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Exploring the Influence of Signal Countdown Timers on Driver Behavior: An Analysis of Pedestrian–Vehicle Conflicts at Signalized Intersections

Abbas Sheykhfard[1], Farshidreza Haghighi[1], Eleonora Papadimitriou[2], Subasish Das[3], and Pieter Van Gelder[2]

Abstract

Although signal countdown timers (SCTs) are likely to enhance efficiency at signalized intersections, there is little research on how they affect road users' behavior. The present study explores factors associated with driver behavior through two approaches to examine how SCTs influence drivers' actions toward pedestrians violating red lights. In the first approach, through an on-road questionnaire survey, the self-reported behavior of 369 drivers when crossing an intersection enabled with SCTs was analyzed. In the second approach, the drivers' behavior was studied through naturalistic driving studies at two signalized intersections equipped with SCTs in Babol, Iran. Analyzing vehicle–pedestrian conflicts indicated that the presence of SCTs had a significant influence on driving behavior. Also, the ending seconds of green lights, as critical times of the SCTs, led to changes in driving behavior. Increasing the vehicle speed, changing lanes, and concurrent increases of speed and changing lanes were the common driver actions affected by critical times of the SCTs. Finally, the effect of critical times on drivers' actions during conflicts was modeled by using the binary and multinomial logistic methods. The results show that SCTs are an external factor that can lead to risky driver behavior, such as errors and violations that might increase the potential for pedestrian accidents.

Keywords

driver behavior, pedestrians, signalized intersection, traffic signals, human factors, safety

Generally, part of the time within the green light phase at signalized intersections is not used by road users at the beginning of the green phase which, consequently, reduces the intersection capacity. The sudden start of the green light and the lack of time for the driver to prepare the vehicle for movement, as well as the presence of pedestrians and motorcyclists, are the most common reasons for this. A signal countdown timer (SCT) at intersections is one of the appropriate traffic management measures for this.

The first installation of countdown signals was in the USA in 1998 (*1*, *2*). Since then, many cities have installed countdown signals for vehicles and pedestrians (*1–3*). SCTs are presumed to increase the capacity at intersections; however, it was found that the anxiety of drivers in the queue and crashes at intersections increased with the presence of SCTs (*4–7*). The primary basis behind the pedestrian countdown signal (PSCTs) is to aid pedestrians in getting off the road before being exposed to oncoming motor traffic (*8*, *9*). SCTs and PSCTs have become common at intersections in numerous countries in recent years. These two tools are simultaneously used at intersections where pedestrian volume requires a separate phase. SCTs and PSCTs function as part of a

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substantial procedure to increase capacity and increase road user safety at such intersections. In many countries, the operation of PSCTs also consists of three phases: a "green walking person" (WALK) phase followed by a "green flashing walking person" (FLASHING DON'T WALK) phase, and then a "red standing person" (STEADY DON'T WALK) phase (*5*, *9*, *10*). The green flashing walking person phase indicates that the red standing person phase is coming soon, and the red standing person phase indicates that one should not start to cross the street. In many studies, the role of SCTs and PSCTs on traffic flow characteristics such as capacity (*3*, *11*, *12*) and traffic safety (*6*, *13–15*) have been investigated. Some previous research reported the influence of using tools on increasing traffic safety (*6*, *14*, *16*). A study by (*17*) revealed that red light violations by drivers were reduced by 29% after the installation of SCTs. Another study showed that the reduction in the number of red light violations as a result of installing SCTs lasts for several months (*1*). A study (*18*) indicated that the installation of an SCT reduced the stress and waiting time for drivers to drive at the beginning of a new phase and that drivers could be more prepared to adapt to new conditions. Consistent with this result, other studies have declared more immediate adaption of drivers to conditions and consequential increases in intersection capacity (*3*, *12*, *14*, *19*, *20*). Also, some studies have reported the positive effects of PSCTs on increasing pedestrian volume. Furthermore, research (*8*, *10*, *21*) has shown that the presence of a PSCTs increases pedestrian reaction time and also increases pedestrian speed (*8*). Besides, the number of pedestrians increased on the Flashing Green (or Amber or Flashing Don't Walk) Signal by installing a PSCTs. Despite the positive influence of SCTs and PSCTs on traffic flow, some studies have reported their negative role in increasing traffic violations. Studies (*22–27*) have revealed that red light violations occurred before the onset of the green phase of SCTs. Likewise, increases in pedestrian red light violations at red phases of PSCTs have also been addressed in previous studies (*5*, *28–30*).

Despite several studies that have been conducted to assess the effectiveness of SCTs or PSCTs (*5*, *28–30*), a comprehensive study focusing on the behavior of drivers encountering pedestrians in the final seconds of SCTs has not been reported. This study aims to evaluate the behavior of drivers encountering pedestrians during the final seconds of SCTs, which coincides with the pedestrian red light violations in the final seconds of the red phase of PSCTs. The study will examine the role of SCTs on drivers' behavioral factors and investigate the naturalistic driving behavior of the drivers using an in-vehicle camera. The study hypothesizes that the final second of green SCTs may result in drivers performing risky actions. The study aims to determine the role of green SCTs on driver behavior and develop suggestions to improve drivers' behavior and SCT application by scrutinizing the results obtained through questionnaire data and real field data.

Material and Methods

Ethics Approval

The Babol Noshirvani University of Technology's human research ethics committee has approved this study, guaranteeing the protection of human participants. All participant data were kept anonymous and confidential throughout the study. Participants were recruited by the announcement of a cooperation request in the Traffic Research Laboratory at the Babol Noshirvani University of Technology, which was shared through local newspapers and social media.

Questionnaire Survey

Inappropriate driving behavior is associated with faults in driver actions that can, in critical situations, lead to accidents (*31–34*). Therefore, the classification and evaluation of different driving faults can aid in the identification of patterns of inappropriate driving behavior.

To design the present questionnaire, we attempted to analyze the set of driver action faults in four groups: lapses, errors, unintentional violations, and intentional violations. Although there are several definitions for these terms, they are similar. The following are some of the definitions in previous studies:

- Lapses: Actions are minor attention or memory failures or absent-minded behavior which may be frustrating or have negative consequences for the driver responsible, but normally do not threaten anyone's safety (*36–39*).
- Errors can be categorized as misjudgments or failures of observation with the potential for hazards or dangerous outcomes (*37–39*).
- Unintentional violations are behaviors that lead to violations of the law without any intention to do so (*39*).
- Intentional violations are behaviors that are intended to harm and violate the law and are considered to be a form of sabotage (*39*).

