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Analysis of traffic conflicts with right-turning vehicles at unsignalized intersections in suburban areas

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ABSTRACT

Right-turn collisions at intersections are one of the most dominant crash types in suburban areas, especially at unsignalized intersections. There is, however, a lack of comprehensive research on the speed patterns of vehicles during right-turn manoeuvres and their impacts on crashes. To provide an in-depth investigation of the factors determining the safety of right-turn manoeuvres, driving behavior data were collected through an instrumented vehicle study. Using this data, binary logistic regression models were developed to identify the factors affecting the probability of vehicle-vehicle (V-V) and vehicle-pedestrian (V-P) conflicts at six suburban intersections in Babol, Iran, during right-turn stage manoeuvres. In total, 1 456 V-V and V-P conflicts were identified from the data analysis. The results from the logistic regression model showed that the vehicle speed, the distance between road users, as well as driver and pedestrian distractions were associated with a higher risk for V-V or V-P conflicts. To estimate the safe right-turn speeds to be selected by drivers at different stages of the right turn, i.e., at the start, during, and end of the movement, linear regression models were developed. The results showed that participants adjust their driving behaviors the same way toward pedestrians as they do toward vehicles. The findings of this study can be leveraged for the development of a robust advanced driving assistance system, the use of which can further improve the safety performance of right-turn manoeuvres.

1. Introduction

Autonomous driving and advanced driver assistance systems (ADASs) are under development by various automakers (Hulse, 2023). An ideal ADAS relies on advanced autonomous driving modules to surpass human driver safety in all situations (Parekh et al., 2022). While current technology does not fully support completely autonomous driving, ADAS can enhance

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safety and comfort through driver-vehicle collaboration. Two ADAS approaches involve automatic vehicle actions in unsafe scenarios and alerts/guidance for drivers (Hulse, 2023). Safety during turning movements, especially at intersections with pedestrians, is critical for integrating autonomous vehicles (AVs) (Šucha et al., 2021). AVs can improve pedestrian safety by reducing human errors and enhancing vehicle awareness (Brar and Caulfield, 2017). Challenges include recognizing pedestrian behaviors, predicting movements, and integrating sophisticated sensors like cameras and radar (Kyriakidis et al., 2019). AVs must follow traffic regulations, adopt defensive driving strategies, and use communication methods to indicate intentions to pedestrians (Ezzati Amini et al., 2019; Rasouli and Tsotsos, 2020). AVs must also interact with pedestrians who are not drivers, posing conflicts that require resolution (Frémont et al., 2020). AV programming should consider research on interactions between pedestrians and human-driven vehicles, and determine when AV behaviors should differ (Utriainen and Pöllänen, 2020). To assess driving behaviors at critical decision points, such as right-turn maneuvers, this research aims to evaluate all hazardous circumstances at intersections involving pedestrians (Shesterov and Mikhailov, 2017; WHO, 2018). Intersection collisions are common, especially involving right-turning vehicles (Fan et al., 2014; Jannat et al., 2018).

