Research Article

TRR
JOURNAL OF THE TRANSPORTATION RESEARCH BOARD

Transportation Research Record
1–17

DOI: 10.1177/03611981241287787
journals.sagepub.com/home/trr
Sage

Behavioral Modeling of Drivers near Speed Control Cameras: A Dual Perspective from Micro and Macro Data

Abbas Sheykhfard[1], Farshidreza Haghighi[1], Soheila Saeidi[2], Mohammad SafariTaherkhani[3], Grigorios Fountas[4], and Subasish Das[5]

Abstract

The present study investigates the efficacy of speed cameras in managing vehicle speeds and their influence on various driver demographics within the operational context of the cameras. The research, conducted as a case study in Iran, comprises both macroscopic and detailed analyses, quantifying vehicle speeds at different spatial points relative to the speed camera location—upstream, adjacent to, and downstream of the camera—using a manual laser speedometer. Furthermore, the study examines diverse driver behavior metrics, including vehicle type, speeds at different locations, lane changes, braking actions, and measures such as obscuring license plates. Statistical analyses show that speed cameras effectively reduce speeds across different user groups and lead to increased braking and lane-changing behaviors, particularly among light vehicle categories. Moreover, the study reveals distinct behavioral patterns between indigenous and non-indigenous drivers. In addition, a multi-layer perceptron neural network model successfully approximates user speed selection behaviors within the operational range of speed cameras. Overall, this research provides valuable insights into the effectiveness of speed cameras and their impact on diverse driver demographics, contributing to a deeper understanding of advanced speed control mechanisms.

Keywords

operations, pedestrians, bicycles, human factors, human factors of vehicles, safety, traffic law enforcement

The emergence of intelligent speed control tools, particularly speed-sensing cameras, has been recognized as an effective strategy for managing drivers' speeds and enhancing traffic safety (*1*, *2*). As global road safety concerns escalate, understanding the advancements in intelligent transportation systems becomes crucial. According to the World Health Organization, without decisive action, road traffic fatalities in developing countries are projected to increase substantially by 2030 (*3*). This alarming forecast underscores the need for transparent planning and effective use of intelligent speed control tools to achieve sustainable reductions in fatal accidents (*4*).

In the pursuit of enhancing traffic safety, the role of speeding fines and the implementation of automatic speed control systems, such as speed cameras, is particularly significant (*5*, *6*). Although these systems have shown promise in supplementing conventional speed monitoring by police, further research is needed to comprehensively understand their influence on driver behavior and their effectiveness in reducing accidents.

This study aims to address this knowledge gap by evaluating the effects of speed control cameras on various

[1]Department of Civil Engineering, Babol Noshirvani University of Technology, Babol, Iran
[2]Department of Civil, Environmental and Geomatics Engineering, Florida Atlantic University, Boca Raton, FL
[3]Department of Civil and Environmental Engineering, University of Maryland, College Park, MD
[4]School of Rural and Surveying Engineering, Aristotle University of Thessaloniki, Thessaloniki, Greece
[5]Ingram School of Engineering, Texas State University, San Marcos, TX

Corresponding Author:
Abbas Sheykhfard, A.Sheykhfard@nit.ac.ir

types of vehicles and establishing behavioral models for drivers when encountering these cameras. Our selected research site, the Amol-Mahmoudabad road in Iran, provides an ideal setting for assessing the impact of speed control cameras in a real-world context. By employing both macroscopic and microscopic approaches, we aim to capture a comprehensive understanding of the interactions between speed control cameras and driver behavior.

Our research methodology involves measurements of vehicle speeds both before and after the speed control cameras, alongside detailed analysis of driver behavior. This dual perspective, combining macro and micro data, contributes significantly to the development of guidelines for enhancing traffic safety. It provides a nuanced understanding of how drivers respond to speed control measures, offering valuable insights for traffic engineers and policymakers alike.

Research Gap and Objectives

This study aims to bridge the gap between theoretical understanding and real-world applications in traffic safety by investigating the influence of speed control cameras on driver behavior. Our research employs a unique dual data approach, combining macroscopic and microscopic analyses to provide a comprehensive view of how speed cameras affect both overall traffic patterns and individual driver behaviors.

Our primary objectives are to:

- Analyze the influence of speed control cameras on driver behavior, including speed reduction patterns, lane change frequencies, and braking behaviors.
- Develop sophisticated behavioral models using neural networks to predict driver responses to speed control cameras under various conditions.
- Provide actionable recommendations for optimizing the placement and implementation of speed control measures to maximize their effectiveness in reducing accidents.

At the macroscopic level, we examine overall traffic flow patterns and speed distributions before and after the implementation of speed control cameras. This provides a broad understanding of the cameras' impact on traffic dynamics. Complementing this, our microscopic analysis focuses on individual driver behaviors, including speed adjustments, lane changes, and braking patterns in proximity to the cameras. This granular approach allows us to capture nuanced driver responses that may not be apparent in aggregate data.

The integration of these two levels of analysis offers a comprehensive view of how speed control cameras influence traffic patterns and driver behaviors. This dual approach enables us to identify potential discrepancies between macroscopic effects and individual responses, providing a more complete picture of the cameras' impact.

To further enhance our analysis, we employ neural networks to model driver behavior based on our collected data. This advanced analytical technique allows us to identify complex patterns in driver responses that may not be evident through traditional statistical methods. This also enables us to develop predictive models that can anticipate driver behavior under various conditions, potentially informing more effective camera placement strategies. The neural network approach can account for multiple variables simultaneously, capturing the intricate interplay of factors influencing driver behavior around speed cameras.

For traffic engineers, our findings offer empirical data to inform the strategic placement of speed control cameras and design of road safety interventions. The behavioral models developed through this research can aid in predicting driver responses to different camera placements and configurations, allowing for more effective system designs. Policymakers can utilize our results to develop evidence-based strategies for reducing road accidents and creating safer road environments. The insights gained from this study can inform decisions on the allocation of resources for traffic safety measures and the development of targeted public awareness campaigns. In the academic realm, our methodology sets a new standard for comprehensive analysis of speed control measures, potentially inspiring similar dual-approach studies in other contexts.

The insights gained from this research can contribute to the design of safer road environments, potentially reducing accidents and saving lives. By offering a comprehensive analysis of driver behavior in response to speed cameras, we contribute to the broader goal of creating safer road environments and reducing traffic-related fatalities and injuries. In conclusion, this research aims to advance our understanding of traffic safety dynamics and provide valuable guidance for enhancing road safety measures through intelligent speed control systems. The subsequent sections of this paper will detail our research methodology, present our data analysis techniques, and discuss our findings, exploring the implications of our results for traffic safety theories and providing practical applications for improving road safety through the optimal use of speed control cameras.

Research Background

The existing literature on speed control measures can be organized into three primary themes: the effectiveness of speed cameras, driver behavior near cameras, and current limitations in research.

Effectiveness of Speed Cameras

Studies consistently show the positive impact of speed cameras on road safety. Job et al. (*7*) reported significant reductions in both injury accidents (16%) and fatal accidents (39%) following speed camera implementation. Similarly, Martínez-Ruíz et al. (*8*) observed reductions in total accidents, injury-related incidents, and fatalities in areas with installed speed cameras. Li et al. (*2*) found that multiple speed cameras within a specific radius were particularly effective in reducing absolute road accidents. These findings are further supported by Blais and Carnis (*9*), who confirmed the effectiveness of France's Automatic Speed Enforcement Program in reducing fatalities across various road user types.

Driver Behavior Near Cameras

Research indicates that speed cameras significantly influence driver behavior. Tavolinejad et al. (*10*) noted a marked reduction in average speed near speed control cameras, particularly in taxi services. Lee and Sheppard (*11*) observed that drivers adopted lower speeds in the presence of camera signs and visible speed limit signs. Vadeby and Forsman (*12*) showed substantial reductions in both average speed and the percentage of drivers exceeding speed limits following the installation of speed cameras.