The present questionnaire evaluates how the role of SCTs negatively affects driving behavior. The initial concept for designing this questionnaire was inspired by the Manchester DBQ (*39*), together with other questionnaires from the existing literature (*40–42*). Accordingly, 12 questions with a six-point Likert scale (0 = never and 5 = nearly all the time) about the possible influence of

SCTs on driver behavior were considered in the present study, which is available in the appendix. The English version of the questionnaire formed the basis for translation into Persian while adapting it through back-translation. Native participants (fluent in Persian and English) cooperated in the translation of the items into Persian. Then, a professional translator translated the questionnaire into English, indicating no differences from the original version. Different expert groups in both countries also tested the questionnaire to confirm the compatibility between the English version and the translation of the test items. In total, 369 questionnaires were completed by 264 male and 105 female drivers of different ages (with a mean age of 29.25 and standard deviation of 8.30, a maximum age of 60 years, and minimum age of 20 years); education (High School, 12%; Bachelor, 61%; Master, 18%; Doctoral, 9%); driving license period (an average of 4.4 years and an average of 3,500 km per year); and occupation. To prevent traffic disruption and safety hazards, people waiting at the red lights were randomly asked to stop their vehicles beyond the intersection to participate in the survey. The intersections are described in the following section.

Factor Analysis. Factor analysis is a statistical technique for analyzing several variables and identifying the factors that explain the relationships between them. In social and behavioral sciences, it is often used to analyze questionnaire data, where researchers seek to identify latent factors contributing to a set of questions (*25*). Varimax rotation is a common method for simplifying the interpretation of factor structures identified in factor analyses (*25*). Factor loadings are rotated after extracting the factors using varimax rotation to maximize the variance of squared loadings. The rotation method simplifies the interpretation of the factor loadings, making it easier to identify the underlying factors that relate to the variables. In factor analysis, the term "factor loading" describes the relationship between each observed variable and the latent variable or construct it is intended to measure, which can be broken down into several principal components. Therefore, factor loading indicates how each observed variable (question) affects the latent variable (principal components). The factor loadings range from 0 to 1, with values closer to 1 indicating stronger effects of the observed variable (question) on the latent variables (*25*).

In questionnaire data analysis, factor analysis and varimax rotation can be used to identify common themes or constructs relevant to the variables being measured. A series of steps is usually followed by researchers when using factor analysis and varimax rotation to analyze questionnaire data. As a first step, they select the relevant questions that are relevant to their research question. As a next step, the data are transformed into a matrix that represents the correlations among the variables. Following this, a factor analysis is conducted to determine which factors are responsible for the correlations observed between the variables. Using varimax rotation on the factor loadings simplifies the interpretation of the factors. Finally, the results are interpreted and conclusions are drawn based on the factors identified.

The present study used SPSS software to perform the factor analysis. A factor analysis was conducted using the varimax rotation to analyze all variables. In addition, considering the coefficient of 0.862 for the Kaiser–Meyer–Olkin (KMO) test and 0.03 for the Bartlett test, the measure of sampling adequacy for using factor analysis in the present research is acceptable. The KMO test determines data suitability for factor analysis. In the test, each variable and the complete model are assessed for sampling adequacy. It measures the proportion of variance among common variables. KMO values between 0.8 and 1 indicate adequate sampling (*43*). The Bartlett's test tests homoscedasticity, that is, whether more than one sample represents the same population. The Bartlett's test can be used to verify that variances are equal across groups or samples, as in an analysis of variance (*44*). A p-value below 0.05 means that the null hypothesis is rejected and the sample is adequate, indicating that no two groups have the same variance. The Cronbach's alpha coefficients for the 12 questions of the four components of the study are: 1) Lapse (0.846); 2) Error (0.862); 3) Unintentional violation (0.884); and 4) Intentional violation (0.904). Therefore, the results show that the items have relatively high internal consistency, as a reliability coefficient of 0.70 or higher is considered "acceptable" in most social science research contexts.

Naturalistic Driving Study (NDS)

An approach called naturalistic driving study (NDS) is used to investigate driving behavior and patterns of drivers in real-world environments, which involves the installation of various data collection equipment such as cameras and sensors in participants' vehicles to record their actual driving behavior. The primary objective of NDS is to obtain a comprehensive overview of driving behavior in naturalistic environments to gain insights into the factors that contribute to road crashes, traffic conflicts, and other driving-related incidents (*45–49*). A traffic conflict occurs when two or more vehicles, pedestrians, or cyclists approach each other in a way that creates a potential risk of collision or when a driver engages in a behavior that increases the risk of an accident. Traffic conflicts are different from actual crashes or accidents, but they can be used to identify potential hazards on the road and areas where improvements in infrastructure or driver behavior are needed to prevent accidents from occurring in the future. Video recordings

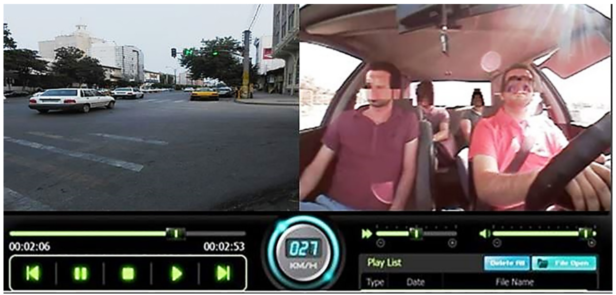

Figure 1. A driver is watching a signal countdown timer (SCT) at the intersection.

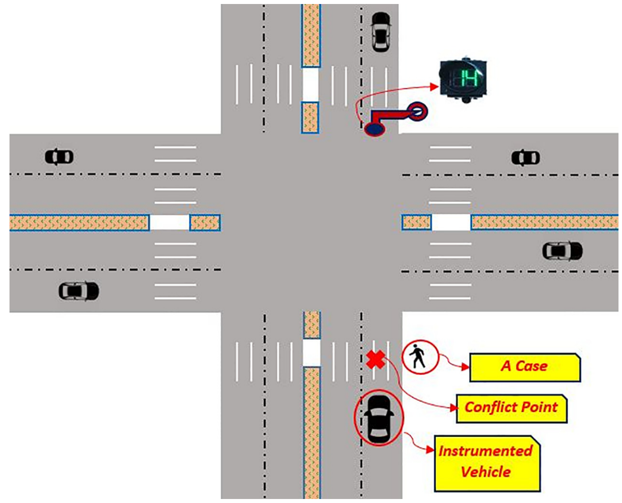

Figure 2. A schematic pattern of case study (pedestrian crossings did not have pedestrian countdown signals [PSCTs]).

from cameras and in-vehicle sensors can be used to identify traffic conflicts by analyzing the footage for instances of close calls, sudden stops, or evasive maneuvers by drivers.

