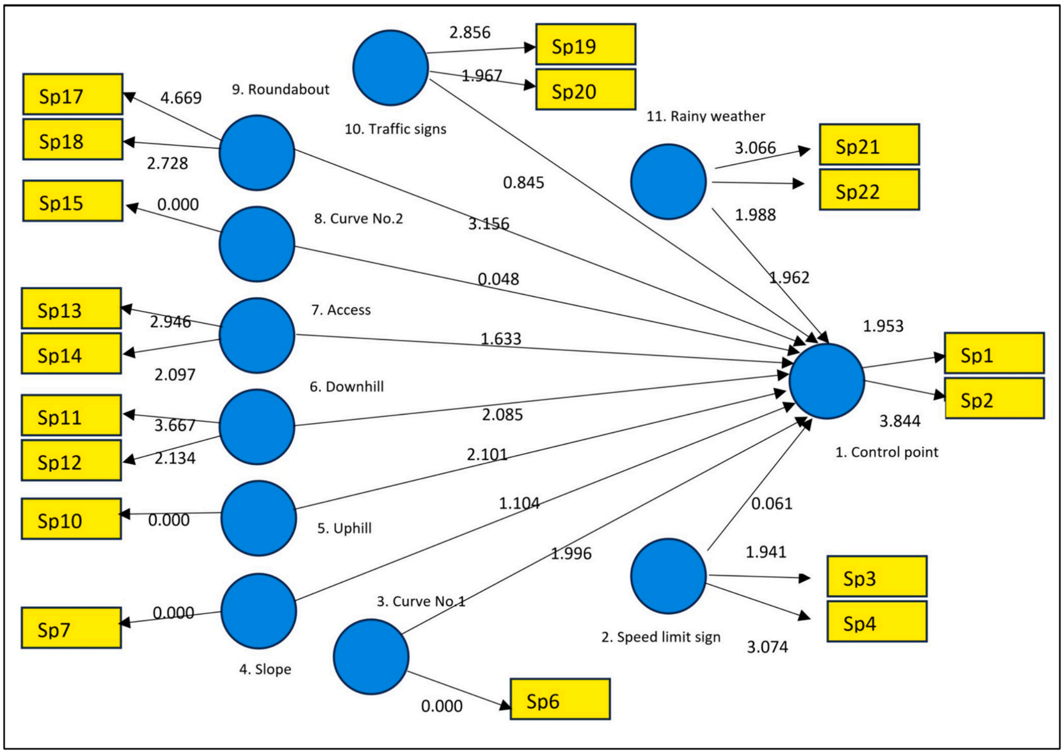


Fig. 6. Structural model of significant coefficients.

Table 8
Examination of internal relationships in the structural model.

Examination of Relationships in the Structural Model	T-Value
Speed limit sign → Control Point	0.081
Horizontal Curve No.1 → Control Point	1.986
Night → Control Point	1.104
Uphill → Control Point	2.101
Downhill → Control Point	2.085
Access → Control Point	1.633
Horizontal Curve No.2 → Control Point	0.048
Roundabout → Control Point	3.156
Traffic Signs → Control Point	0.845
Rainy Weather → Control Point	1.962

Table 9
Impact of the Studied Variables.

Impact Rank	Variable	Impact on Control Point
1	Roundabout	0.34
2	Uphill	0.27
3	Downhill	0.26
4	Horizontal Curve No.1	0.25
5	Rainy Weather	0.23
6	Accessibility	0.15
7	Night	0.12
8	Horizontal Curve No.2	0.09
9	Traffic Signs	0.08
10	Speed limit sign	0.07

variables and the dependent variable, and it fluctuates between 0 and 1. The closer this coefficient is to 1, the stronger the correlation between the independent variables and the dependent variable. The value of 0.808 suggests a strong correlation.

Regression analysis of variance is used to examine the existence of a linear relationship between independent variables and the dependent variable. Table 12 illustrates the results of the analysis of variance. The null hypothesis is rejected since the sig is less than 5%. This indicates that at least one of the independent variables has a linear relationship with the dependent variable. The results of the initial regression model using SPSS software are presented in Table 13, where all variables were examined.