Existing Limitations and Areas for Further Research

Despite the evident benefits of speed cameras, several areas require further investigation. Lee et al. (*11*) highlighted the need for careful consideration in selecting speed camera sites, particularly in sensitive areas such as schools and residential neighborhoods. Freeman et al. (*13*) identified the impact of gender on driver behaviors and speed indicators as an area requiring more research. In addition, Luoma et al. (*14*) pointed out the need to evaluate the effects of reducing the threshold of automatic speed enforcement systems on rural roads.

Although the existing literature provides valuable insights into the effectiveness of speed cameras and their impact on driver behavior, there remains a significant gap in our understanding of the nuanced behavioral responses of drivers in diverse traffic contexts. The studies discussed above have primarily focused on aggregate effects and general trends. However, there is a pressing need for more sophisticated driver behavior modeling to capture the complex interactions between drivers and speed control measures. Our study aims to address this gap by employing advanced neural network techniques to model driver behavior near speed cameras. This approach allows us to account for multiple variables simultaneously and identify subtle patterns that may not be apparent through traditional statistical methods. By developing more accurate and comprehensive driver behavior models, we can inform the design of more effective traffic safety interventions. Furthermore, our dual approach of combining macroscopic and microscopic analyses provides a unique perspective that bridges the gap between overall traffic patterns and individual driver responses. This research thus builds on the existing literature while pushing the boundaries of our understanding of driver behavior in the context of speed control measures.

Method

To examine the impact of speed control cameras on the speed decisions of drivers and their reactions when encountering these devices, a multi-step process involving collection of speed data, analysis through artificial neural networks (ANN), and interpretation of the analysis results is implemented. The key hypothesis of this research is that fixed speed control cameras will significantly reduce vehicle speeds in the immediate vicinity of the cameras, with some speed recovery occurring after passing the cameras, but still maintaining an overall speed reduction effect. Each step of the analysis process will be detailed sequentially in this section to thoroughly investigate the research hypothesis and accomplish the research objectives of the study. A comprehensive overview of the analysis process and methodological steps followed in this study are shown in Figure 1.

Research Area

Mazandaran is a province in Iran, accounts for over 9.6% of the total deaths on rural roads nationwide, ranking it third with reference to casualty rates (*15*). Data from the Mazandaran Legal Medicine Organization indicate that these rural roads contribute to over 60% of the province's road fatalities (*15*). As a result, Mazandaran is recognized as a high-risk area for road safety in Iran, calling for a comprehensive investigation into the factors affecting crash severity on its rural roads.

The Amol-Mahmoudabad route is a popular tourist spot in Mazandaran province and plays a strategic role in linking the city of Amol with the province's western region. This segment, which spans approximately 14 km, has four distinct lanes and is known for high vehicle speeds. During holiday periods, this segment sees noticeable traffic. Furthermore, the Mahmoudabad-Amol route connects the city of Mahmoudabad with the Haraz Road. An inspection revealed that there are currently two cameras installed on the Amol to Mahmoudabad direction and one camera on the Mahmoudabad to Amol direction (Figure 2).

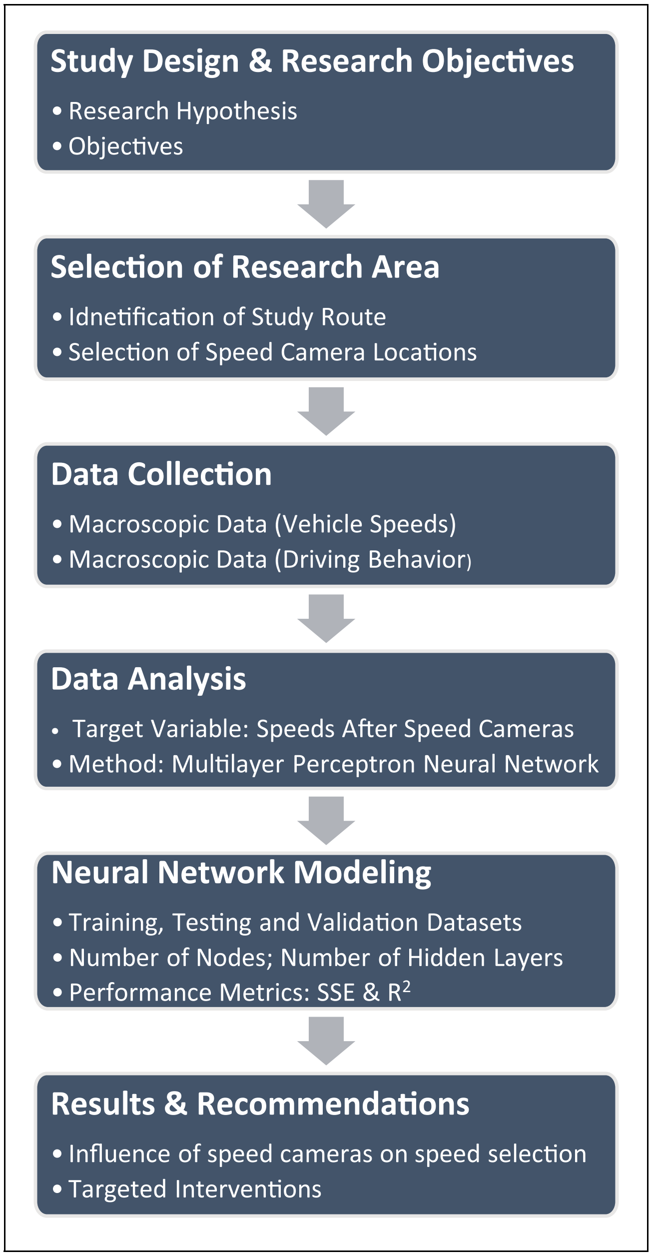

Figure 1. Flowchart with a comprehensive overview of the analysis process.

Data Collection

The data required for this research are divided into two main categories. The first category, referred to as the macroscopic data, comprises information on vehicle speed, sorted by vehicle types at three distinct locations relative to each camera: before (upstream), at, and after (downstream) the camera site. Specifically:

- "Before": within 300 m approaching the camera
- "At": the immediate vicinity of the camera (within 10 m)
- "After": within 300 m after passing the camera

The second category, known as the microscopic data, involves collecting individual driver behavior data when they encounter the camera. The key indicators used for the evaluation of the effectiveness of speed cameras were identified in light of relevant, well-regarded studies and articles (*16*, *17*).

Once data are collected from an appropriate study location that aligns with the research goals and a database is created, the analysis will concentrate on the macroscopic data and model the speed choice behavior of drivers using the microscopic data.

Our data collection was conducted over a three-day period from February 16 to February 19, 2023. Speed data at the macro level were collected using the LASER 500 laser speed recording camera (Figure 3). This portable device, mountable on a tripod, uses laser measurement and speed sensing systems to calculate speed from a distance of 500 m. By measuring the time it takes for light to travel to a vehicle and back to the speed sensor, the camera accurately measures vehicle speed. It is important to note the significantly faster travel of light emitted from a laser speed sensor compared with sound. During the macro-level statistical measurement process, the cameras were positioned in concealed areas to avoid disrupting drivers' concentration and attention, ensuring normal traffic behavior and uninterrupted traffic flow. Speeds of both passenger and heavy vehicles were separately recorded within a 300-m radius before and after the camera location following installation.

At the micro-level, filming within a moving vehicle was conducted to capture leading car indicators, including speed at various points relative to the camera, vehicle type, local conditions, lane changes, positioning, concealment behind other vehicles, and braking within the camera's coverage area. In addition, examination of posted speed limits on signboards along the study area revealed permitted speeds of 90 km/h for light vehicles and 80 km/h for heavy vehicles.