In the present study, the behavior of 28 drivers was studied through NDS in Babol, Mazandaran, Iran (Figure 1). The 28 participants (16 men, 12 women; 18–40 years; valid driving license with an average of 4.1 years; and an average of 3,800 km per year) participated during peak hours (7:30–8:30, 12:30–13:30, and 17:30–18:30) in this research. In the present study, the number of data (traffic interaction) for sufficient statistical power exceeded the suggested values using Cochran's formula. Cochran's formula is a statistical formula used to calculate the sample size needed for a categorical data analysis with a specified level of precision and confidence interval. It is typically used in survey research to determine the appropriate sample size needed to estimate the proportion or frequency of a specific attribute or characteristic in a target population. The participants in the NDS were not among those who filled in the on-road questionnaire; this was to avoid the influence of a participant's prior knowledge about the purpose of the study and the presence of SCTs so that this does not affect their actual driving behavior. However, the intersections considered in both the questionnaire and the NDS approaches were the same locations. The drivers drove on urban roads in Babol city, Mazandaran province, Iran, with a maximum annual average daily traffic (AADT) of 4,550 vehicles per day (vpd) and a 30 km/h posted speed limit. Participants were asked to drive for about 1 h along these roads. The vehicle-mounted camera was the CARPA-120 Dual Dashcam that records both what is happening inside and outside of the vehicle. When playing the recording back, it is possible to get GPS map data pinpointing participants' exact location as well as speed and rate of acceleration in G's (the acceleration of gravity). The CARPA-120 also records the interior audio and has a playback resolution of 640 × 480 DVD quality. Two intersections (Shahrebani and Ganjineh) located in Babol were selected for further analysis. The two intersections are located on Modaress street, which has a high daily traffic volume (maximum annual average daily traffic of 4,000 vpd) as it is the central street of Babol (Pedestrian volume: 209 ped/h). Neither location had PSCTs at pedestrian crossings. Considering the various turning directions in each of these intersections, the possible influence of SCTs on driver actions was investigated.

Figure 2 presents a typical layout of one of the intersections. It can be seen that left turns are not permitted and the right lane is simultaneously used for right turns and straight forward movements. Each signal phase gives permission to the straight and right turn movements for both directions of the road with a constant cycle length of 60 s.

In total, out of 303 vehicle–pedestrian interactions, 117 cases of vehicle–pedestrian conflicts (Figure 2) were identified by manually examining the videos recorded inside the vehicle frame by frame. A conflict case was considered as any change in movement style or direction by the pedestrian or driver when encountering each other to prevent a collision (*50–52*).

The set of independent variables on the behavior of drivers and their different actions were identified during the conflicts with pedestrians crossing the intersection. By observing the videos recorded during driving, the independent variables were considered at different time intervals (Table 1).

Binary Logistic and Multinomial Regression Models. The binary logistic regression technique is used to analyze the relationship between a set of predictor variables and a binary

Table 1. Variables

Code	Variable	Description	Value
SPD	Speed	The speed of the vehicle	(km/h)
DST	Distance	The distance between vehicle and pedestrian at the time of encounter	meters
LIC	License	Driver's license time	years
T	Time	Ending seconds of SCTs when the driver makes a decision	seconds
EXP	Experience	Crash experience	Yes = 1, No = 0
D.AGE	Driver age	Driver age	Under 25 years = 1, 25–35 years = 2, + 35 years = 3
D.GDR	Driver gender	Driver gender	Male = 1, Female = 0
D.PRF	Driver action	Does the driver change their current style of driving while encountering a pedestrian at the SCTs?	Yes = 1, No = 0
T.D.PEF	Type of driver action	What kind of reaction does the driver have when they encounter an SCT at the intersection?	Acceleration: 1 Changing lane:2 Braking: 3 Deceleration: 4 Horn: 5 Lighting (high beam) on the front vehicle: 6

Note: SCT = signal countdown timer.

outcome variable. It is particularly useful when the outcome variable has only two possible outcomes, often referred to as success or failure (*48*). Binary logistic regression involves estimating probability based on the values of the predictor variables to estimate the likelihood of the outcome variable. Predictor variables can either be continuous (e.g., vehicle speed) or categorical (e.g., driver age). A binary outcome variable could be used in this case to indicate whether the driver successfully avoided a pedestrian (1) or not (0). An analytical logistic regression model transforms a linear combination of predictor variables using a logistic function that maps the linear combination to a value between 0 and 1. With the logistic function, it is possible to model the relationship between predictors and success probabilities in a way that is suitable for binary outcomes (*48*). Typically, a logistic regression model requires a data set that contains observations of the predictor variables and corresponding outcomes. Following this, the model estimates the coefficients associated with each of the predictor variables, indicating the degree and direction of their influence on the outcome. These coefficients are often interpreted as odds ratios, which quantify the change in odds of success (or failure) for a one-unit change in the predictor variable. Based on the values of the predictor variables, the logistic regression model can predict the probability of success for new observations. It provides insights into the factors contributing to successful outcomes and can be used to identify areas that require improvement or intervention (*48*).

In the present study, the goal of using a binary logistic regression model is to identify the factors determining the probability of driver action, considering all observed interactions at SCTs. In the binary logistic regression, there are only two possible outcomes for the dependent variable (i.e., driver action versus no driver action). The explanatory variables indicate the factors affecting the probability that a vehicle–pedestrian interaction may result in a conflict. The general form of the logistic regression model is as follows (*43*). Pr (Y_i) is the probability of the driver performing a given action (Y = 1 for action, Y = 0 for non-action) at the ith interaction; Xk,I denotes the independent variable k affecting the occurrence of driver action for each interaction i, with β_k being the coefficient for each X.

$$\mathrm{logit}(p_i) = \ln\left(\frac{p_i}{1-p_i}\right) = \alpha + \beta_1 X_{1,i} + \beta_2 X_{2,i} + \ldots + \beta_k X_{k,i}, \qquad i = 1, 2, \ldots, n \tag{1}$$

$$\Pr(Y_i = 1|x) = \frac{e^{\mathrm{logit}(p_i)}}{1 + e^{\mathrm{logit}(p_i)}} \tag{2}$$

The multinomial logistic regression method is a statistical method for analyzing the relationship between multiple categorical response variables and a set of predictor variables (*48*). It is an extension of binary logistic regression, which predicts binary outcomes. Multinomial logistic regression involves a dependent variable with three or more categories. On the basis of the values of the predictor variables, the probability of each category occurring is estimated. The model assumes that the relationship between the predictor variables and the probabilities of different responses follows a multinomial distribution.