Uncontrolled intersections in developing nations pose a significant challenge due to a lack of traffic discipline, resulting in frequent traffic conflicts (Choudhary and Velaga, 2019). These conflicts occur when drivers make individual decisions on maneuvers at unsignalized intersections, potentially leading to collisions (Sheykhfard and Haghighi, 2019; Tageldin and Sayed, 2016). Factors influencing these decisions include the perception of distances to nearby vehicles and pedestrians, vehicle speed, and acceleration capabilities (Chai et al., 2017; Ahmed et al., 2016; Yu et al., 2016). Past research has highlighted the importance of continuously investigating the safety of right-turn maneuvers at unsignalized intersections, particularly for autonomous driving systems that require precise input. Studies have focused on safety implications during right-turn movements, identifying factors like assessing oncoming traffic and safe gaps as key causes of right-turning crashes (Chai et al., 2017). Field studies proposed a weaving-merging right-turn model, reducing conflict occurrence (Ahmed et al., 2016). Micro-simulation studies found that the spacing between gaps significantly influenced conflicts during right-turn maneuvers in Singapore (Chai and Wong, 2014). Though several factors influencing collisions have been studied, research specifically on right-turn maneuvers is limited. Understanding these factors is vital for improving road safety in developing countries. Addressing drivers' behavior, gap spacing, and environmental conditions can help mitigate risks at unsignalized intersections. More comprehensive strategies are required for safer and more efficient traffic flow (Qi et al., 2010; Qu et al., 2014; Wen et al., 2019; Olowosegun et al., 2022). Further research is necessary to explore additional factors and develop strategies to enhance safety at uncontrolled intersections. Traffic conflicts and surrogate safety measures are crucial for evaluating safety at unsignalized intersections (Ahmed et al., 2016; Babu and Vedagiri, 2018; Bonela and Kadali, 2022). Traffic conflicts occur when vehicles or pedestrians come close to colliding (Chai and Wong, 2014; Minh et al., 2014; Tageldin and Sayed, 2016) and serve as indicators of potential safety issues. Conflict analyses involve studying near-miss events between road users, providing valuable data for identifying high-risk locations and evaluating safety countermeasures (Ahmed et al., 2016; Khashayarfard and Nassiri, 2021). Surrogate safety measures are used as indicators correlated with the likelihood of crashes or near-crash events (Lu et al., 2022; Mazaheri et al., 2023). A proactive approach to safety assessment is offered by examining observable parameters and potential crash risks (Bonela and Kadali, 2022; Wang et al., 2021). Studies have used surrogate safety measures to assess conflicts between pedestrians and right-turn vehicles at intersections. Examples include detecting blind zones using the GT indicator (Zhao et al., 2012), utilizing post encroachment time (PET) and relative time to collision (RTTC) for vehicle-pedestrian (V-P) conflicts (Chen et al., 2017), and comparing surrogate safety measures from simulations with a field crash analysis (Yan et al., 2008). Researchers have also investigated the safety impact of channelized right turns (Jiang et al., 2020) and presented critical reviews of surrogate safety measures (SSMs) at unsignalized intersections (Bonela et al., 2022). Recent papers have assessed intersection safety using SSMs in various contexts, such as evaluating right-turning V-P conflicts in China (Detoc et al., 2020; Moreno-Camacho et al., 2019). Moreover, uncontrolled intersections in suburban areas pose a significant concern due to their high rates of right-turn collisions and V-P accidents, as highlighted in a study by Bonela and Kadali (2022). The Iranian Legal Medicine Organization reports Mazandaran in northern Iran as the province with the highest number of road crashes (Iranian Legal Medicine Organization, 2022). More than half of the fatalities on Mazandaran roads occur at intersections, where about 700 fatalities are reported each year. Additionally, more than 85 % of crashes occur at unsignalized intersections, and the share of right-turn crashes is significant (about 69 %) (Iranian Legal Medicine Organization, 2022). Surprisingly, half of these crashes occur in the Babol County (population: 531 930) (Iranian Legal Medicine Organization, 2022). In light of this, the primary focus of our research is to investigate the conflicts that occur between vehicles or vehicles and pedestrians specifically at suburban intersections. Our study's main objective is to identify the contributing factors to right-turn collisions at unsignalized intersections by closely analyzing the driving behaviors during the turning process. To achieve this, we utilize naturalistic data obtained from an instrumented vehicle study, which allows us to gain valuable insights into the various aspects of driving behaviors when encountering other vehicles and pedestrians while making right-turns. Additionally, a key aspect of our investigation is understanding the speed patterns that drivers consider safe to prevent collisions with both vehicles and pedestrians during right-turn maneuvers. We hypothesize that drivers exhibit similar behavioral adaptation patterns regardless of the type of road users they encounter.

Currently, there is a notable lack of comprehensive research on traffic safety during turning movements at unsignalized intersections, particularly concerning the speed patterns of vehicles and their impacts on crashes. Our study aims to fill this knowledge gap by conducting an in-depth examination of driving behaviors near unsignalized intersections using data gathered from the instrumented vehicle study. To achieve our objectives, we will employ binary logistic regression models, enabling us to estimate the likelihood of V-V and V-P conflicts during right-turn maneuvers at different intersections. Through this thorough analysis, we hope to contribute to the understanding of traffic safety and enhance measures for accident prevention in suburban areas.

2. Methods

2.1. Study area

According to the 2022 report from the Iranian Legal Medicine Organization, suburban intersections that connect adjacent roads in Mazandaran province have been responsible for more than 220 fatalities (Iranian Legal Medicine Organization, 2022). Among these accidents, the majority, specifically over 170 fatalities, occurred during right-turn movements. Additionally, the report highlights that in the city of Babol, over 78 fatalities have been recorded in similar areas, with a significant portion of these incidents happening in west belt regions. To study right-turn maneuvers, we selected four intersections that connect Modarres Road to Janbazan Road (West Belt) and two intersections that connect Shariati Road to Janbazan Road (West Belt) in Babol, Iran (see Fig. 1). These intersections, linking adjacent roads, are known for their elevated risk of vehicle-vehicle (V-V) and V-P crashes, particularly during right-turn movements. The detailed geometric and operational characteristics of these intersections are presented in Table 1. Moreover, these intersections are linked to main roads with four lanes each (see Fig. 2).