Key Behavioral Indicators and Speed Metrics

To investigate the research hypothesis of the study and subsequently gain deeper insights into driver behavior, four key behavioral indicators were considered to collect appropriate microscopic data:

1. Lane changing: Any lateral movement to switch lanes near the camera
2. Brake light usage: Activation of brake lights, indicating speed reduction
3. Distance to vehicle ahead: Changes in gap between vehicles

Figure 2. A view of the cameras in the study areas.

4. Return-to-lane movement: Lateral movement back to the original lane after passing the camera

These indicators were chosen as they represent observable actions that drivers might take in response to speed cameras, potentially reflecting attempts to avoid detection or adjust behavior temporarily. In addition, several speed metrics were deployed to capture speed differences at critical points (upstream, at and downstream of the camera location).Table 1 presents the variables that were examined to capture the impact of speed control cameras on driving behavior and speed selection.

User Types. The study categorizes users based on their speed before, at, and after encountering a speed control camera. Initial driver reactions to the visibility of cameras generally fall into one of four categories:

- "Conformers": Drivers who consistently adhere to the speed limit before, at, and after the camera site.
- "Deterred": Drivers who maintain a legal speed well before reaching the camera site and continue to do so after passing it. This group is often composed of local drivers or those familiar with the road.
- "Manipulators": Drivers who noticeably reduce their speed as they approach the camera and then accelerate after passing it.
- "Defiers": Drivers who consistently exceed the speed limit, showing little or no change in speed near the camera site.

The ultimate goal of speed control cameras is to increase driver compliance rates, maintain the number of rule-abiding individuals, and decrease the number of opponents and manipulators. This study aims to gather more information about these groups.

By collecting data such as the local status of vehicle license plates and the speed of users before, at, and after the speed control camera, users can be reasonably categorized during the analysis process.

Lane Change. Speed control cameras come in single-line and multi-line types. Single-line systems can only monitor one lane, whereas multi-line cameras can monitor up to four lanes, recording and processing speed violations across these lanes with fines imposed on speeding vehicles. The speed monitoring and recording process is swift, taking less than a second, making it difficult for drivers to evade the camera by quickly changing lanes. The modern speed control system can integrate automatic number

Figure 3. Macro versus micro traffic data collection. Top: Speed measurement (macro). Middle: Filming for data (micro). Bottom: Schematic comparison of macro-level and micro-level traffic data collection methods.

plate recognition (ANPR) data, effectively tracking all lanes, dispelling the myth that lane changes can confuse road cameras. Despite this advancement, lane changes on the road can contribute to driving incidents and are seen as an evaluative indicator in traffic data collection, where a lane change is recorded as "1," and maintaining lane consistency is recorded as "0" within the camera's range.

Speed Reduction Under the Camera. Certain drivers incorrectly believe they can evade fines by reducing their speed when passing speed cameras. Speed cameras come in two types: instant speed cameras and average speed record cameras. with instant speed cameras, if a driver reduces their speed under the camera, the recorded speed remains within the legal limit, and no fine is issued. Conversely, the average speed record camera operates differently. It

Table 1. Variables Used in the Data Analysis

Variable symbol	Variable description
Vb	Speed before speed control camera
Vi	Speed at the location of speed control camera
Va	Speed after speed control camera
LC	Lane change
B	Brake
H	Hiding behind another vehicle
SL	Lane positioning
N	Local condition

involves two cameras situated several kilometers apart. The initial camera records the vehicle's speed and entry time into the designated zone, and the second camera records the vehicle's speed and passage time. The central processing system then calculates the vehicle's average speed over the distance between the two cameras. If this calculated average speed surpasses the speed limit, the driver receives a fine. In addition, as regards statistical recording for users, the activation of brake lights within the camera range is recorded as "1," whereas maintaining speed within the camera's zone is recorded as "0."

Hiding Behavior Behind Another Vehicle. When queried about the capability of speed control cameras to detect license plates when closely spaced vehicles pass in front of them, it is crucial to understand that these cameras capture two photos only a fraction of a second apart. This process serves to refute erroneous claims of incorrect speed detection and provides photographic evidence of the violation. If two vehicles pass the camera simultaneously, the images can clearly identify which vehicle, or both, exceeded the speed limit. Moreover, as regards statistical recording, a "1" is logged for users who significantly reduce the distance between their vehicle and the one in front within the camera range, whereas a "0" is recorded if they maintain an appropriate distance from the front vehicle within the camera zone.

Lane Positioning. When drivers approach the camera, they may attempt lane changes or overtaking maneuvers that cause their vehicle's path to deviate from a straight line. However, if conditions prove unsuitable for completing the lane change, they return to their original lane. In statistical recording, a "1" is logged for users who exhibit this behavior within the camera's range, whereas a "0" is recorded if this behavior isn't observed.

Data Collection Method

Driver behavior can be inferred from the vehicle's characteristics during the driving task. In the process of collecting micro-traffic data and modeling driver behavior, a method involving a mobile vehicle following the lead car is sometimes employed to control driving behavior in relation to the leading vehicle in a traffic lane. The aim of the research is to identify the parameters significantly influencing the driver's speed choice at each moment from a micro perspective. It is pertinent to note that in this data recording method, the speed of the vehicle in which the data is being recorded must match the speed of the vehicles being followed without deviating. During data collection, the following user should record and document the desired study variables based on the behavior of the leading vehicle.

Macroscopic speed analysis entails examining and comparing speeds at various points: before, near, and after passing the camera. Subsequent statistical analyses such as average speed, 85th percentile speed, and the percentage of individuals exceeding the speed limit are used to evaluate the significance of differences. It is crucial to carefully select the comparison section, ensuring that it closely resembles the camera's placement location concerning geometric, traffic, and surrounding usage conditions. This section should reflect typical traffic speeds that users would experience in the absence of a speed control system. In addition, a speed recording camera within the appropriate operational radius should facilitate speed measurement in the comparison section, operated by a roadside operator and distinct from the violation record system. Therefore, the comparison section should be at least 300 m away from the speed cameras based on the effective range of speed influence from cameras (200–300 m), as per previous study results. By ensuring these conditions in a specific area, if a significant difference in average instantaneous speed of passing vehicles is observed between the section adjacent to the camera and the comparison section, this can be attributed to the implementation of speed control conditions. This shows the effects of applying the system to reduce speed in that area.

Neural Network

In recent years, the use of artificial intelligence and computational applications in the analysis, prediction, and management of transportation infrastructure has seen a significant increase. Several researchers have used ANN methods to analyze factors related to data processing. A neural network is essentially a tool designed to emulate the fundamental workings of the human brain, drawing on studies of its biological and psychological aspects. An ANN consists of interconnected artificial neurons that mimic certain characteristics of biological neurons. The role of a biological neuron is to aggregate inputs and produce an output. This output is only relayed to subsequent neurons if the signal exceeds a certain threshold; if not, the signal is not transmitted to the next neuron. In the network that's been created, an artificial neuron is essentially a system with multiple inputs and a single output, and each neuron operates in two modes: training and performance. In training mode, the neuron learns to respond to specific input patterns, whereas in performance mode, it provides the corresponding output when a recognized input pattern is introduced. In the network, a neuron calculates the weighted sum using Equation 1. Based on the input XI, weight Wi, and a comparison with the threshold value, the neuron activates and transmits the signal if the sum surpasses the threshold value. If not, the neuron remains inactive, and the flow ceases.

$$I = \sum\nolimits_{i=1}^{n} W_i.X_i \quad (1)$$

In reference to Equation 1, I represents the input vector, W_i denotes the weight (dimensionless), and X_i signifies the input (dimensionless). Therefore, each weight w is paired with a corresponding x. The neural network's objective is to identify and adjust these weights and biases in accordance with Equation 2 such that the output derived from the neural network minimizes the error when compared with the actual value.

$$\text{Network} = b + \sum\nolimits_{i=1}^{n} W_i.X_i \quad (2)$$

In this approach, a certain portion of the data, 70%, is set aside for the network to learn from, whereas another portion (e.g., 15%) is reserved for validation. The neural network, based on the training it undergoes, self-evaluates using this validation set to gauge how well its training aligns with the actual data. If there are any deficiencies in the training, the network adjusts itself accordingly. Lastly, a portion (e.g., 15%) is earmarked for the testing process to evaluate how closely the results derived from the neural network match the actual outcomes.