Table 2. Factor Analysis Result

Component/Question	Factor loading	Mean
Lapse (coefficient: 0.246)		
1. Trying to cross the intersection in third gear or higher to observe the last seconds of SCTs.	0.59	0.39
5. You are distracted from the road by a SCTs and as a result, it is difficult for you to detect whether the vehicle in front has slowed down and you have to brake to avoid a crash.	0.89	1.45
7. Because of the long time remaining on the SCT for a particular phase, you have chosen another, albeit longer, route.	0.41	0.42
Error (coefficient: 0.853)		
8. At intersections, regardless of the main traffic light, check for permissible or unauthorized crossings only by viewing the SCT.	0.93	1.12
9. As soon as SCT starts, you would not check the intersection before moving to make sure the remaining vehicles are out from the previous phase.	0.90	1.39
11. You are distracted by seeing the SCT and do not notice the pedestrians crossing the street.	0.88	1.09
Unintentional violation (coefficient: 0.342)		
2. After observing the SCT and crossing the intersection, look at your speedometer and realize that you unintentionally exceeded the speed limit.	0.53	0.91
6. Viewing the SCT makes you unable to see a vehicle coming from behind.	0.71	0.82
12. By observing the last seconds of SCT you have forgotten to engage the indicator before beginning a right or left turn maneuver.	0.87	1.32
Intentional violation (coefficient: 0.693)		
3. Observing the last seconds of SCT causes you to overtake the vehicle in front in any way possible (zigzag movement, unauthorized speed).	0.86	1.29
4. To cross the intersection before stopping in the last seconds of the SCT, you show aggressive behavior such as sequential beeps or high beams to poll over the front vehicle.	0.73	1.15
10. The long time remaining on the of SCT in the early morning or late at night encourages you to cross the intersection at excessive speed.	0.82	0.88

Note: SCT = signal countdown timer.

Model parameters are estimated using maximum likelihood estimation (*48*). Parameters represent the effect of predictor variables on the odds or probabilities of each category relative to a reference category. The model employs a set of binary logistic regression equations, one for each category of response, where the probability of a particular category is compared with the probability of a baseline or reference category. Each category's probabilities areodellind using a logistic function, which ensures that the predicted probabilities are between 0 and 1.

The present study examined, through multiple logistic regression, the impact of independent variables on the type of driver action following the definition of independent variables by logistic regression. It is possible to categorize drivers' performance while encountering pedestrians into different types, including braking, deceleration, acceleration, horn/high beam, and changing lanes of travel (see Table 1). For a dependent variable Y with K categories, and a set of independent variables X_1, X_2, …, X_p, the probability of Y taking on each category k is given by:

$$P(Y = k) = \exp(\beta_{k0} + \beta_{k1}X_1 + \beta_{k2}X_2 + \ldots + \beta_{kp}X_p)/1 + exp(\beta_{K0} + \beta_{K1}X_1 + \beta_{K2}X_2 + \ldots + \beta_{Kp} \times X_p) \quad (3)$$

where β_{k0}, β_{k1}, β_{k2}, …, β_{kp} are the coefficients associated with each independent variable X_p for category k. In essence, the model calculates the probabilities of each category of the dependent variable based on the values of the independent variables. The coefficients determine the relationship between the independent variables and the log-odds of the respective categories. The model uses the softmax function to normalize the probabilities and ensure they sum up to 1 for all categories.

Results

Analyzing the Questionnaire Data Using Factor Analysis

Table 2 shows the factor loadings of each question for each group (component). Table 2 also presents the results of the questionnaire data analysis in the form of descriptive statistics (mean and standard deviation), factor loading, and other characteristics of the questions related to the four components. The factor loading and each factor are presented in Table 2. T-values were used to evaluate the fit of the structural model. At a 95% confidence level, t-values > 1.96 indicate a statistically significant result for the relationship between factors in the model. It should be noted that the values only represent the accuracy of a relationship, not its strength. Statistically, the variables included in the model were significant through relationships between variables at a 95% level. Survey responses were recorded for the SCTs. Table 2 illustrates the relationship between the latent variables and questions based on driver responses. Additionally, all four components are significant influences on driver responses at a 95% confidence level (t-test); their coefficients can be found in Table 2. A low coefficient indicates that the factor has little impact on driver behavior. Therefore, unintentional violations (coefficient: 0.342) and lapses (coefficient: 0.246) had a lesser impact on driver behavior. In addition, driving errors (coefficient: 0.853) and intentional violations (coefficient: 0.693) are two important factors affecting driver behavior.

Analyzing the NDS Data Using the Regression Model

Studies of films recorded during the experiment showed that participants displayed various actions when observing the ending seconds of the SCTs, especially in the last 10 s. In other words, they changed their current driving styles especially in short intervals (0–10 s) with actions such as increasing or decreasing speeds or changing lanes to overtake other vehicles before the light went off.

Of the 117 conflict samples detected in which drivers reacted, 22 reacted within the last 3 s of green SCTs. In addition, 21 reactions and 20 reactions were identified in the 3 to 6 and 6 to 9 time periods, respectively. Other behavioral changes by drivers at different time intervals are shown in Figure 3. Overall, more than half of the drivers' reactions were applied in the final 10 s of the green SCTs. Therefore, to evaluate the behavior of individuals accurately, three intervals of 0 to less than 3 s, 3 to less than 6 s, and 6 to less than 9 s were selected as critical times in evaluating the action of drivers (Figure 3).