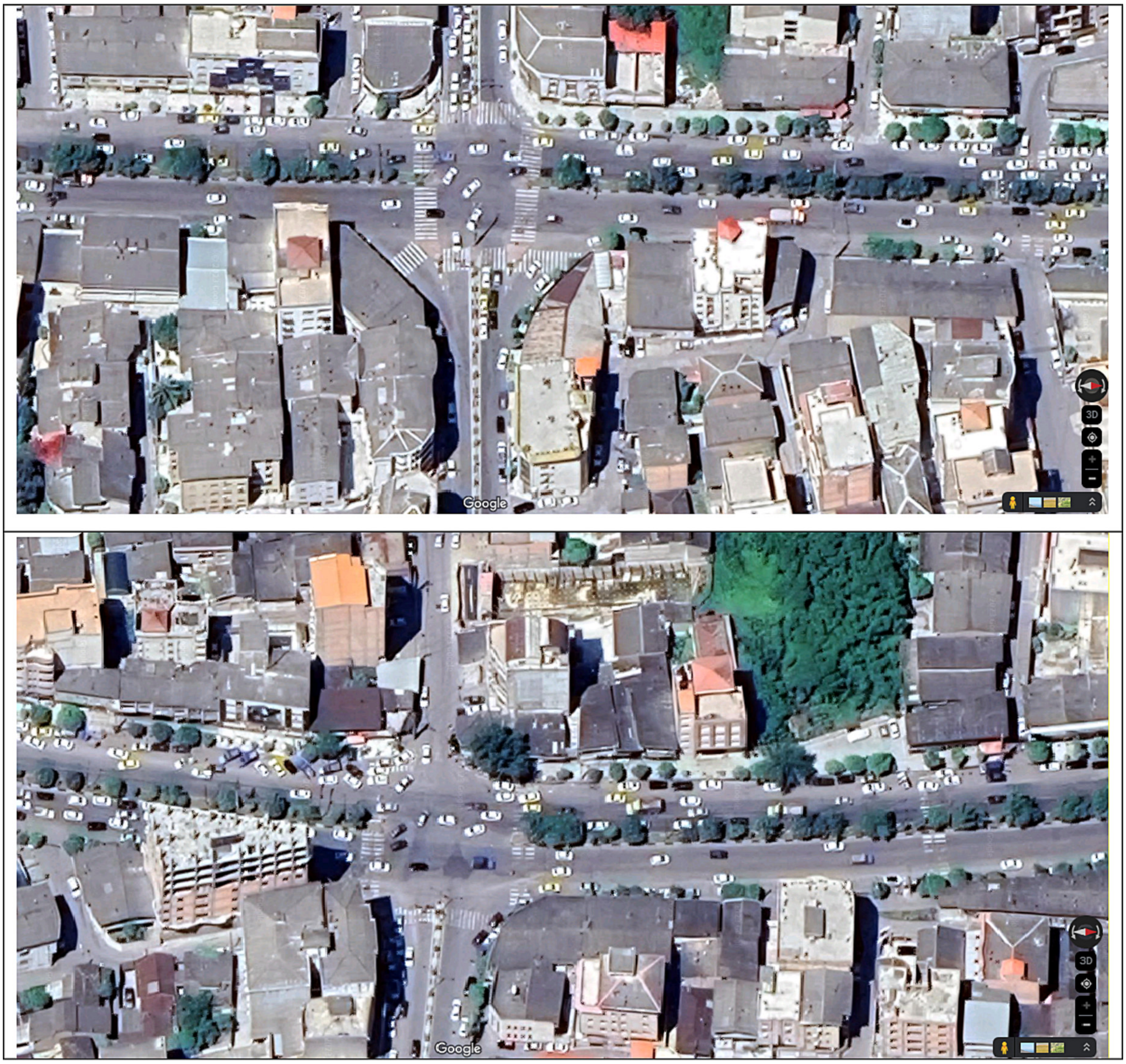

Fig. 1. Study sites in Babol city, Iran: top figure (Modarres Road to Janbazan Road); bottom figure (Shariati Road to Janbazan Road).

Table 1
Features of Intersections.

Intersection feature	Intersection number					
	1	**2**	**3**	**4**	**5**	**6**
Stop sign	none	none	none	none	none	none
Posted speed limit/(km · h^{-1})	40	40	40	40	40	40
Total of lanes	3 + median	3 + median	3 + median	3 + median	3 + median	3 + median
Direction of traffic	Two-way	Two-way	Two-way	Two-way	Two-way	Two-way
Number of lanes/direction	One	One	One	One	One	One
Lane width/m	3.65	3.65	3.65	3.65	3.65	3.65

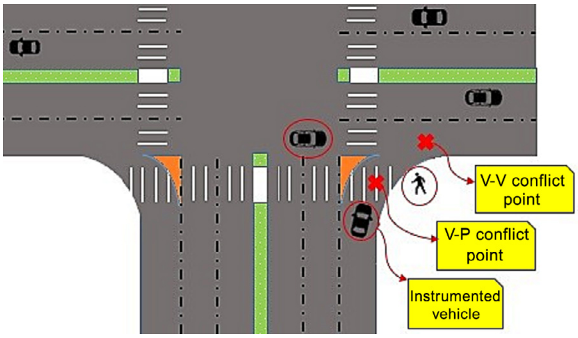

Fig. 2. Schematic image of one of the intersections.