As shown in Table 13, variables Access, Traffic Signs, Night, Speed limit sign, and Horizontal Curve No. 2 have a significance level of greater than 0.05, and were removed from the model because of having minimal impact on the dependent variable (Control Point). The modeling process then continued with the remaining independent variables, and the results are presented in Table 14.

The constant value and coefficients of the independent variables in the regression equation are specified in this table. The coefficients include two types: unstandardized coefficients (B) and standardized coefficients (β). In unstandardized coefficients, the scales of the variables are not equal, whereas in standardized coefficients, the scales of the variables are equal, allowing for comparison of variables. Therefore, for comparing the impact of several independent variables on a dependent variable, the column of standardized coefficients is used regardless of their sign.

Table 14 highlights that the significance levels of the regression coefficients for the variables 'Downhill', 'Rainy Weather', 'Horizontal Curve No.1', 'Uphill', and 'Roundabout' are less than 0.05. Therefore, these variables are statistically significant at the 95% confidence level. Finally, the regression relationship of the obtained model is defined as follows:

$$y = 0.781 + 0.202x_1 + 0.092x_2 + 0.134x_3 - 0.271x_4 + 0.314x_5$$

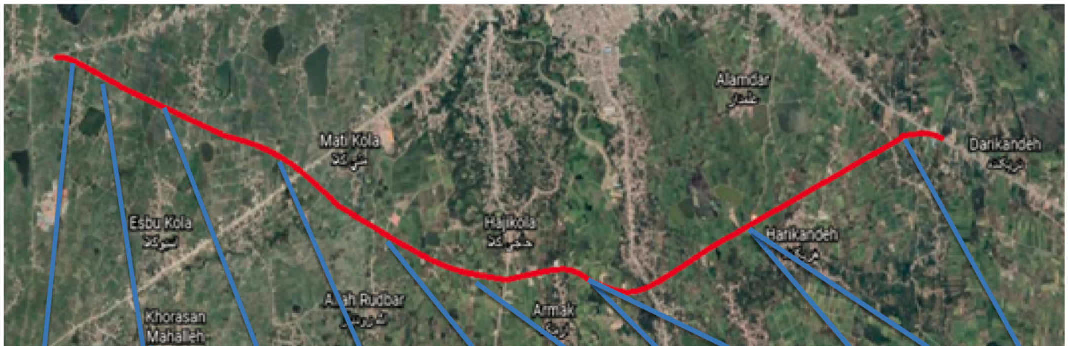
Where y is the Control Point.

The column of standardized coefficients (β) indicates that the variables 'Roundabout', 'Uphill', 'Downhill', 'Horizontal Curve No.1', and 'Rainy Weather' have the most significant impact on the Control Point, in that order.

Another assumption of regression analysis is that the independent variables should not be correlated or have multicollinearity, which is assessed using collinearity tests. Multicollinearity indicates that an independent variable is a linear function of other independent variables.

Table 10
Summary of SEM model results.

Study route



Variable Name	Horizontal Curve No.1	Speed limit sign	Control Point	Horizontal Curve No.2	Roundabout	Access	Uphill	Downhill	Rainy Weather	Night	Traffic Signs
Initial model	Sp5	Sp3	Sp1	Sp15	Sp17	Sp13	Sp9	Sp11	Sp21	Sp7	Sp19
	Sp6	Sp4	Sp2	Sp16	Sp18	Sp14	SP10	SP12	SP22	SP8	SP20
Final model (Revised)	Sp6	Sp3	Sp1	Sp15	Sp17	Sp13	Sp10	Sp11	Sp21	Sp7	Sp19
		Sp4	Sp2		Sp18	Sp14		Sp12	Sp22		Sp20
Impact ranking	4	10	_	8	1	6	2	3	5	7	9

Speed profile change

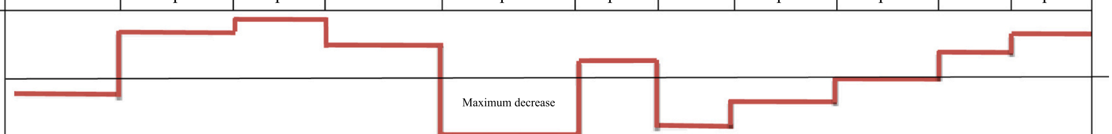


Table 11
Normality test results for control point.

Variable Name	Kolmogorov-Smirnov Test Value
Control Point	0.000

Table 12
Results of analysis of variance.