A Binary Logistic Regression Model

The probability of a change in driver behavior during the last seconds of the SCTs was investigated through the logistic regression method. The model's dependent variable indicates any change in the behavior of drivers (Y = 1) or a lack of change (Y = 0; continued with the previous driving style). In other words, whenever a driver changes their driving behavior style by performing actions such as accelerating, decelerating, or changing lane, this

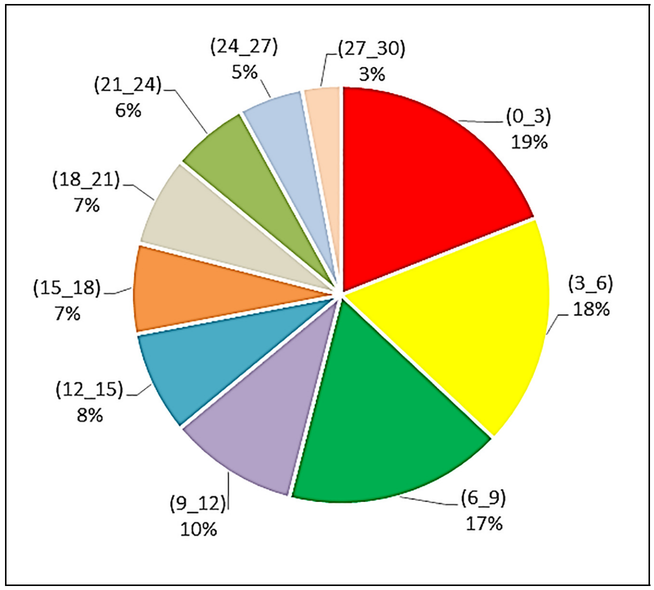

Figure 3. Changes in driving behavior of participants at different time intervals of signal countdown timers (SCTs).

event is considered a change in driver behavior. As a first step, non-significant variables were identified by their coefficients. After determining these variables (coefficients greater than 0.05), they were eliminated from the original model, and the modelling process was resumed with the remaining variables. Correlations between continuous and discrete variables were also determined by Pearson and Chi-square tests. The results indicated that there was no significant correlation between the variables.

The effects of SCTs on the action of drivers on effective time intervals of 0 to 3, 3 to 6, and 6 to 9 s were identified (critical times), and models of driver actions facing pedestrians were eventually based on vehicle speed, the distance from the vehicle to the pedestrian crossings, and the driver's age (Table 3). The goodness of fit for the model was evaluated using the Hosmer–Lemeshow test. The test compares the number of observed events to the expected number of events. Considering the p-value of this test (above 0.05), the model is fitted to the data well. According to Table 3, in various time intervals of SCTs, drivers show different behaviors while approaching the intersections. Analyzing the collected data showed that the independent variables (Speed, Distance, and Age) do not affect the same trends in driver behavior during the final seconds of SCTs. In fact, in different time intervals, each of these variables can have either a positive or negative effect on the probability of a change in driver behavior.

Multinomial Regression Model

The multinomial logistic regression model was used to model the specific type of driver actions. As mentioned in

Table 3. Estimation Logistic Regression Model on Driver Action

Variable	βi (Coefficient) 0–3	3–6	6–9	p-value 0–3	3–6	6–9
SPD	−0.081	−0.302	+ 0.79	0.002	0.001	0.01
DST	+ 0.72	+ 1.63	−0.34	0.015	0.019	0.00
D.AGE	−0.274	−0.57	+ 0.351	0.010	0.013	0.027
Constant	−1.161	−0.630	−0.855	0.004	0.000	0.001

Note: SPD = speed; DST = distance; D.AGE = driver age.

Table 4. Estimation of Multinomial Logistic Regression Models on Driver Action (Acceleration as the Reference Group)

		Changing lane $h_1(x)$			Braking $h_2(x)$			Deceleration $h_3(x)$			Horn/high beam $h_4(x)$		
Model	Variable	βi	p-value	Odds ratio	βi	p-value	Odds ratio	βi	p-value	Odds ratio	βi	p-value	Odds ratio
I(0-3 s)	DST	0.421	0.013	1.524	0.515	0.005	1.674	0.255	0.140	1.291	0.404	0.027	1.498
II(3-6 s)	SPD	0.121	0.037	1.129	0.236	0.021	1.267	NS	NS	NS	NS	NS	NS
	DST	NS	NS	NS	NS	NS	NS	0.181	0.038	1.199	NS	NS	NS
Model information		Model fitting criteria				I (0-3 s)					II (3-6 s)		
		-2 log-likelihood:				(95.594); (70.126)					(151.189); (118.663)		
		(intercept only); (final)				12					12		
		Likelihood ratio tests				0.013					0.001		
		df									181.358		
		Sig									0.228		
Goodness-of-fit		Pearson (chi-square)				74.648					0.205		
		Sig				0.844							
		McFadden's pseudo R-squared				0.248							

Note: SPD = speed; DST = distance; D.AGE = driver age; NS = non-significant.

the previous section, three significant intervals were used as critical times of the SCTs on driver action changes. Three different multinomial regression models were used to examine more accurately how each of the variables could affect each driver's specific actions. Each of these intervals shows the model of driver action selection at each 3-s time interval. Table 4 shows the variables and their coefficients for the five actions. In the present study, vehicle acceleration was taken as the base action in the model estimation, then the parameter estimates of other actions were defined and compared with it. Moreover, given the low frequency of behavior such as sounding the horn and showing a high beam, the two actions were merged. The models of driver actions during critical countdown times are presented in Table 4. The model fitting information in Table 4 compares the full model (i.e., containing all the independent variables) against a null (or intercept-only model, i.e., no independent variables) for all models of critical countdown times. Statistical significance for all three models indicates that the full model represents a significant improvement in fit over the null model (p-value < 0.05). Also, Pearson's chi-square tests for all models indicate that the models fit the data well (p-value > 0.05). Table 4 shows that the variables of speed and distance at different times can influence the decision of the driver resulting in them performing different actions at a 95% significance level (p-value $\leqslant 0.05$). According to Table 4, and by applying the acceleration as the base action, the odds ratio of the other actions to this type of driver action is determined for each of the independent variables.

Discussion

Lapse

Based on Table 2, drivers reported being distracted by the SCTs (lapses component) as a result of observing the SCTs. Subsequently, drivers were sometimes forced to slow down by other vehicles on the road. In the absence of a safe distance (Q5; FL: 0.89), it is foreseeable that abrupt brake pedal changes will lead to rear-end collisions. Some drivers reported that in some cases they were willing to cross the intersection in third or even fourth gear, causing them to pay less attention to oncoming traffic and drive at a higher speed (Q7; FL: 0.41). Another group of drivers reported that observing a timer with a high time cycle affected their route (Q1; FL: 0.59). The possibility of route changes increasing traffic on a specific road can be created if the demand for route changes exceeds the road's capacity. Given the lack of attention given by drivers to pedestrian traffic and traffic on other roads, incomplete data have been collected from the route, and consequently, the road environment has not been properly understood. As a result, drivers were most likely not able to see the pedestrians on the road and pedestrian crashes were inevitable if pedestrians were not careful.