It is important to note that the collected data may include nominal variables. These nominal independent variables cannot be directly input into the model. Therefore, to incorporate these variables into the impact assessment model, dummy variables are used. As explained in previous sections, a zero and one code are assigned to nominal variables. Generally, if a nominal variable has K states, K-1 dummy variables are used to examine the effect and relationship of that variable with the independent variable.

In the present study, we employ a feedforward ANN to analyze the factors influencing driver speed after passing speed cameras. Specifically, we use a multilayer perceptron neural network with an input layer of seven nodes (representing behavioral variables and bias), a hidden layer of five nodes (using a hyperbolic activation function), and an output layer of one node (representing the constant speed of users after passing the camera). For training, we use 70% of our dataset (547 cases), with 15% (117 cases) reserved for testing, and the remaining 15% used for validation during the training process. This split ensures robust learning and evaluation of the model's performance. The input variables include speed before camera, local status, lane change behavior, lane positioning, hiding behavior, braking, and a bias term. Our dependent variable (output) is the speed after passing the camera, and we use the standardized method for employing the dependent variable. The network is trained using the Lomborg–Marquardt algorithm, which is known for its efficiency in training medium-sized neural networks. We use the sum of squared errors (SSE) as our performance error metric. Considering expected output, our model aims to predict the driver's speed after passing the camera based on the input variables.

Results and Discussion

This section will commence by presenting information about the study area, focusing on the specifics of the study location and the camera specifications. Following this, an analysis of the collected data will be conducted, and the results obtained will be presented using the methods outlined in the third section. This will involve a macroscopic examination of speed distribution within the camera's range, followed by a study into the behavioral characteristics of users when they encounter the speed control camera and the resulting changes in speed. Subsequently, a neural network will be used to model drivers' speed selection behavior in response to the variables described in the previous section. The final part of this section will involve an evaluation of the results and the aforementioned model through statistical tests.

Descriptive Statistics

Macroscopic Analysis of Data. Table 2 offers a summary of the statistical attributes of motor vehicle speeds within the range of fixed speed control cameras on the stretch from Amol to Mahmoudabad.

Comparing the average speeds recorded by drivers before reaching the fixed speed control camera with those at the camera location reveals a notable reduction in vehicle speeds. The average speed of users at the camera location decreased by 13.87% compared with before reaching it. Furthermore, speed data within 300 m after the fixed speed control camera were collected to observe the post-camera speed trends and driver behavior. This data collection sought to determine how drivers' behavior changes after passing the camera. A comparison of the average speeds before and after the camera shows a

Table 2. Statistical Features of Vehicle Speeds Near Speed Control Cameras

Location	85th percentile speed (km/h)	Average speed (km/h)	Standard deviation (km/h)	Minimum speed (km/h)	Maximum speed (km/h)
Camera 1					
Before control speed camera	93.9	84.00	10.19	52	141
At control speed camera	81	72.54	7.4	57	93
After passing control speed camera	92.05	81.52	11.3	48	122
Camera 2					
Before control speed camera	94	85.89	8.03	64	107
At control speed camera	84	74.4	7.46	58	102
After passing control speed camera	92	84.58	8.33	62	119
Camera 3					
Before control speed camera	93.35	85.48	7.76	63	105
At control speed camera	80.35	72.98	6.99	52	94
After passing control speed camera	89	81.34	7.64	56	104
Total data					
Before control speed camera	93.6	85.12	7.86	52	141
At control speed camera	81	73.31	7.33	52	102
After passing control speed camera	92	82.48	9.34	48	122

3.10% decrease in average speed. It is evident that users tend to reduce their speed on sighting the camera, and although they partially compensate for this reduction after passing it, their average speed post-camera remains lower than before. This indicates an observable impact on reducing user speeds owing to the presence of a sense of control and surveillance through the camera.

In addition, apart from calculating the average speed, the 85th percentile speed, minimum speed, maximum speed, and standard deviation were also computed in each study section, all of which affirm the observable impact of the camera's presence on speed selection. The trend of changes in the 85th percentile speed at the location and after passing the fixed speed control camera is presented in Table 3. The 85th percentile speed at the camera location decreased by 13.08% compared with before, and it experienced a 1.7% reduction before and after passing the camera.

The vehicle speeds before, at, and after passing a camera were analyzed and compared using Statistical Package for the Social Sciences (SPSS) software. Statistical tests, including one-sided analysis of variance (ANOVA) and the Tukey follow-up test, were conducted to identify whether there are statistically significant differences in vehicle speeds upstream, at, and downstream of camera locations. The null hypothesis of the ANOVA tests is that there are no significant differences among the mean speeds observed before, at, and after passing the camera location. The results established statistically significant differences in average speeds at these three positions, thus rejecting the null hypothesis at a 95% confidence level. This was further reinforced by a robust test for analysis of variance, which has the same null hypothesis as the aforementioned ANOVA tests. The significance value (sig) of 0.000 at all three positions denotes statistically significant differences in vehicle speeds.

Microscopic Analysis of Data. In this section, all indicators are initially analyzed without distinguishing between specific groups. Following this, the analyses are repeated with the categorization of vehicle types into light and heavy, and the consideration of the local status of users, to examine the behavioral differences among users in various groups. This allows for a more nuanced understanding of user behavior in relation to speed control cameras.

Behavioral Indicator Analysis Across All Vehicle Types. Table 4 presents the statistical indicators associated with the speed of users before, at the location, and after the speed control camera. As per Table 4, those who exceed the maximum speed limit include light vehicle users with speeds surpassing 90 km/h and heavy vehicle users with speeds exceeding 80 km/h.

Figure 4 illustrates the speed distribution of users in the areas before the camera, within the camera range, and after passing the camera. These distributions are obtained using two data collection methods: macroscopic and microscopic. As suggested by these figures and Table 5, there is a reasonable correlation between the speeds recorded by the microscopic method and the speeds recorded with the camera in the macroscopic method. This correlation validates the use of these measurements in the modeling process. A comparison of speed data in the two macroscopic and microscopic modes, conducted using the one-sided variance method in SPSS, further confirms the similarity between the two modes.

Table 3. The 85th Percentile Speed at the Location and After Passing the Fixed Speed Control Camera

	N	Mean	SD	95% confidence interval for mean		Minimum	Maximum	Between-component variance
				Lower bound	Upper bound			
Before speed camera control	755	85.000	8.0000	84.000	85.000	52.0	141.0	NA
In the place of speed camera	755	73.000	7.0000	72.000	73.000	52.0	102.0	NA
After speed camera control	755	82.000	9.0000	81.000	83.000	48.0	122.0	NA
Total	2265	80.000	9.0000	79.000	80.000	48.0	141.0	NA
Model fixed effects			8.0000	79.000	80.000	NA	NA	NA
Random effects				64.000	95.000	NA	NA	38.0000

Note: NA = not applicable; SD = standard deviation.