Model	Sum of squares	Degrees of freedom	Mean squares	F statistic	Significance level
Regression	21.398	5	1.150	17.163	0.000
Residual	10.750	394	0.067		
Total	32.148	399			

High multicollinearity in a regression equation implies a high correlation among independent variables, which mean that despite a high R^2, the model is not reliable, or the independent variables is not significant. According to studies, there would be no multicollinearity among the independent variables if the Tolerance values are greater than 0.1 and the Variance Inflation Factor (VIF) values are less than 5. The Tolerance values are greater than 0.1 and the VIF values are less than 5, indicating that there is no multicollinearity among the independent variables, and the assumption of their independence is accepted.

3.5. Discussion on the model results and comparison with previous studies

Using structural equation modeling and data from infrared speed sensors, we identified several influential roadway and contextual elements affecting speed selection. Notably, the presence of roundabouts with entry deflection angles of 20–30 degrees and circulatory roadway widths of 5–6 m, uphill grades of 5% or more, downhill grades of 3% or

Table 13
Results of the initial multiple linear regression model.

Variable	Unstandardized Coefficients (B)	Standardized Coefficients (β)	t-statistic	Significance Level	Collinearity Test	
					Tolerance	Variance Inflation Factor
Constant	0.734	_	3.598	0.000	_	_
Downhill	0.202	0.119	2.424	0.016	0.871	1.148
Accessibility	0.091	0.077	1.668	0.096	0.988	1.012
Rainy Weather	0.182	0.109	2.188	0.029	0.838	1.193
Traffic Signs	0.007	0.023	0.487	0.627	0.930	1.076
Horizontal Curve No.1	0.109	0.118	2.479	0.014	0.920	1.087
Night	0.071	0.036	0.780	0.436	0.972	1.029
Uphill	−0.302	−0.169	−3.545	0.000	0.924	1.082
Roundabout	0.343	0.18	3.681	0.000	0.875	1.143
Speed limit sign	0.004	0.011	0.249	0.803	0.992	1.008
Horizontal Curve No.2	0.024	−0.023	−0.497	0.619	0.992	1.008

Table 14
Results of the Final Multiple Linear Regression Model.

Variable	Variable Marker	Unstandardized Coefficients (B)	Standardized Coefficients (β)	t Statistic	Significance Level	Collinearity Test	
						Tolerance	Variance Inflation Factor
Constant	constant	0.781		3.199	0.000		
Downhill	x_1	0.202	0.125	2.571	0.010	0.884	1.131
Rainy Weather	x_2	0.092	0.119	2.413	0.016	0.858	1.165
Horizontal Curve No.1	x_3	0.134	0.120	2.522	0.012	0.923	1.083
Uphill	x_4	−0.271	−0.169	−3.572	0.000	0.932	1.073
Roundabout	x_5	0.314	0.180	3.737	0.000	0.894	1.118

steeper, horizontal curves with radii between 100 and 200 m, and rainy weather conditions significantly influenced drivers' chosen speeds. These results emphasize the critical role of specific roadway geometries and contextual factors in shaping driver behavior and their impact on road safety.

The impact of roundabouts on speed selection was particularly noteworthy. Our findings indicate that roundabouts with entry deflection angles of 20–30 degrees were most effective in reducing approach speeds. This aligns with the principle that greater deflection angles force drivers to reduce speed more significantly. Additionally, circulatory roadway widths of 5–6 m appeared to strike an optimal balance between maneuverability and speed control. These specific design parameters provide valuable guidance for traffic engineers and urban planners in designing roundabouts that effectively moderate vehicle speeds.

Regarding road gradients, our study found that uphill grades of 5% or more led to significant speed reductions, likely due to the increased power demand on vehicles. Conversely, downhill grades of 3% or steeper were associated with higher speeds, suggesting a need for additional speed control measures on such descents. These findings underscore the importance of considering vertical alignment in road design and its impact on driver behavior.

Horizontal curves with radii between 100 and 200 m emerged as a critical factor in speed selection. This range appears to represent a threshold where drivers perceive the need to reduce speed significantly. Curves with larger radii may not prompt the same level of speed reduction, while tighter curves might be associated with more extreme speed adjustments or potential safety risks.