Error

Failure to pay attention to other roads can also lead to a computational error when estimating distances to other vehicles and pedestrians (Q11; FL: 0.88). Moreover, data analysis shows distracted drivers are less likely to pay attention to the main traffic light at the intersection (Q8; FL: 0.93). Countdown problems can be associated with disrupting traffic, causing congestion, or causing other traffic delays. For example, consider stopping the countdown because of a fault in the technical system, or having trouble showing the green or red at once; traffic delays will occur in other phases. Some drivers also stated that as soon as the SCTs entered the green phase (Q9; FL: 0.90), they would start moving through the intersection without paying attention to whether it was empty. It seems that the SCTs can be served as a motivating tool to encourage drivers to take faster, but also riskier, actions.

Unintentional Violation

Unintentional violations include failing to show the type of turning movement (left or right) by drivers in the last seconds of SCTs. The increasing complexity of driving conditions can be associated with drivers' loosing focus and crossing the intersection quickly without declaring their movement type (turning movement). Such behavior can be associated with side- and rear-end crashes if not anticipated by other drivers. Also, observing the last seconds of SCTs can be associated with reducing drivers' focus on their actions based on their direct movement, maintaining current conditions, and also the actions of other drivers (approaching the vehicle), according to the reports from drivers.

Intentional Violation

The study also identified some intentional violations. The category of intentional violation includes aggressive behavior, such as overtaking with horns or high beams and acceleration with horns (Q3; FL: 0.86). Zigzag movements (Q4; FL: 0.73) to cross the intersection before the end of SCTs are also risky behavior that can be associated with causing traffic disruption, increasing the likelihood of collisions with other vehicles or pedestrians, and inducing anxiety among drivers. Furthermore, SCTs at intersections can be associated with abnormal and illegal behavior, such as crossing at red lights at midnight or in the morning at intersections when they are not accommodated for multiple traffic volumes throughout the day (Q10; FL: 0.82).

Distance

During the intervals of 0 to 3 s and 3 to 6 s, drivers were more prone to changes in their driving behavior at distances beyond the intersection. When they notice that there is less time remaining, drivers who are far from the intersection tried to cross the intersection by changing their behavior, possibly realizing that, without the change, they would not be able to cross the intersection before the time runs out. By reviewing the recorded films, it was found that 43% of the drivers changed their behavior by accelerating, 14% by changing lane, 21% by both accelerating and changing lane, and 11% by sounding their horn. Also, 14% of drivers decreased their vehicle speed, considering they would not be able to get out of the intersection within the remaining time. For intervals of 6 to 9 s, drivers at short distances did not make any significant changes to their position, but at further distances, about 25% of drivers slowed down and stopped before the intersection.

Driver Age

In general, many traffic safety studies have shown that driving action depends to a great extent on the physical and mental characteristics of drivers with regard to processing, analysis, decision making, and response. The ability to process and analyze information better and faster in challenging driving conditions is more pronounced in younger drivers than older drivers. According to the current study, young drivers are more likely to change their driving behavior when approaching an intersection for periods of 0 to 3 s and 3 to 6 s. On reviewing the recorded films, it was found that 29% of the drivers changed their behavior by accelerating, 19% by changing lanes, and 15% by both accelerating and changing lanes. Older drivers prefer to maintain the same driving behavior, despite their not being able to cross the intersection before the end of the remaining time. As a result of reviewing the recorded films, it was determined that 67% and 56% of the drivers drove at the same speed and in the same direction. In 6 to 9 s, behavioral changes were not observed among younger groups, while older drivers showed a greater tendency to change driving behavior during NDS studies.

Speed

Drivers who decide to cross the intersection at critical times (less than 10 s) make different decisions with regard to driving speed. Speed variable coefficients are negative in time intervals of 0 to 3 s and 3 to 6 s. This shows that drivers who drove at higher speeds were less likely to change their behavior. Investigating the recorded films (for the time interval of 6 to 9 s) showed that the tendency for acceleration (54%), deceleration (17%), and changing lanes (26%) was increased by drivers. In this situation, drivers were more likely to change their driving style. In intervals of 6 to 9 s, the speed variable coefficient is positive. The results of this study show that drivers who drive at higher speeds are more likely to change their behavior. The recorded films showed a tendency for drivers to accelerate (61%), decelerate (12%), and change lanes (19%).

Different Types of Driver Action

Table 4 shows that only in the time intervals of 0 to 3 and 3 to 6 s, do the two variables of speed and distance lead to behavior changes in drivers. For example, during a time from 0 to 3 s, distance is the main factor that affects a driver's decision to react by changing lanes, braking, or horn/high beam rather than acceleration. A βi coefficient of 0.421 for the ratio of changing lanes to acceleration during the time interval 0 to 3 s indicates that when the distance between the vehicle and the pedestrian is high, drivers are more likely to react by changing lanes to try and cross the intersection. Assessing recorded videos showed that 10 cases of conflicts came up when the drivers changed lanes, whereas only eight cases resulted from a driver's decision to accelerate. The odds ratio of these two variables (1.524) shows that the driver's decision to change the lane compared with acceleration increases the probability of vehicle–pedestrian conflict by 52%. The probability of a vehicle–pedestrian conflict in times from 0 to 3 s where the driver intends not to cross the intersection by braking is 67% higher than if the driver attempts to cross the intersection by accelerating. Based on recorded videos, 10 of the conflicts occurred when drivers braked, while six occurred when drivers attempted to accelerate. Besides, although the driver braking behavior led the pedestrian to start crossing, there was not enough time (safe gap) for pedestrians to cross the road. Consequently, this driver's decision increases the potential for collision between vehicles and pedestrians. That is why the pedestrian reacts with behaviors such as running or returning to the edge of the road to prevent a collision with the vehicle. During the time interval of 0 to 3 s, the driver's decision to use a horn/high beam was another factor that would increase the odds of a vehicle–pedestrian conflict by 49% compared with the decision to accelerate. In fact, at long distances with a short time interval on the SCT until the lights turn red, drivers decided to pull the front vehicles off the road by activating their horn/ high beam, which subsequently increases the possibility of collision between those vehicles and pedestrians crossing the road. Meanwhile, the evaluation recorded videos showed that the driver's decision to use the horn/high beam was observed in five cases of conflict. This aggressive driver behavior reduces pedestrian safety. In the second time interval of 3 to 6 s, there is a relatively similar effect of the role of time on the distance variable as well as the vehicle speed on the probability of vehicle–pedestrian conflict. According to the results of the models in Table 4, speed is a factor that encourages the driver to attempt to cross the intersections by changing lanes during the rest times in the green phase of SCT. In this case, the probability of a conflict between a vehicle and a pedestrian increases by 12% compared with only accelerating. In 23 cases of conflicts, the drivers changed lane, while in 18 cases the driver decided to accelerate. Table 4 also indicates that for each unit increase in the speed of the vehicle, the possibility of a vehicle-pedestrian conflict occurring would increase by 26% when the driver decides to brake. Although the ratio of conflicts between a driver's braking decision and a driver's acceleration decision was one-third (6 cases versus 18 cases), this action increased the odds of a conflict occurring. The lack of a proper safe gap for pedestrians, in this case, was a factor that led pedestrians to perform evasive behavior such as running or turning back to prevent a collision with the vehicle. This also occurred when the driver's action was deceleration. In this situation, the pedestrian starts crossing the road given the long distance between them and the approaching vehicle, but they do not have enough time to cross the road given the high speed of the vehicle (despite the driver's action being deceleration). Table 4 shows that in this case, the odds of a conflict occurring increase by about 20% compared with the case of the driver deciding to cross the intersection with an acceleration action. It should be noted that the results show that none of the variables were significant in the time interval of 6 to 9 s, so the results are not presented in Table 4. Based on the recorded films, drivers' actions in conflicts with the pedestrians in a time interval of 6 to 9 s were: acceleration (6 cases), changing lanes (6 cases), braking (9 cases), deceleration (2 cases), and horn/high beam (4 cases).