2.2. Participants

To ensure the safety of human participants and the project's integrity, the human research ethics committee of the Babol Noshirvani University of Technology reviewed and approved the study. Participants were recruited by the Babol Noshirvani University of Technology's Traffic Research Laboratory, upon the launch of a cooperation request. The latter was shared through local newspapers and social media. To conduct the study, 39 drivers (22 males and 17 females, aged between 18 and 60, with different educational backgrounds and occupations) participated in the present study. Fig. 3 shows a scene of one of the participants during a right-turn manoeuvre. The drivers' behaviors were recorded using an in-vehicle camera. The camera was a high-quality dual-task (including two cameras) (640x480 pixels and 25 frames per second) mounted under the front mirror and simultaneously recorded both inside and outside the cabin (ahead of the vehicle).

2.3. Data collection

The study was conducted on different days of the week during May, June, and July in 2019. The analysis of recorded videos showed that 895 V-V interactions and 561 V-P interactions occurred, of which 605 cases were V-V conflicts and 410 cases were V-P conflicts. An interaction occurs when a driver travelling along a road observes a pedestrian who wants to cross or

Fig. 3. Views captured by the camera.

observes a vehicle approaching the point where they will pass (Bella and Nobili, 2020). Also, a traffic conflict is defined as when two or more road users approach each other in time and space to such an extent that a collision is imminent if their movements remain unchanged (Amundson and Hydén, 1977). Therefore, in a conflict situation, at least one of the road users has taken evasive action to prevent colliding with other users. The evasive action included any changes in the speed and direction of the movement by drivers or pedestrians. Besides, in 30 cases of V-P interactions, and 58 cases of V-V interactions, no action was taken, which indicated a low risk of conflicts between them.

2.4. Variables

In this study, variables that are expected to influence drivers' behaviors and decisions when encountering pedestrians and other vehicles are presented in Table 2. The vehicle speed was measured using an in-vehicle camera (Fig. 3), and the vehicle's distance to the location of the potential collision with the pedestrians or other vehicles was measured by investigating the recorded videos frame-by-frame.

2.5. Methodology of statistical analysis

The first goal of the analysis is to identify the factors determining the probability of a conflict occurrence, considering all observed interactions. The second goal is to investigate the factors determining the acceptable speed for safe right-turn manoeuvres. To identify and model acceptable speeds, we only consider interactions that do not result in any conflicts between the participants' vehicle and other road users across the various stages of the right-turn manoeuvre.

Logistic regression models were estimated to identify the factors influencing the probability of V-V and V-P conflicts. In the binary logistic regression, there are only two possible outcomes for the dependent variable (i.e., conflict *vs* no conflict). The explanatory variables indicate the factors affecting the probability that a V-V interaction or a V-P interaction may result in a conflict. The general form of the logistic regression model is as follows (Bella and Nobili, 2020):

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

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

where $\Pr\ (Y_i)$ is the probability of the occurrence of a V-V or V-P conflict ($Y = 1$ for conflict, $Y = 0$ for non-conflict) at the i^{th} interaction, $X_{k,i}$ denotes the independent variable k affecting the occurrence of a conflict for each interaction i, and β_k denotes the coefficient for each X.

Moreover, linear regression models were estimated to analyze acceptable right-turn speeds that can prevent traffic conflicts at different stages of the right-turn manoeuvre. Separate linear regression models were estimated for speeds that can prevent V-V and V-P conflicts at each stage of the right-turn manoeuvre.

In linear regression, the dependent variable (safe speed) is estimated as a function of independent variables, $X_1, X_2, X_3, \cdots, X_k$. The linear regression equation reads as follows (Bella and Nobili, 2020):

$$Y = b_0 + b_1 X_1 + b_2 X_2 + \cdots + b_k X_{k,} \tag{3}$$

where the parameters $b_1, b_2, \cdots, b_k$ are the coefficients corresponding to X, and b_0 denotes a constant term.

In both linear regression and logistic regression models, Pearson and Chi-square tests were used to examine the correlation between the independent variables. Also, across all modelling stages, only the variables providing strong evidence of statistically significant impacts on the dependent variable (p-value < 0.05) were kept in the model; as such, all the independent variables included in the model specifications were statistically significant at a minimum 95 % level of confidence. The models providing the best statistical fit have been presented in this paper.

3. Results

3.1. Descriptive statistics

The analysis of the recorded data showed that the drivers made several speed changes to make a right turn. Specifically, each driver makes a right turn in three stages, including 1) the start of the turn, 2) during the turn, and 3) the end of the turn. Fig. 4 schematically presents these three stages in right-turn manoeuvres. The first stage (start of the turn) involves slowing down and changing the vehicle's steering angle. The second stage involves keeping the speed constant, and the final change of the steering angle with increasing speed indicates the third stage of the right-turn manoeuvre.