Table 4. Distribution of Average Speeds

Camera number	Average speed before camera	Average speed at camera location	Average speed after camera	Number of users exceeding speed limit (before camera)	Number of users exceeding speed limit (at camera location)	Number of users exceeding speed limit (after camera)
1	87.84	77.67	86.74	106	7	91
2	89.16	77.81	87.32	112	3	90
3	91.90	77.07	86.43	146	5	75
Total	89.60	77.52	86.83	364	15	256

Table 5. Comparison of Users' Speed Distribution

State	Vb	Vi	Va	Approach	State
Mean					
Macroscopic	85.13	73.31	82.49	Macroscopic	85.13
Microscopic	89.6	77.52	86.83	Microscopic	89.6
SD					
Macroscopic	8.763	7.333	9.341	Macroscopic	8.763
Microscopic	7.723	6.118	8.723	Microscopic	7.723

Note: SD = standard deviation; Va = speed after speed control camera; Vb = speed before speed control camera; Vi = speed at the location of the speed control camera.

The data encompassed three distinct camera ranges, encompassing a total of 781 surveyed users, with 575 identified as local and 206 as non-local. Camera Range 1's breakdown revealed 62 local and 203 non-local plates, totaling 265 plates, whereas Camera Range 2 had 262 plates, consisting of 189 local and 73 non-local. Similarly, Camera Range 3 comprised 254 plates, with 183 local and 71 non-local. Of note, 26% of local users were found to be from the cities of Amol and Mahmoudabad, indicating a substantial portion.

Lane-changing behavior was observed across 781 users, revealing that 253 users changed lanes while 528 maintained their lanes. A detailed breakdown per camera range indicated that in Camera Range 1, 107 users changed lanes out of 265, with 75 and 71 opting for lane changes in Camera Ranges 2 and 3, respectively. Of note, 32% of total users exhibited a lane change when a camera was present.

Brake light usage as an indicator of reduced speed was observed in 314 cases, whereas 467 users showed no change in speed. Specifically, in Camera Range 1, 96 users had their brake lights on, followed by 121 in Range 2 and 97 in Range 3, signifying that 40% of the total users slowed down in response to the presence of the braking camera.

Considering the distance with the vehicle ahead, 13 users decreased the gap, whereas 768 increased it. Camera Range 1 saw eight users reducing the gap out of

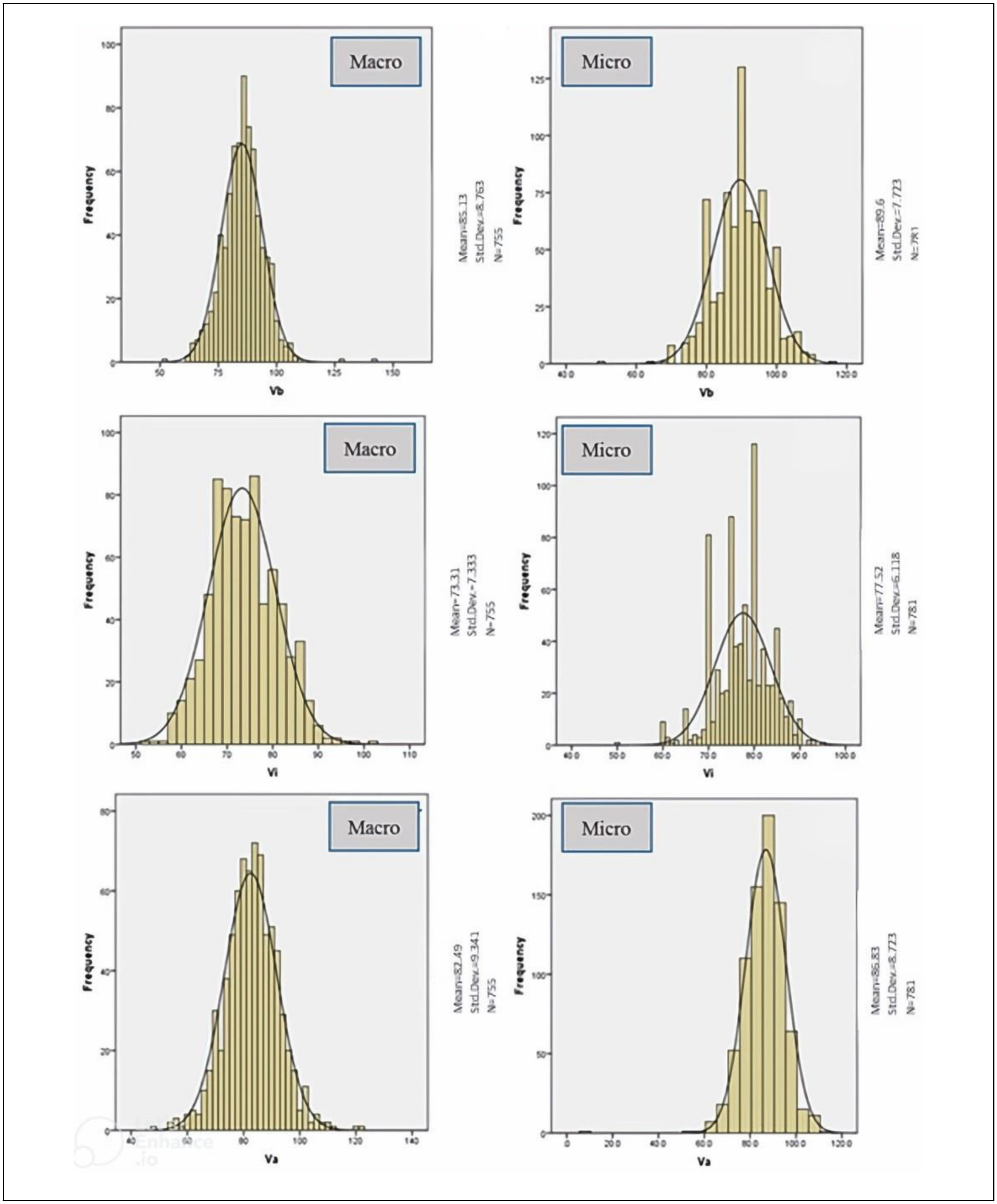

Figure 4. Speed distribution: pre-camera (upper figure), at-camera (middle figure), and post-camera (lower figure).

Table 6. Distribution of Average Speed of Users

Vehicle type	Average speed before camera	Average speed at camera location	Average speed after camera	Violators max. speed limit (before)	Violators max. speed limit (at location)	Violators max. speed limit (after)
Camera 1						
Light vehicle	88.28	77.84	87.22	94	3	82
Heavy vehicle	81.66	74.94	80.05	9	4	9
Camera 2						
Light vehicle	89.41	77.96	87.60	104	2	83
Heavy vehicle	83.75	74.58	81.41	8	1	7
Camera 3						
Light vehicle	92.64	77.30	86.99	131	0	64
Heavy vehicle	84.47	74.69	80.78	15	5	11
Total						
Light vehicle	90.05	77.72	87.28	329	5	229
Heavy vehicle	83.35	74.75	80.67	32	10	27

Note: Max. = maximum.

265, with just two users attempting the same in Range 2 and 3, amounting to only 2% of total users.

A total of 268 users exhibited a return-to-lane movement, whereas 513 maintained their directional movement. Camera Range 1 had 92 users returning to their lane, followed by 82 in Range 2 and 94 in Range 3, indicating that 34% of the total users executed a return-to-lane movement.

Behavioral Analysis by Vehicle Type. The data from 781 cases revealed that the majority of vehicles, accounting for 93.2% or 728 cases, were light vehicles, whereas the remaining 6.8% or 53 cases were heavy vehicles. Delving into individual camera locations, Camera 1 recorded 247 light vehicles and 18 heavy vehicles out of 265 total vehicles. Camera 2 captured 250 light vehicles and 12 heavy vehicles out of 262 total vehicles, and Camera 3 documented 231 light vehicles and 23 heavy vehicles out of 254 total vehicles.