Comparing these findings with prior studies, Lee et al. (2008) and Ghasemzadeh et al. (2018) also highlighted the substantial effect of weather conditions on drivers' speed choices, corroborating the current study's observations regarding rainy weather. Our results indicated a notable speed reduction during rainy conditions, emphasizing the need for weather-responsive traffic management strategies.

Additionally, Tola and Gebissa (2019) and Vos et al. (2021) emphasized the importance of road alignment and curve characteristics, aligning with the present research's focus on specific horizontal curve radii as a notable factor influencing driver speed selection. Our findings provide quantitative support for these earlier studies, offering precise radius ranges that significantly impact speed choice.

In contrast, the present study highlights that factors like access points and nighttime conditions exert relatively less influence on drivers' speed selection. This aligns with the analysis results by Goralzik et al. (2017), which demonstrated that under specific speed limits and road geometry changes, drivers' average speed remained largely unaffected. These consistent findings across varied research contexts provide valuable support for the stability of influential factors.

The integration of psychological factors in speed selection, as explored by Sadia et al. (2018) and Javid et al. (2022), complements our findings on roadway and contextual factors. While our study focused primarily on physical and environmental elements, it's important to recognize that speed choice is also influenced by driver attitudes, risk perception, and other psychological variables (Sheykhfard et al. (2022); Sheykhfard et al. (2023)) [44,45]. Future research could benefit from integrating these psychological factors with the specific roadway geometries identified in our study to provide a more comprehensive understanding of speed selection behavior.

Furthermore, the incorporation of diverse geographical settings and traffic conditions in reviewed studies enriches our comprehension of the broad spectrum of influences on driver speed selection. From the impact of road geometry and surface quality, as illuminated by Anastasopoulos and Mannering (2016), to the influence of adverse weather conditions on driver behavior, as elucidated by Ghasemzadeh et al. (2018), the amalgamated findings contribute to a comprehensive understanding of the dynamic factors shaping driver speed decisions.

The integration of advanced methods, such as virtual simulation employed by Xu et al. (2022) and trajectory-level data analysis conducted by Nasim Khan et al. (2020), offers valuable insights into the association between driver behavior and roadway and contextual factors. These methodological strides align with our study's use of structural equation modeling and infrared speed sensors to comprehensively understand the roadway and contextual influences on driver speed selection. Future research could potentially combine these approaches, using virtual simulations to test the impact of specific roadway geometries identified in our study under controlled conditions.

4. Summary and conclusion

The analysis revealed that roundabouts with specific design features (entry deflection angles of 20–30 degrees and circulatory roadway widths of 5–6 m), uphill grades of 5% or more, downhill grades of 3% or steeper, horizontal curves with radii between 100 and 200 m, and rainy weather conditions emerged as the most prominent influencers on drivers' speed selection. Conversely, variables such as access points, nighttime conditions, and certain road geometries demonstrated comparatively lower impact on drivers' chosen speeds.

These findings provide concrete, actionable insights for road design and traffic management. For instance, the identified optimal roundabout parameters can guide the design of new roundabouts or the modification of existing ones to enhance their effectiveness in speed reduction. Similarly, the specified grade percentages for uphill and downhill sections can inform decisions about where to implement additional speed control measures or warning signs.

The robustness of the measurement model and the overall model used in the research was confirmed, affirming the meticulousness of the study's methodology and data analysis. This statistical validation lends credence to the reliability and generalizability of our findings within similar contexts.

The influential roadway and contextual factors identified in this study have significant practical implications for transportation infrastructure planning and road safety interventions. By incorporating these specific insights into road design and planning, more effective measures can be developed to manage and regulate drivers' speeds, ultimately enhancing road safety and reducing accident rates. For example, designing roundabouts with the identified optimal entry deflection angles and circulatory roadway widths can effectively reduce approach speeds. Similarly, careful consideration of road gradients and horizontal curve radii can help modulate driver speed choices in specific roadway conditions.

Looking ahead, future research could explore additional roadway and contextual factors that influence drivers' speed selection, including more detailed aspects of road surface conditions (e.g., texture depth, skid resistance), specific types of roadside vegetation and their impact on perceived lane width, and the influence of various intersection configurations beyond roundabouts. Expanding the investigation to encompass a broader geographical area or diverse regional settings would provide valuable insights into the variability of roadway and contextual influences on driver behavior across different cultural and environmental contexts.