Fig. 5 shows the frequency distribution of conflicts and non-conflicts for V-V and V-P interactions at different stages of the right turn manoeuvre. At the start of the turn, 72 % of V-V conflicts occurred at speeds above 40 km/h (i.e., the posted speed limit), while 97 % of the non-conflict cases were at lower speeds. Similarly, 73 % and 31 % of V-P conflicts, occurred at speeds over 30 km/h and 40 km/h, respectively. For speeds less than 30 km/h, 62% of interactions did not result in a conflict. At the

Table 2
Variables extracted from data collection.

Code	Variable description	Type	Description
SPEED	Vehicle speed	Continuous	The speed at the beginning of the event (km/h)
DISTANCE	The distance of the vehicle to a pedestrian or another vehicle		Meters (m)
MUP	Group size		Number of pedestrians when crossing
LICENSE	Driving experience		
P.C.L	Pedestrian crossing place	Discrete	Marked: 1; unmarked: 0
P.BEH	Behavioral status of the pedestrian before crossing		Crossing with controlling the status: 1;crossing carelessly: 0
H.CROSS	The manner of pedestrians' crossing		Running: 0; walking: 1
D.GENDER	Gender of the participating driver		Male: 0; female: 1
P.GENDER	Gender of the pedestrian		
S.D.Gender	Gender of the vehicle driver involved in the conflict		
P.SEEN	The place where the pedestrian is seen by the driver		Middle of the way: 0; at the edge of the sidewalk: 1
P.SECWORK	Secondary task of pedestrian		Cell phone: 0; talking to other pedestrians: 1; without factor: 2
EDUCATION	Drivers' education		Diploma and below: 0; associate's degree and Bachelor's degree: 1; master's degree and Ph.D.: 2
MUSIC	Music		Driver listening to music; Yes: 1; No: 0
D.CONV	Driver talking with passengers		Yes: 1; No: 0
DISTRACTION	Driver's inattention		Paying attention to the road traffic flow; Yes: 1; No: 0
LV	Driver's vision limitation		Barriers to seeing pedestrians or other vehicles by the driver such as: A vehicle parked on the way; Yes: 1; No: 0
HURRY	Haste and rush of the driver		Speed more than the authorized limit
PLT	Vehicle leadership in the road		The loneliness of the vehicle in its road; Yes: 1; No: 0
ALLOW	Asking for passing		Requesting passing permission by pedestrian; Yes: 1; No: 0
MUV	Grouping of vehicles		Whether there are other vehicle on the road; Yes: 1; No: 0
Conflict (DV)	Conflict of the participants' vehicles with pedestrians or other vehicles while interacting with each other -dependent variable of the logistic regression models		The participating driver or pedestrian (for V-P interaction) or the driver of another vehicle (for V-V interaction) acts to prevent a collision at the point where they come together. Conflict occurrence: 1; no conflict occurrence: 0

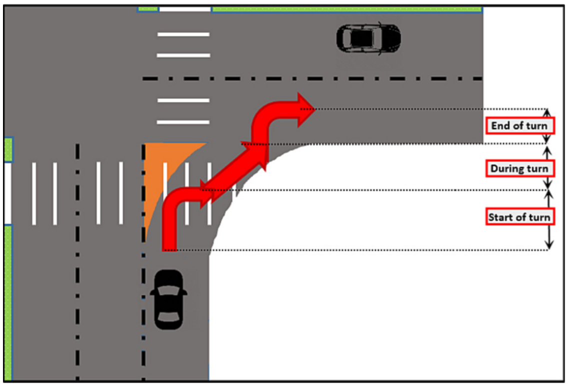

Fig. 4. The schematic pattern of various stages of a right-turn manoeuvre.

end of the turn, 50 % of V-V conflicts and 49 % of V-P conflicts occurred at speeds of above 30 km/h. At speeds of less than 30 km/h, 86 % of V-V interactions and 66 % of V-P interactions did not lead to a conflict. Also, 76 % and 74 % of V-V and V-P conflicts occurred at speeds of above 30 km/h.

3.2. Models of conflict occurrence

The logistic regression models were developed through the SPSS (v.24) software. Table 3 shows the best model specifications encompassing the influential variables of the V-V and V-P conflicts, which were identified as statistically significant.

According to Table 3, four variables influence the probability of a conflict occurrence. Remarkably, the determinants of V-V and V-P conflicts (excluding the variable P.SECWORK for V-P conflicts) are similar. Specifically, the speed, distance, and driver's distraction had similar impacts on the conflict type. The positive coefficient for the speed variable indicates that the probability of a V-V conflict or V-P conflict increases as the vehicle's speed increases. A unit increase in the speed value