Table 6 presents statistical indices pertaining to the speed of users before, at the location, and after the camera, categorized by the type of vehicle. At the camera location, users of light vehicles exhibited a 13.69% reduction in speed compared with before the camera, and after passing the camera, speed control led to a 3.07% reduction. For heavy vehicles, these reductions were 10.31% and 3.21%, respectively. Moreover, the number of speed violations decreased after passing the camera, with a reduction of 4.18% for light vehicles and 15.62% for heavy vehicles compared with before camera observation. Of note, both light and heavy vehicles adhered to the speed limit at the camera location.

Among the 728 users with light vehicles, 32.41% exhibited lane-changing behavior in the presence of the camera, whereas this behavior was observed in 32.07% of the 53 users with heavy vehicles. Diving into individual camera locations, in Camera 1, out of 247 light vehicles, 100 changed lanes and 147 maintained their lanes, whereas among the 18 heavy vehicles, 7 changed lanes and 11 maintained their lanes. Similarly, in Camera 2, out of 250 light vehicles, 71 changed lanes and 179 maintained their lanes, and among the 12 heavy vehicles, 4 changed lanes and 8 maintained their lanes. Lastly, in Camera 3, out of 231 light vehicles, 65 changed lanes and 166 maintained their lanes, whereas among the 23 heavy vehicles, 6 changed lanes and 17 maintained their lanes.

Another observation pertained to speed reduction, notably manifested by 42.9% of the 728 users with light vehicles and 22.6% of the 53 users with heavy vehicles. At the individual camera locations, the data revealed specific patterns in speed reduction behaviors across both vehicle categories. Furthermore, 1.1% of the 728 users with light vehicles and 1.88% of the 53 users with heavy vehicles were seen to decrease the gap with the front vehicle. Lastly, 34.8% of the 728 users with light vehicles and 26.4% of the 53 users with heavy vehicles exhibited a lane deviation and return behavior in the presence of the camera.

In addition, out of the total 781 individuals examined, 206 or 26.37% were identified as local users. This data provided valuable insights into the geographical distribution of the user base, allowing for potential implications in traffic management, infrastructure development, and policy-making.

Table 7 depicted the distribution of statistical speed indices for users before, at the location, and after passing the camera, categorized by local status. The table indicated that local users at the camera location exhibited a 13.69% decrease in speed compared with before, with a 13.40% reduction in speed after passing the camera. Conversely, the reduction in speed for non-local users was 13.40% and 3.08%, respectively, signaling a similarity between the two groups. Furthermore, the number of

Table 7. Speed and Violation Behavior Among Local and Non-local Users

Local status	Average speed before camera	Average speed at camera location	Average speed after camera	Violators max. speed limit (before)	Violators max. speed limit (at location)	Violators max. speed limit (after)
Camera 1						
Local	87.90	77.79	86.74	27	5	200
Non-local	87.81	77.63	86.73	76	2	71
Camera 2						
Local	90.60	78.52	88.41	33	2	27
Non-local	88.59	77.52	86.90	79	1	63
Camera 3						
Local	92.31	76.38	86.05	34	0	19
Non-local	90.83	77.33	86.57	112	5	56
Total						
Local	89.86	77.56	87.09	94	7	66
Non-local	89.50	77.50	86.74	267	8	190

Note: Max. = maximum.

speed violations after passing the camera decreased by 29.78% for local users and 28.83% for non-local users, indicating compliance with permissible speed limits for both groups at the camera location.

Among the 206 local users, 29.61% were observed to change lanes in the presence of the camera, in contrast to 33.39% of the 575 non-local users. Examining individual camera locations, Camera 1 saw 22 out of 62 local users and 85 out of 203 non-local users changing lanes. For Camera 2, the corresponding figures were 19 out of 73 local users and 56 out of 189 non-local users. Camera 3 showed 20 out of 71 local users and 51 out of 183 non-local users changing lanes. The behavior of engaging in braking was notably observed in 58.73% of the 206 local users, whereas only 33.56% of the 575 non-local users exhibited this behavior. Looking at individual camera locations revealed specific patterns in braking behavior across both local and non-local user groups. Considering reducing the distance to the vehicle ahead, a striking contrast was observed, with 7 out of 62 local users and only 1 out of 203 non-local users opting to reduce their distance in the presence of the first camera. Similar trends were evident at the other camera locations. Lane positioning behavior was prevalent among both local and non-local users. Specifically, 27 out of 62 local users and 65 out of 203 non-local users exhibited this behavior in the presence of the first camera. Comparable trends were observed at the second and third camera locations.

Table 8. Neural Network Model Information

Input layers	Speed before camera	
	Local status	
	Lane change	
	Lane positioning	
	Hiding	
	Braking	
	Number of nodes	7
Hidden layer	Number of hidden layers	5
	Activation function	Hyperbolic tangent
Output layer	Dependent variable	Speed after camera
	Number of units	1
	Method of employing the dependent variable	Standardized
	The function of operation	Lomborg–Marko art algorithm.
	Performance error	Sum of squared errors

Modeling

To determine the optimal structure for the ANN, we experimented with various network configurations, each differing in the number of neurons in the hidden layer and the learning rates. We conducted a set of simulations to identify the ideal value for each network parameter. The mean squared error (MSE) was used as a crucial measure in all simulations, reflecting the network's ability to identify existing patterns. After finalizing these parameters, we found that a structure with seven neurons in the input layer, five neurons in the hidden layer, and one neuron in the output layer was suitable for pattern recognition (Table 8).

The neural network process reveals that out of 781 total samples, 547 (70%) are included in the training sample, 117 (15%) are part of the validation sample, and 117 (15%) comprise the testing sample. Of note, no samples have been excluded from the analysis, ensuring that data from all individuals contribute to the network analysis.

The model uses a feedforward network, which includes an input layer with seven nodes, to train the

Table 9. Weight Coefficients and Biases of the Hidden Layer used in the Final Model.

Neuron number	Weight coefficients of the relationship between input variables and the hidden layer							Biases of neurons in the hidden layer	Weight coefficients of the output neuron
	Vb	Vi	LC	SL	H	B	N		
1	−3.41	2.52	0.49	−5.31	−2.18	0.13	0.91	2.98	−0.07
2	0.23	0.85	−0.10	−0.17	0.43	0.36	−0.13	0.59	0.37
3	0.03	−8.47	2.40	4.68	−1.08	5.03	10.22	0.95	0.07
4	0.42	13.76	−2.44	−2.85	−1.23	−13.15	−4.01	2.7	0.10
5	0.44	−0.4	2.5	0.06	0.7	0.17	0.09	4.03	0.41

Note: B = brake; H = hiding behind another vehicle; LC = lane change; N = local condition; SL = lane positioning; Vb = speed before speed control camera; Vi = speed at the location of speed control camera.

neural network. The total count of input units includes not only the behavioral variables but also the bias. This network is also equipped with a hidden layer containing five nodes. The output layer represents the constant speed control of the users after passing the camera.

Output and Validation of the Neural Network Model. Table 9 showcases the coefficients attributed to each variable that contributes to the modeling of the ANN. It is noteworthy that the second and fifth layers bear the most significant weights in output estimation. In the second layer, the speed within the camera range has the most positive effect with a weight coefficient of 0.85, whereas lane deviation, with a coefficient of −0.17, exerts the most negative influence on this layer. Moreover, in the fifth node, lane change, with a coefficient of 0.52, has the most positive effect, and speed at the camera location, with a coefficient of −0.40, has the most negative influence on the fifth node. Table 9 succinctly illustrates the weights assigned to each node in the input and hidden layers during the learning phases of the neural network. These weights are modeled values that the network has successfully implemented and predicted.

The efficacy of the multilayer perceptron neural network was assessed using two primary indices, MSE and R^2. These indices offer a numerical evaluation of the network's capacity to model the choice of driving speed. The R^2 values for the training, validation, and testing datasets were scrutinized. The R^2 value for the training data stood at 0.782, signifying a robust correlation between the observed and forecasted values. This implies that the model was successful in learning from the training data. The R^2 value for the validation data was 0.642. For the testing set, which is crucial for assessing the model's ability to generalize to new, unseen data, the R^2 value was also 0.642.