Furthermore, integrating real-time data and advancements in sensor technology could enable dynamic monitoring and analysis of drivers' speed behaviors in response to roadway and contextual stimuli. This could lead to the development of adaptive traffic management systems that respond to changing conditions in real-time. Exploring the integration of advanced driver-assistance systems (ADAS) and intelligent transportation systems (ITS) to modulate driver behavior based on roadway and contextual factors also holds promise for future research. For instance, vehicle-to-infrastructure (V2I) communication could potentially use the specific roadway geometry data identified in our study to provide targeted speed recommendations to drivers.

Our study examined the relationship between specific roadway geometries, contextual factors, and driver speed selection, shedding light on their significance. Nonetheless, we recognize the complexity and multifaceted nature of this relationship. Moving forward, future research should strive to capture this complexity more comprehensively by considering a broader range of conditions and incorporating both moderating and mediating factors. Expanding the variable set to include elements like traffic density, vehicle types, and driver demographics, examining moderating factors such as driver experience and route familiarity, and exploring mediating psychological factors like risk perception and cognitive load are key steps to enhancing our understanding. Employing controlled study designs, conducting longitudinal research, utilizing advanced statistical techniques, and adopting an interdisciplinary approach can further enrich our insights into the relationship between road attributes and speed choice, facilitating more effective road design and safety interventions. While our study offers valuable insights, it's important to acknowledge inherent limitations. The findings are specific to a particular geographical context, cautioning against broad generalizations to diverse settings. The transferability of optimal roundabout designs or curve radii may vary in different cultural or environmental contexts. Moreover, focusing solely on specific roadway and contextual factors may overlook the synergistic effects of multiple influencers and their dynamic interactions on driver speed choices. This limitation underscores the necessity for holistic studies that consider the interconnectedness of various factors in shaping driver behavior. Additionally, exploring potential confounding variables and external influences not accounted for in the study is vital to bolstering the robustness and practicality of the findings. Factors like traffic density, vehicle type distribution, and law enforcement presence merit further investigation to develop a more comprehensive model of speed selection behavior. Incorporating these variables in future studies will yield a more nuanced understanding of driver behavior and contribute to more effective road safety measures.

In conclusion, this study provides specific, quantitative insights into the roadway geometries and contextual factors that significantly influence driver speed selection. By considering these practical implications, potential for implementation, avenues for future research, and acknowledging study limitations, the study's impact and contributions can be contextualized within the broader landscape of transportation research and road safety initiatives. The findings offer a solid foundation for evidence-based road design and traffic management strategies, potentially leading to safer and more efficient transportation systems.