The Findings and Comparison with Previous Research

The findings of the present study indicate that SCTs are associated with influencing driver behavior, with drivers reporting lapses, errors, unintentional violations, and intentional violations when faced with SCTs. Inattention to traffic flow and pedestrians crossing when observing SCTs, as well as inattention to the main traffic light, were identified as significant factors contributing to driver behavior. The study also revealed that factors such as vehicle speed, the distance between the vehicle and the pedestrian, and driver age are associated with influencing driver decision making in such situations. The study further examined the effects of green SCTs on driver actions at different time intervals, with the results indicating that driver behavior changes significantly in the first 6 s. The comparison of self-reported and naturalistic driving data showed that SCTs are associated with increasing the potential for collisions with other road users, particularly pedestrians. The study suggests that SCTs may have a negative influence on driving behavior and highlights the need for further research to better understand their impact. There have been several previous studies on the influence of SCTs and pedestrian signal countdown timers (PSCTs) on driver behavior. Some of these studies have shown that SCTs and PSCTs can reduce pedestrian–vehicle conflicts and improve safety at signalized intersections by improving driver awareness of the remaining time for the signal phase (*53*, *54*). Other studies have found that SCTs and PSCTs can have unintended consequences, such as increasing driver anxiety, reducing compliance with traffic signals, and increasing the likelihood of red light running (*55*, *56*).

In comparison with previous studies, the present research specifically focused on the influence of SCTs on driver behavior when encountering pedestrians. The study found that SCTs are associated with making drivers exhibit risky behavior, such as unintentional and intentional violations when encountering pedestrians at signalized intersections. The study also identified several factors that can be associated with these risky behaviors. These factors include inattention to traffic flow and pedestrians crossing when observing SCTs, as well as inattention to the main traffic lights at the intersection. The study highlights the potential negative consequences of SCTs on driver behavior and the importance of properly functioning SCTs in preventing traffic disruption and congestion. Looking at consistency with previous studies, the finding that SCTs can influence driver behavior and lead to unintentional violations is consistent with the findings of previous studies (*19*). Additionally, the finding that SCTs can increase the potential for collisions with other road users, particularly pedestrians, is consistent with the findings of previous studies (*57*, *58*).

Conclusions and Further Research

In the present research, driver behavior and action when encountering pedestrians under the influence of SCTs were studied through an on-road questionnaire study and NDS in Babol city, Mazandaran province, Iran. The results of the questionnaire data analysis confirmed the hypothesized effect of SCTs on driver behavior. Accordingly, self-reported driver behavior when faced with SCTs was categorized into four categories: lapse, error, unintentional violation, and intentional violation. There were three significant factors contributing to these driver behaviors, including their inattention to traffic flow and pedestrians crossing when they observed SCTs as well as their inattention to the main traffic lights at the intersection. When the countdown process is not functioning properly, these can be associated with traffic disruption and congestion.

An analysis of the subset of NDS data recorded at epochs less than 10 s confirmed the hypothesized effect of SCTs on driver behavior. The results indicate that there were three significant factors contributing to these driver behaviors, including their inattention to traffic flow and pedestrian crossings when they observed SCTs, as well as their inattention to the main traffic lights at the intersection. As a result, when the countdown process fails to function properly, there is a chance of occurrence of traffic disruption and congestion. Also, factors such as vehicle speed, the distance between the vehicle and pedestrian, and the driver's age are all likely to influence driver decisions in such situations. Finally, the effects of green SCTs on specific types of driver actions at different intervals of 0 to 3 s, 3 to 6 s, and 6 to 9 s (critical times) were presented using the multinomial logistic regression method. Based on our findings, the drivers perform almost the same in intervals of 0 to 6 s. In contrast, their behavior during the period of 6 to 9 s differs from that observed during the period of 0 to 6 s. As a result of the changes in the behavior of the drivers in the first 6 s being significant at a 95% level, the variables of distance and speed had an effective impact on these changes. At the 95% level, however, none of the reactions in the range of 6 to 9 s were significant.

The comparison of the results from the drivers' self-reported behavior in the questionnaire-based data as well as the natural driver behavior in the NDS-based data showed that SCTs change driving behavior. These changes can be associated with the increase in the potential for collisions with other road users, especially pedestrians, given the potentially risky behavior of the driver. Inadequate timing for an action, failure to choose an appropriate action, or even not taking action as a result of an incorrect judgment, can be related to the observation of the SCTs. These are consequences that indicate the negative influence of SCTs can have on driving behavior.

Below are some of the implications that can be drawn based on the provided research findings. In addition, some practical suggestions can be made based on these implications.