It is important to note that the consistent performance across the validation and testing sets (both with R^2 = 0.642) indicates good generalization capabilities of our model. This consistency suggests that the model performs equally well on completely new data as it does on the validation set used during training.

Discussion and Comparison with Previous Research

This research offers crucial insights into the impact of fixed speed control cameras on driver behavior. The installation of these cameras results in a notable decrease in the average vehicle speed, with drivers significantly reducing their speed at the camera location and for a certain distance beyond it. The study showed an observable reduction in the speed of most drivers at the camera location, indicating the effectiveness of the speed camera intervention at the particular point. The microscopic data analysis supports the research hypothesis and provides additional insights into driver behavior around speed cameras. The statistically significant reduction in speed at the camera location, observed both macroscopically and microscopically, indicates that the cameras are effective in slowing traffic. The partial speed recovery after passing the camera suggests a temporary behavior change, but the maintained overall speed reduction implies a potentially lasting effect.

The reliability of microscopic data in modeling was confirmed through an analysis of user speed distribution. It was found that drivers modify their behavior, such as changing lanes and braking, on encountering the camera. The high percentages of lane changing, brake light usage, and return-to-lane movements suggest that many drivers actively adjust their behavior in response to the cameras. However, the low percentage of drivers decreasing their gap to the vehicle ahead indicates that tailgating is not a common strategy for avoiding camera detection.

The study also underscored the consistent influence of the camera on speed selection, regardless of the user's local status. The similar speed reductions between local and non-local users at the camera location suggest that the cameras are equally effective for both groups. However, the higher speed reduction for local users after passing the camera implies a more lasting effect, possibly owing to increased awareness of potential enforcement. Lastly, the study showed the efficacy of a neural network model in simulating the speed selection behavior of users within the camera range.

The findings of this study are in line with and expand on the existing literature on the effect of speed control measures on road safety and driver behavior. In agreement with the findings of Job et al. (*7*), our study discovered that the installation of a fixed speed control camera effectively reduced the average vehicle speed, with a decrease of 13.87% at the camera location and 3.10% within 300 m after the camera. This supports the claim that speed cameras can lead to a significant reduction in injury accidents and fatal accidents. However, owing to the study design, the results cannot provide evidence as to whether such a speed reduction is maintained at a longer downstream distance, beyond the benchmark of 300 m. Future investigations should expand the downstream observation range in an effort to better track the speed patterns over longer distances beyond the camera sites. Our study also found that the speed of the 85th percentile at the camera location decreased by 13.08%, which aligns with the findings of Tavolinejad et al. (*10*) that the average speed near speed control cameras was significantly lower. This further emphasizes the need for interventions to enhance road safety. Interestingly, our study found that users tend to reduce their speed on observing the camera and partially compensate for the speed reduction after passing it. This finding extends the work of Lee and Sheppard (*11*), who observed that drivers adopted lower speeds in the presence of camera signs and when speed limit signs were visibly displayed on road signs. Our study also found that the frequency distribution related to lane change shows that among the 781 users under investigation, 32% have changed lanes when confronted with the camera. This finding is consistent with the work of Tawfeek et al. (*18*), who revealed statistically significant differences in drivers' braking behavior at intersections and mid-road sections.

Concerning the impact of speed control measures on different types of vehicles, both light and heavy vehicles exhibited fewer speed violations after passing the camera. Our study found that users of light vehicles at the camera location have a 13.69% decrease in speed compared with before it, and after passing the speed control camera, they have a 3.07% reduction in speed. This reduction for heavy vehicles is 10.31% and 3.21%, respectively. This finding extends the work of Lyu et al. (*19*), who showed that advanced driver assistance systems (ADAS) significantly influenced braking behavior and driver acceptance across different driving contexts. Focusing on other driving behaviors, whereas light and heavy vehicles showed similar lane-changing behaviors, light vehicles were more likely to use brake lights, possibly owing to their ability to decelerate more quickly. Local users exhibited higher rates of brake light usage compared with non-local users, perhaps owing to greater familiarity with camera locations.

The current research introduces several novel contributions to the existing literature. It uniquely compares macroscopic and microscopic methods for recording user speeds at various points relative to the camera location, finding a reasonable approximation between the two. This study also examines the local status of license plates, revealing that 26% of the users studied are local to Amol and Mahmoudabad counties. Detailed statistics on various behavioral changes in response to the camera, such as lane change, speed reduction, user concealment, and lane deviation, offer a nuanced understanding of driver behavior. The impact of speed control measures is differentiated by vehicle type and indigenous status of users, providing a more detailed understanding of how different groups respond to these measures.

Conclusions and Recommendations for Future Research

This research has offered significant insights into how fixed speed control cameras affect driver behavior. It has shown that these cameras result in a substantial decrease in the average vehicle speed, with drivers markedly reducing their speed at the camera location and for a certain distance beyond it. The study also observed a reduction in the speed of most drivers at the camera location, indicating effective speed regulation. Moreover, the analysis of user speed distribution validated the reliability of microscopic data in modeling and showed that drivers modify their behavior, such as changing lanes and braking, on encountering the camera. Both light and heavy vehicles exhibited fewer speed violations after passing the camera. Importantly, this study underscored the consistent influence of the camera on speed selection, regardless of the user's local status.

Furthermore, this study introduces several novel contributions to the existing literature. It uniquely compares macroscopic and microscopic methods for recording user speeds at various points relative to the camera location, finding a reasonable approximation between the two. It also examines the local status of license plates and provides detailed statistics on various behavioral changes in response to the camera, offering a nuanced understanding of driver behavior. The impact of speed control measures is differentiated by vehicle type and indigenous status of users, providing a more detailed understanding of how different groups respond to these measures. Lastly, the use of a multilayer perceptron neural network model to simulate the speed selection behavior of users within the camera range is a novel contribution to the field. These unique aspects extend our understanding of the impact of speed control measures on driver behavior and road safety, providing valuable insights for the development of more effective traffic safety measures and strategies.

Although this study has illuminated the impact of fixed speed control cameras on driver behavior, there are several areas that merit further investigation. We acknowledge, however, that our study does have limitations as regards generalizability. Although the selection of Mazandaran province focuses on rural roads with high crash rates, it represents a specific case study. The unique combination of road geometry, traffic patterns, and surrounding land use in our study area may not be representative of all road types across Iran or internationally. To address this limitation, we suggest that future work could expand the study to include a wider range of road types and locations. This could involve examining speed camera effectiveness in urban settings within Mazandaran and other provinces, comparing results across different rural road configurations, investigating the impact of speed cameras in areas with different climate conditions and topography, and conducting multi-province or even multi-country comparisons to account for varying cultural and regulatory contexts.

Furthermore, future research should focus on the long-term effects of speed cameras on driver behavior and road safety. In this context, a case-control study design could be considered in the future to compare areas with and without speed cameras; control areas without speed cameras but with comparable traffic volumes, road geometry, and surrounding land use could be leveraged to thoroughly evaluate the long-term impact of speed cameras on driving behavior. By considering the sustainability of the observed impacts over time, researchers can gain a more comprehensive understanding of the lasting influence of fixed speed control cameras. Furthermore, the study's findings suggest that driver behavior is influenced not only by the presence of the cameras but also by the type of vehicle and the local status of the drivers. Future studies could delve deeper into these factors, exploring how specific vehicle types and driver demographics interact with speed control measures. Understanding the nuanced nuances related to these variables can inform targeted interventions and policies tailored to different user groups. Moreover, although the multilayer perceptron neural network model showed promising potential in modeling speed selection behavior, further research could explore the application of advanced modeling techniques and artificial intelligence in predicting and understanding complex driver behaviors. This could lead to the development of more sophisticated and accurate predictive models, providing deeper insights into driver behavior near speed control measures. In addition to the continued research on the long-term effects of fixed speed control cameras, it would be beneficial to investigate the societal and economic impacts of these devices. Understanding how these cameras affect overall traffic flow, environmental factors, and economic considerations, such as potential cost-effectiveness in reducing accidents and improving transportation efficiency, could provide a more comprehensive understanding of the broader impacts of these devices.