CRediT authorship contribution statement

Abbas Sheykhfard: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Writing – original draft. **Farshidreza Haghighi:** Conceptualization, Methodology, Project administration, Supervision, Validation, Writing – review & editing. **Soheila Saeidi:** Formal analysis, Methodology, Writing – original draft. **Mohammad SafariTaherkhani:** Formal analysis, Writing – original draft. **Subasish Das:** Methodology, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] D. Shinar, Traffic Safety and Human Behavior, Emerald Publishing Limited, 2017.
[2] E. O'Connor, Guidelines on Traffic Calming for Town and Villages on National Routes, Government of Ireland, 1999.
[3] W.H.O, W.H.O. Global status report on road safety 2018, 2018, 12/19/2023]; Available from: https://www.who.int/publications/i/item/9789241565684.
[4] N. Stamatiadis, K. Bailey, T. Grossardt, J. Ripy, A. Strombotne, Evaluation of highway design parameters on influencing operator speeds through casewise visual evaluation, Transp. Res. Rec. 2472 (1) (2018) 1–8.
[5] S.C. Himes, E.T. Donnell, Speed prediction models for multilane highways: simultaneous equations approach, J. Transp. Eng. 136 (10) (2010) 855–862.
[6] J.-Y. Lee, J.-H. Chung, B. Son, Analysis of traffic crash size for Korean highway using structural equation models, Crash Anal. Prevent. 40 (6) (2008) 1955–1963.
[7] K. Fitzpatrick, P. Carlson, M. Brewer, M. Wooldridge, S.P. Miaou, Design factors that affect driver speed on suburban streets, Transp. Res. Rec. 1751 (1) (2000) 18–25.
[8] C.F. Ng, K.A. Small, Tradeoffs among free-flow speed, capacity, cost, and environmental footprint in highway design, Transportation 39 (6) (2012) 1259–1280.
[9] S.H. Hamdar, L. Qin, A. Talebpour, Weather and road geometry impact on longitudinal driving behavior: exploratory analysis using an empirically supported acceleration modeling framework, Transp. Res. Part C: Emerg. Technol. 67 (2016) 193–213.
[10] J. Xu, H. Li, X. Zhang, F. Ma, Z. Sun, The influence of freeway curve characteristics on drivers' speed perception accuracy, PLoS One 17 (5) (2022) e0267250.
[11] J. Vos, H. Farah, M. Hagenzieker, How do Dutch drivers perceive horizontal curves on freeway interchanges and which cues influence their speed choice? IATSS Res. 45 (2) (2021) 258–266.
[12] L.I. Griffin III, R.N. Reinhardt, A review of two innovative pavement marking patterns that have been developed to reduce traffic speeds and crashes, 1995.
[13] A.M. Tola, A. Gebissa, Assessment on the impacts of road geometry and route selection on road safety: a case of Mettu-Gore road, Ethiopia, Am. J. Civ. Eng. Architect. 7 (1) (2019) 13–19.
[14] H. Rakha, M. Farzaneh, M. Arafeh, E. Sterzin, Inclement weather impacts on freeway traffic stream behavior, Transp. Res. Rec. 2071 (1) (2007) 8–18.
[15] A. Ghasemzadeh, B.E. Hammit, M.M. Ahmed, R.K. Young, Parametric ordinal logistic regression and non-parametric decision tree approaches for assessing the impact of weather conditions on driver speed selection using naturalistic driving data, Transp. Res. Rec. 2672 (12) (2018) 137–147.
[16] M. Nasim Khan, A. Das, M.M. Ahmed, Non-parametric association rules mining and parametric ordinal logistic regression for an in-depth investigation of driver speed selection behavior in adverse weather using SHRP2 naturalistic driving study data, Transp. Res. Rec. 2674 (11) (2020) 101–119.
[17] Y.M. Lee, S.Y. Chong, K. Goonting, E. Sheppard, The effect of speed limit credibility on drivers' speed choice, Transport. Res. F: Traffic Psychol. Behav. 45 (2017) 43–53.
[18] A.K. Jägerbrand, J. Sjöbergh, Effects of weather conditions, light conditions, and road lighting on vehicle speed, SpringerPlus 5 (1) (2016) 505.
[19] A.J. Anarkooli, M.H. Hosseinlou, Analysis of the injury severity of crashes by considering different lighting conditions on two-lane rural roads, J. Saf. Res. 56 (2016) 57–65.
[20] K.M. Kockelman, Changes in flow-density relationship due to environmental, vehicle, and driver characteristics, Transp. Res. Rec. 1644 (1) (1998) 47–56.
[21] M.-I.M. Imprialou, M. Quddus, D.E. Pitfield, D. Lord, Re-visiting crash–speed relationships: a new perspective in crash modelling, Crash Anal. Prevent. 86 (2016) 173–185.
[22] C. Goldenbeld, I. van Schagen, The credibility of speed limits on 80 km/h rural roads: the effects of road and person(ality) characteristics, Accid. Anal. Prev. 39 (6) (2007) 1121–1130.
[23] R. Hamzeie, P.T. Savolainen, T.J. Gates, Driver speed selection and crash risk: insights from the naturalistic driving study, J. Saf. Res. 63 (2017) 187–194.
[24] P.C. Anastasopoulos, F.L. Mannering, The effect of speed limits on drivers' choice of speed: a random parameters seemingly unrelated equations approach, Analytic Methods Crash Res. 10 (2016) 1–11.