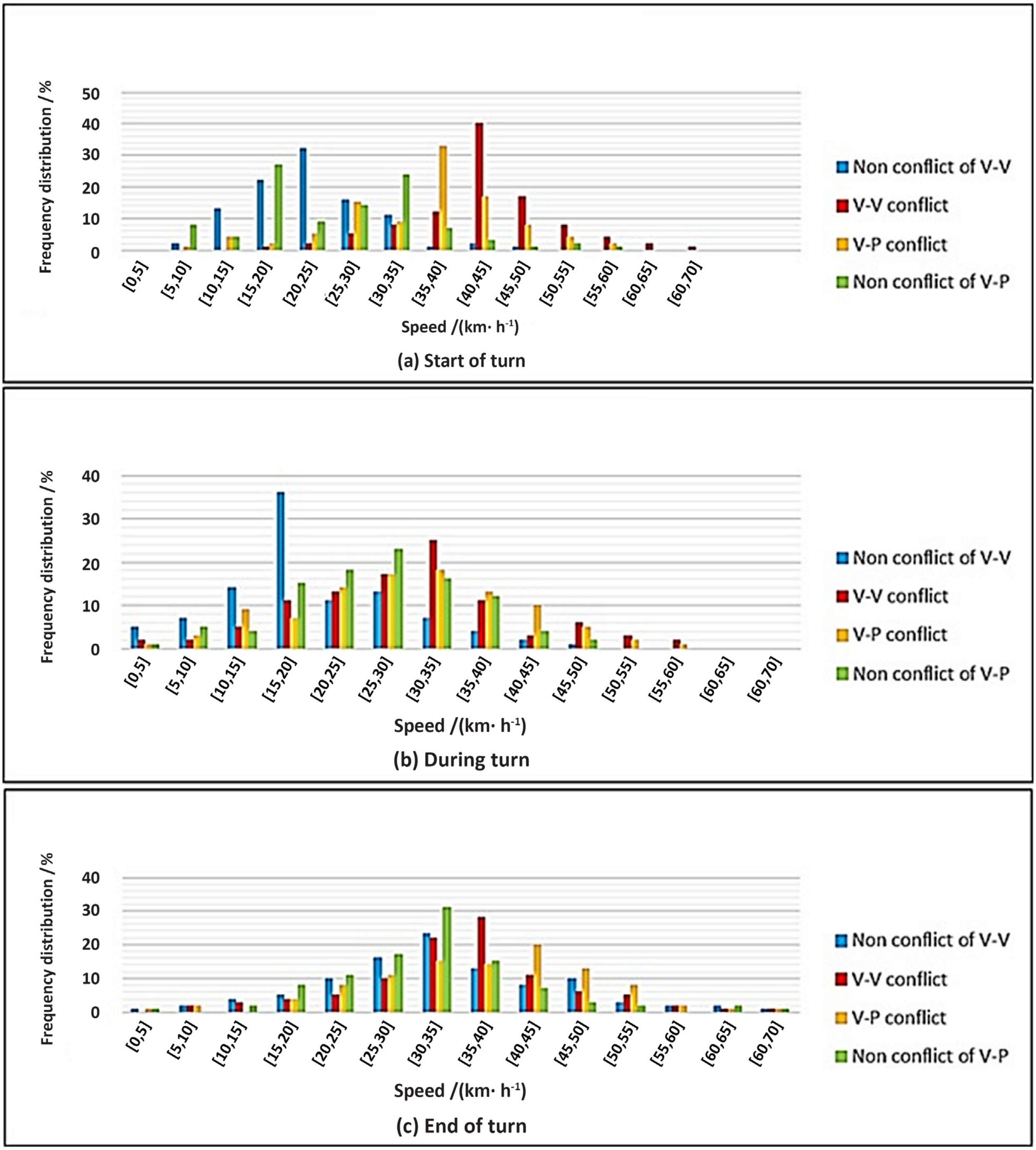

Fig. 5. Distribution of conflicts and non-conflicts per speed range for different right-turn maneuver stages.

leads to an increase in the occurrence probability of a V-V conflict occurrence by 5.56 times (odd ratio = $e^{1.716} = 5.56$) and in the probability of a V-P conflict by 8.59 times (odd ratio = $e^{2.151} = 8.59$). As such, the occurrence probability of a V-P conflict is about 1.54 times that of V-V conflict.

On the other hand, distance was also found to determine the conflict probability but with a different effect. The negative coefficient indicates the opposite relationship of this variable with the probability of a conflict. Precisely, a lower distance between the vehicle and other users increases the conflict possibility, which is an intuitive finding. Observing videos showed that most of the conflicts between road users occurred within a short distance. In this case, the driver or other road users

Table 3
Estimated logistic regression models of conflict occurrence.