Author Contributions

The authors confirm contribution to the paper: study conception and design: Abbas Sheykhfard, Farshidreza Haghighi; data collection: Abbas Sheykhfard, Farshidreza Haghighi; analysis and interpretation of results: Abbas Sheykhfard, Farshidreza Haghighi, Soheila Saeidi, Mohammad SafariTaherkhani, Grigorios Fountas, Subasish Das; draft manuscript preparation: Abbas Sheykhfard, Farshidreza Haghighi, Soheila Saeidi, Mohammad SafariTaherkhani, Grigorios Fountas, Subasish Das. All authors reviewed the results and approved the final version of the manuscript.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

ORCID iDs

Abbas Sheykhfard https://orcid.org/0000-0002-9536-3108
Farshidreza Haghighi https://orcid.org/0000-0002-6823-4458
Soheila Saeidi https://orcid.org/0009-0002-3332-1233
Mohammad SafariTaherkhani https://orcid.org/0000-0002-0909-5574
Grigorios Fountas https://orcid.org/0000-0002-2373-4221
Subasish Das https://orcid.org/0000-0002-1671-2753

References

1. Kanitpong, K., M. Ekpanyapong, and T. Inmor. Evaluation of Point-to-Point Speed Cameras to Control Speeding Behavior in Thailand. *Journal of Safety Research*, Vol. 88, 2024, pp. 31–40. https://doi.org/10.1016/j.jsr.2023.10.006.
2. Li, H., M. Zhu, D. J. Graham, and G. Ren. Evaluating the Speed Camera Sites Selection Criteria in the UK. *Journal of Safety Research*, Vol. 76, 2021, pp. 90–100. https://doi.org/10.1016/j.jsr.2020.11.013.
3. Global Status Report on Road Safety 2023. World Health Organization. https://www.who.int/publications-detail-redirect/9789240086517. Accessed December 23, 2023.

4. Shaaban, K., A. Mohammad, and A. Eleimat. Effectiveness of a Fixed Speed Camera Traffic Enforcement System in a Developing Country. *Ain Shams Engineering Journal*, Vol. 14, No. 10, 2023, p. 102154. https://doi.org/10.1016/j.asej.2023.102154.
5. Li, H., M. Zhu, D. J. Graham, and Y. Zhang. Are Multiple Speed Cameras More Effective than a Single One? Causal Analysis of the Safety Impacts of Multiple Speed Cameras. *Accident Analysis & Prevention*, Vol. 139, 2020, p. 105488. https://doi.org/10.1016/j.aap.2020.105488.
6. Li, H., Y. Zhang, and G. Ren. A Causal Analysis of Time-Varying Speed Camera Safety Effects Based on the Propensity Score Method. *Journal of Safety Research*, Vol. 75, 2020, pp. 119–127. https://doi.org/10.1016/j.jsr.2020.08.007.
7. Job, R. F. S. Evaluations of Speed Camera Interventions Can Deliver a Wide Range of Outcomes: Causes and Policy Implications. *Sustainability*, Vol. 14, No. 3, 2022, p. 1765. https://doi.org/10.3390/su14031765.
8. Martínez-Ruíz, D. M., A. Fandiño-Losada, A. Ponce de Leon, D. Arango-Londoño, J. C. Mateus, C. Jaramillo-Molina, F. J. Bonilla-Escobar, H. Vivas, W. Vanlaar, and M. I. Gutiérrez-Martínez. Impact Evaluation of Camera Enforcement for Traffic Violations in Cali, Colombia, 2008-2014. *Accident Analysis & Prevention*, Vol. 125, 2019, pp. 267–274. https://doi.org/10.1016/j.aap.2019.02.002.
9. Blais, E., and L. Carnis. Improving the Safety Effect of Speed Camera Programs Through Innovations: Evidence from the French Experience. *Journal of Safety Research*, Vol. 55, 2015, pp. 135–145. https://doi.org/10.1016/j.jsr.2015.08.007.
10. Tavolinejad, H., M.-R. Malekpour, N. Rezaei, A. Jafari, N. Ahmadi, A. Nematollahi, E. Abdolhamidi, E. Foroutan, M. Mehr Hasan, and F. Farzadfar. Evaluation of the Effect of Fixed Speed Cameras on Speeding Behavior Among Iranian Taxi Drivers Through Telematics Monitoring. *Traffic Injury Prevention*, Vol. 22, No. 7, 2021, pp. 559–563. https://doi.org/10.1080/15389588.2021.1957100.
11. Lee, Y. M., and E. Sheppard. Effects of Position of Speed Limit Signs and the Presence of Speed Camera on Malaysian Drivers' Speed Choice: An Eye-Tracking Study. *Transportation Research Part F: Traffic Psychology and Behaviour*, Vol. 74, 2020, pp. 386–395. https://doi.org/10.1016/j.trf.2020.08.030.
12. Vadeby, A., and Å. Forsman. Speed Distribution and Traffic Safety Measures. Presented at the Transport Research Arena (TRA) 5th Conference: Transport Solutions from Research to Deployment, Paris, France, 2014.
13. Freeman, J., S.-A. Kaye, V. Truelove, and J. Davey. Is There an Observational Effect? An Exploratory Study into Speed Cameras and Self-Reported Offending Behaviour. *Accident Analysis & Prevention*, Vol. 108, 2017, pp. 201–208. https://doi.org/10.1016/j.aap.2017.08.020.
14. Luoma, J., R. Rajamäki, and M. Malmivuo. Effects of Reduced Threshold of Automated Speed Enforcement on Speed and Safety. *Transportation Research Part F: Traffic Psychology and Behaviour*, Vol. 15, No. 3, 2012, pp. 243–248. https://doi.org/10.1016/j.trf.2012.01.002.
15. Iranian Legal Medicine Organization. 2022. http://www.lmo.ir/web_directory/53999-%D8%AA%D8%B5%D8%A7%D8%AF% D9%81%D8%A7%D8%AA.html.
16. Pantangi, S. S., S. S. Ahmed, G. Fountas, K. Majka, and P. C. Anastasopoulos. Do High Visibility Crosswalks Improve Pedestrian Safety? A Correlated Grouped Random Para3 Approach Using Naturalistic Driving Study Data. *Analytic Methods in Accident Research*, Vol. 30, 2021, p. 100155. https://doi.org/10.1016/j.amar.2020.100155.
17. Sarwar, M. T., G. Fountas, C. Bentley, P. C. Anastasopoulos, A. Blatt, J. Pierowicz, K. Majka, and R. Limoges. Preliminary Investigation of the Effectiveness of High-Visibility Crosswalks on Pedestrian Safety Using Crash Surrogates. *Transportation Research Record: Journal of the Transportation Research Board*, 2017. 2659: 182–191.
18. Tawfeek, M. H., and K. El-Basyouny. A perceptual forward collision warning model using naturalistic driving data. *Canadian Journal of Civil Engineering*, Vol. 45, No. 10, 2018, pp. 899–907.
19. Lyu, N., C. Deng, L. Xie, C. Wu, and Z. Duan. A Field Operational Test in China: Exploring the Effect of an Advanced Driver Assistance System on Driving Performance and Braking Behavior. *Transportation Research Part F: Traffic Psychology and Behaviour*, Vol. 65, 2019, pp. 730–747. https://doi.org/10.1016/j.trf.2018.01.003.