[25] A. Goralzik, M. Vollrath, The effects of road, driver, and passenger presence on drivers' choice of speed: a driving simulator study, Transp. Res. Procedia 25 (2017) 2061–2075.
[26] C. Wilson, C. Willis, J.K. Hendrikz, R. Le Brocque, N. Bellamy, Speed cameras for the prevention of road traffic injuries and deaths, Cochrane Database Syst. Rev. 11 (2010).
[27] S.A. Gargoum, K. El-Basyouny, Exploring the association between speed and safety: a path analysis approach, Accid. Anal. Prev. 93 (2016) 32–40.
[28] K. Kim, P. Pant, E. Yamashita, Measuring influence of accessibility on crash severity with structural equation modeling, Transp. Res. Rec. 2236 (1) (2011) 1–10.
[29] S. Oltedal, T. Rundmo, The effects of personality and gender on risky driving behaviour and accident involvement, Saf. Sci. 44 (7) (2006) 621–628.
[30] J. Liu, J. Cai, S. Lin, J. Zhao, Analysis of factors affecting a driver's driving speed selection in low illumination, J. Adv. Transp. 2020 (2020) 1–8.
[31] R. Sadia, S. Bekhor, A. Polus, Structural equations modelling of drivers' speed selection using environmental, driver, and risk factors, Crash Anal. Prevent. 116 (2018) 21–29.
[32] E. Peer, The time-saving bias, speed choices and driving behavior, Transport. Res. F: Traffic Psychol. Behav. 14 (6) (2011) 543–554.
[33] M.S. Horswill, M.E. Coster, The effect of vehicle characteristics on drivers' risk-taking behaviour, Ergonomics 45 (2) (2002) 85–104.
[34] M.A. Javid, N. Ali, M. Abdullah, S.A.H. Shah, Integrating the norm activation model (NAM) theory in explaining factors affecting drivers' speeding behaviour in Lahore, KSCE J. Civ. Eng. 25 (7) (2021) 2701–2712.
[35] M.A. Javid, N. Ali, S.A.H. Shah, M. Abdullah, Structural equation modeling of drivers' speeding behavior in Lahore: importance of attitudes, personality traits, behavioral control, and traffic awareness, Iran. J. Sci. Technol. Trans. Civ. Eng. 46 (2) (2022) 1607–1619.
[36] M. Zolali, B. Mirbaha, M. Layegh, H.R. Behnood, A behavioral model of drivers' mean speed influenced by weather conditions, road geometry, and driver characteristics using a driving simulator study, Adv. Civ. Eng. 2021 (2021) 1–18.
[37] H.M. Hassan, M.A. Abdel-Aty, Analysis of drivers' behavior under reduced visibility conditions using a structural equation modeling approach, Transport. Res. F: Traffic Psychol. Behav. 14 (6) (2011) 614–625.
[38] M.A. Abdel-Aty, A.E. Radwan, Modeling traffic crash occurrence and involvement, Crash Anal. Prevent. 32 (5) (2000) 633–642.
[39] M.A. Hadi, J. Aruldhas, L.-F. Chow, J.A. Wattleworth, Estimating safety effects of cross-section design for various highway types using negative binomial regression, Transp. Res. Rec. 1500 (1995) 169.
[40] R. Van Der Horst, S. De Ridder, Influence of roadside infrastructure on driving behavior: driving simulator study, Transp. Res. Rec. 2018 (1) (2007) 36–44.
[41] B. Wilmots, E. Hermans, T. Brijs, G. Wets, Speed control with and without advanced warning sign on the field: an analysis of the effect on driving speed, Saf. Sci. 85 (2016) 23–32.
[42] R. Bandyopadhyaya, S. Mitra, Modelling severity level in multi-vehicle collision on indian highways, Procedia Soc. Behav. Sci. 104 (2013) 1011–1019.
[43] A.K. Celik, E. Oktay, A multinomial logit analysis of risk factors influencing road traffic injury severities in the Erzurum and Kars provinces of Turkey, Crash Anal. Prevent. 72 (2014) 66–77.
[44] A. Sheykhfard, X. Qin, K. Shaaban, S. Koppel, An Exploration of the Role of Driving Experience on Self-Reported and Real-World Aberrant Driving Behaviors, Accident Analysis & Prevention 178 (2022) 106873, https://doi.org/10.1016/j.aap.2022.106873.
[45] A. Sheykhfard, F. Haghighi, G. Fountas, S. Das, A. Khanpour, How Do Driving Behavior and Attitudes toward Road Safety Vary between Developed and Developing Countries? Evidence from Iran and the Netherlands, Journal of Safety Research 85 (2023) 210–221, https://doi.org/10.1016/j.jsr.2023.02.005.