Variable	Type of conflict (model)	β_i (Coefficient)	Odd ratio	*p*-value
SPEED	V-V	+1.716	5.562	0.01*
	V-P	+2.151	8.593	0.00*
DISTANCE	V-V	−0.851	0.426	0.01*
	V-P	−1.127	0.324	0.01*
P.SECWORK	V-V	-	-	-
	V-P	+1.142	3.133	0.00*
DISTRACTION	V-V	+0.382	1.465	0.015*
	V-P	+0.627	1.871	0.022*
MUP	V-V	−0.157	0.854	0.082
	V-P	−0.274	0.760	0.135
LICENSE	V-V	+0.241	1.272	0.178
	V-P	+0.124	1.132	0.153
P.C.L	V-V	−0.125	0.882	0.085
	V-P	−0.824	0.438	0.207
P.BEH	V-V	−0.745	0.474	0.186
	V-P	−0.592	0.553	0.162
H.CROSS	V-V	-	-	0.083
	V-P	+0.256	1.291	0.098
D.GENDER	V-V	−0.452	0.636	0.084
	V-P	−0.174	0.840	0.125
P.GENDER	V-V	-	-	0.145
	V-P	+0.142	1.152	0.152
S.D.Gender	V-V	−0.127	0.880	0.253
	V-P	−0.715	0.489	0.131
P.SEEN	V-V	-	-	1.057
	V-P	+0.201	1.222	1.156
EDUCATION	V-V	−0.058	0.943	0.139
	V-P	−0.167	0.846	0.078
MUSIC	V-V	+0.985	2.677	0.101
	V-P	+1.102	3.010	0.067
D.CONV	V-V	+1.056	2.874	0.096
	V-P	+1.471	4.353	0.080
LV	V-V	+0.162	1.175	0.068
	V-P	+0.086	1.089	0.085
HURRY	V-V	+0.329	1.389	0.105
	V-P	+0.107	1.112	0.147
PLT	V-V	−0.096	0.908	0.084
	V-P	−0.173	0.841	0.069
ALLOW	V-V	-	-	0.107
	V-P	+0.156	1.168	0.096
MUV	V-V	−0.032	0.968	0.103
	V-P	−0.150	0.860	0.163
CONSTANT	V-V	−1.313	0.269	0.00
	V-P	−0.627	0.534	0.00
Summary model fit statistics	− 2*Log-Likelihood (LL(0): (Intercept only)	V-V model:101.221; V-P model:128.916		
	−2*Log-Likelihood LL(β): (Final) -	V-V model:81.210; V-P model:94.519		
LRT	Degrees of freedom	V-V model:12; V-P model:12		V-V model:*p*-value = 0.022; V-P model:*p*-value = 0.013
Goodness-of-fit	Pearson (Chi-square)	V-V model:93.114; V-P model: 103.125		V-V model:*p*-value = 0.754; V-P model:*p*-value = 0.818
	McFadden's pseudo *R*-square	V-V model:0.296; V-P model: 0.313		V-V model:*p*-value = 0.001; V-P model:*p*-value = 0.008

* the significance at level of 5 % (p-value < 0.05).

were forced to take an evasive manoeuvre to avoid colliding with each other. The coefficient shows that for an one-unit reduction of distance, the probability of occurrence of a V-V conflict increases by 2.34 times ($\text{odd ratio} = \frac{1}{e^{-0.851}}$ = 2.34) and the probability of a V-P conflict increases by 3.08 ($\text{odd ratio} = \frac{1}{e^{-1.127}}$ = 3.08).

Moreover, distraction was also found as a significant determinant of conflicts. A positive coefficient indicates that if the driver is distracted, the probability of a V-V conflict increases by 1.46 (odd ratio = $e^{0.382} = 1.46$) and the probability of a V-P conflict increases by 1.87 times (odd ratio = $e^{0.627} = 1.87$). Only for V-P conflicts, pedestrian behavior was also identified as a critical factor. The results show that the distraction of pedestrians due to their secondary tasks while crossing (i.e., texting, talking over a cell phone, and having conversation with other pedestrians) could lead to an increase in the conflict probability by 3.13 times (odd ratio = $e^{1.142} = 3.13$). In this situation, the behavior of the approaching driver constitutes a vital factor in preventing the collision with this pedestrian. If a delay in the driver's decision or a driving error occurs, it is highly likely that there will be a collision with the pedestrian.

The LRT [-2*(LL($\boldsymbol{\beta}$) – LL(0)] results show that the final V-V and V-P models (i.e., the models that include all the predictor variables) provide significantly better fit compared to the intercept-only models (i.e., the models that include no predictor variables). The LRT is a Chi-squared distributed test (Washington et al., 2020), and the *p*-values for both models suggest the superiority of the V-V and V-P final models (over the intercept-only counterparts) for 97.8 % and 98.7 % levels of confidence, respectively. In addition, a Pearson Chi-square test was also conducted to identify whether the model fits the observed data well. The *p*-values of the test for both V-V and V-P models are quite large (greater than any standard significance level, e.g., 0.05), thus suggesting that the estimated models provide reasonable fit to the data. In other words, the model-predicted probabilities of conflict occurrence align reasonably well with the observed data, and there is no significant difference between the observed and expected frequencies.

The Hosmer-Lemeshow test is a statistical test used to evaluate how well a logistic regression model fits the data. It compares observed and expected frequencies in groups formed based on predicted probabilities from the model. If the *p*-value is above a significance level (e.g., 0.05), the model fits well. In the present research, the test was used to assess the accuracy of the models. According to the *p*-values for these tests (V-V model: *p*-value = 0.351; V-P model: *p*-value = 0.625), the models are well fitted to the data.