1. Lapses and distractions: The presence of SCTs can lead to driver distractions, particularly in observing the SCTs themselves. This distraction can result in lapses in attention and drivers being forced to slow down abruptly because of other vehicles on the road. These abrupt braking actions increase the risk of rear-end collisions, highlighting the importance of maintaining a safe distance.
   - Road authorities should carefully consider the placement and design of SCTs to minimize driver distractions.
   - Drivers should be educated about the potential distractions caused by SCTs and encouraged to maintain focus on the road and surrounding traffic.
   - Emphasize the importance of maintaining a safe following distance to allow for smooth and gradual braking, reducing the risk of rear-end collisions.
2. Route changes and traffic: Driver attention to SCTs, especially timers with longer cycles, can influence their route decisions. If the demand for route changes exceeds the road capacity, it can lead to increased traffic on specific roads, potentially causing congestion and delays.
   - Provide real-time traffic updates and alternative route suggestions through GPS navigation systems or mobile applications to help drivers make informed decisions and distribute traffic more evenly.
   - Implement dynamic traffic management systems that adjust signal timings based on traffic conditions, allowing for smoother flow and reducing the likelihood of congestion.
3. Pedestrian safety: Drivers' lack of attention to pedestrians and other roads as a result of SCT distractions can result in incomplete data collection and a lack of understanding of the road environment. This lack of attention increases the likelihood of pedestrian crashes if pedestrians are not careful. Enhancing driver awareness and attentiveness to pedestrians is crucial for pedestrian safety.
   - Increase driver awareness and attentiveness to pedestrian crossings through public awareness campaigns and driver education programs.
   - Implement infrastructure improvements, such as clearly marked crosswalks, pedestrian signals, and traffic calming measures, to enhance pedestrian safety.
4. Errors and computational issues: Inattentiveness to other roads and traffic lights as a result of SCT distractions can lead to errors in estimating distances to other vehicles and pedestrians. This computational error can increase the risk of collisions. Technical issues with countdown timers or difficulties in perceiving green or red lights can disrupt traffic flow and cause delays.
   - Regularly maintain and calibrate signal countdown timers to ensure their accuracy and reliability.
   - Conduct comprehensive testing and quality control measures to minimize technical issues with countdown timers.
   - Improve visibility and legibility of traffic lights to enhance drivers' ability to perceive green and red lights accurately.
5. Intentional violations: SCTs may contribute to aggressive driving behavior, such as overtaking with horns or high beams and making risky maneuvers, such as zigzag movements, to cross the intersection before the end of the countdown. These intentional violations can disrupt traffic, increase the likelihood of collisions with vehicles and pedestrians, and induce anxiety among other drivers.
   - Enforce strict traffic regulations and penalties for aggressive driving behaviors, such as horn usage, unsafe maneuvers, and violations during signal countdowns.
   - Increase traffic law enforcement and surveillance at intersections to deter intentional violations.
   - Educate drivers on the potential risks associated with aggressive driving and the importance of patient and responsible behavior.
6. Driver age and behavior: Younger drivers tend to exhibit more behavior changes when approaching an intersection within specific time intervals, while older drivers tend to maintain their driving behavior. Understanding the age-related differences in driver behavior can inform targeted interventions and training programs to improve safety for different age groups.
   - Develop targeted training programs and interventions tailored to specific age groups to address their unique driving behaviors and promote safe driving practices.
   - Raise awareness among younger drivers about the potential consequences of behavior changes near intersections and the importance of maintaining consistent driving behavior.
7. Speed and driving behavior: Drivers' decisions to cross the intersection and their behavior depend

on their driving speed. Higher speeds are associated with less behavior change, while lower speeds increase the likelihood of behavior changes such as acceleration, deceleration, or changing lanes. Drivers' speed choices can influence their driving style and potentially affect safety.
   - Conduct speed management campaigns to promote responsible driving and adherence to speed limits.
   - Implement traffic calming measures, such as speed humps or roundabouts, to naturally encourage lower speeds and safer driving behavior near intersections.
8. Driver actions and conflicts: Analysis of driver actions during specific time intervals revealed the relationship between speed, distance, and different types of driver behavior. Factors such as changing lanes, braking, sounding the horn, or using high beams had varying effects on the likelihood of conflicts between vehicles and pedestrians. Understanding these relationships can help identify critical points where interventions could be implemented to improve safety.
   - Enhance driver education with regard to the relationship between speed, distance, and different types of driver behavior to improve decision making at critical points.
   - Implement targeted interventions, such as signage or road markings, to mitigate conflicts between vehicles and pedestrians in identified high-risk areas.

It should be noted that implementing these suggestions may require coordination between road authorities, traffic engineers, law enforcement agencies, and driver education programs. Continual monitoring and evaluation of the implemented measures are also essential to assess their effectiveness and make necessary adjustments.

The present study acknowledges several limitations that may affect the generalizability of its findings. Firstly, the study was conducted in a specific geographic location (Babol city, Mazandaran province, Iran) and may not be representative of driver behavior in other regions or countries. Therefore, caution should be exercised when generalizing the results to other populations. Secondly, the sample size for both the questionnaire study and NDS was relatively small, which could limit the statistical power of the analyses. Additionally, the NDS only recorded driving behavior during the daytime, which may not fully capture driver behavior at night or in different weather conditions. Finally, the study relied on self-reported data from the questionnaire, which may be subject to response bias or social desirability bias. In addition, the NDS may have limitations in capturing all aspects of driving behavior, as it was not possible to observe all traffic conditions or driver actions. To address the limitations of the present study, future research could consider using larger sample sizes from different geographic locations to increase the generalizability of the findings. Future studies should include a greater number of drivers to examine the differences in behavior among drivers by analyzing variables such as driving experience, age, and gender. Additionally, it may be beneficial to include a control group that does not encounter SCTs to compare their driving behavior and actions with those who do encounter SCTs. Furthermore, to overcome the potential bias of self-reported data, future studies could incorporate a combination of NDS and objective measures of driver behavior, such as eye-tracking or physiological measures. Lastly, future research could investigate the potential impact of other contextual factors, such as weather conditions or time of day, on the effects of SCTs on driver behavior and pedestrian safety. This would provide a more comprehensive understanding of the relationship between SCTs, driver behavior, and pedestrian safety.

Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: Abbas Sheykhfard, Farshidreza Haghighi, Eleonora Papadimitriou; data collection: Abbas Sheykhfard, Farshidreza Haghighi; analysis and interpretation of results: Abbas Sheykhfard, Farshidreza Haghighi, Eleonora Papadimitriou, Subasish Das, and Pieter Van Gelder; draft manuscript preparation: Abbas Sheykhfard, Farshidreza Haghighi, Eleonora Papadimitriou, Subasish Das, and Pieter Van Gelder. All authors reviewed the results and approved the final version of the manuscript.

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Supplemental Material

Supplemental material for this article is available online.

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