3.3. Models of safe speeds for preventing V-V conflicts

Data was prepared in the SPSS software to determine the appropriate speeds in each of the three stages of the right-turn manoeuvre. The selected speed of the driver is considered safe when the V-V conflicts are avoided throughout the right-turn movement. Separate regression models were estimated for each stage of the right-turn manoeuvre.

A fundamental hypothesis of the linear regression is that the dependent variable is normally distributed (19). Hence, the Kolmogorov-Smirnov test was used to test this hypothesis before starting the modelling process. The results show that, for each stage of the right-turn manoeuvre, the significance level is over 0.05 (95 % confidence level); therefore, the assumption regarding the normality of the dependent variable is not violated. To identify potential correlations between independent variables (linearity) and, as such, avoid any multicollinearity issues, the Pearson correlation test was used for quantitative variables and the Chi-square test was used for nominal variables.

Findings revealed that the time taken for obtaining the driving license, the instances of driver and passenger talking each other (D.CONVE), driver rush (HURRY), the leadership of vehicles (PLT), the grouping of vehicles (MUV), driver's education, driver's gender in the second vehicle, and driver's vision limitations (LV) were correlated to other variables. Hence, these variables were eliminated from the modelling process. The remaining variables were analyzed, and the final model's output is shown in Table 4. Due to the differences in measurement units of variables, it is impossible to conclude from the values of the column β_i (i.e., unstandardized coefficients) that the variable with a higher coefficient has a more pronounced impact on the dependent variable. Therefore, to compare the variable effects, the standardized beta coefficients column (irrespective of the sign) is used.

We estimated the coefficient of determination (R^2) for each model to ascertain how much of the variance of the dependent variable can be explained by each model at each stage of the right-turn manoeuvre. The coefficient of determination (R^2) is a statistical measure that assesses how well a regression model fits the data. It represents the proportion of the variance in the dependent variable that can be predicted from the independent variables. R^2 ranges from 0 to 1, with higher values indicating a better fit. The *F*-statistic tests the overall significance of the model, measuring the ratio of explained variance to unexplained variance. A high *F*-statistic suggests a better model fit, and a low *p*-value associated with it indicates that the model is statistically significant. For instance, in the start-of-turn model, the given model has an *R*-squared value of 0.785, indicating that approximately 78.5 % of the dependent variable's variability can be explained by the included independent variables. The high *F*-statistic value of 217.518 and the low *p*-value of 0.001 suggest that the model significantly outperforms a null model and has a strong predictive power. Overall, the model performs well and provides a good fit to the data. Also, to investigate the independence of the errors from each other, the Durbin-Watson statistic was used, which should be in the range of 1.5 to 2.5 to accept the lack of correlation among errors; this statistic fell within this range for each model. The values of Durbin-Watson tests for models of start of turn, during turn, and end of turn were 1.958, 2.02, and 1.856, respectively. The Durbin-Watson statistic for the start-of-turn-model is 1.958, indicating little to no autocorrelation in the residuals and likely satisfying the assumption of independent residuals. For the during turn model, the Durbin-Watson statistic is 2.02, slightly above 2, suggesting a very small positive autocorrelation. Nevertheless, the deviation from 2 is minimal, so the assumption of independent residuals is still likely met. The end-of-turn model has a Durbin-Watson statistic of 1.856, close to 2, indicating little to no autocorrelation in the residuals, similar to the first model. Hence, the assumption of independent residuals is likely satisfied for this model as well. Overall, all three models exhibit little to no autocorrelation in their residuals.

3.4. Models of safe speed for preventing V-P conflicts

This section presents the models of safe speeds so that V-P conflicts can be avoided at each stage of the right-turn manoeuvre. As with the V-V conflicts, separate models were estimated for the different phases of the manoeuvre. The

Table 4
Results of the linear regression models for V-V conflicts.

Variable	Stage	Unstandardized coefficient (β_i)	Standardized coefficient (β)	*p*-value
Constant	Start of turn	0.65	-	0.01*
	During turn	1.78	-	0.02*
	End of turn	1.11	-	0.01*
Distance	Start of turn	1.725	3.51	0.004*
	During turn	2.023	4.13	0.009*
	End of turn	2.509	6.85	0.015*
Distraction	Start of turn	−0.719	−6.55	0.01*
	During turn	−0.134	−3.71	0.008*
	End of turn	−0.112	−2.91	0.012*
Music	Start of turn	−0.953	−9.31	0.01*
	During turn	−0.335	−7.88	0.015*
	End of turn	−0.306	−7.2	0.01*
D. Gender	Start of turn	−0.621	−5.78	0.04*
	During turn	−0.199	−5.14	0.033*
	End of turn	−0.128	−3.55	0.03*
SPEED	Start of turn	−1.106	−4.25	0.123
	During turn	−1.625	−5.25	0.141
	End of turn	−1.768	−5.74	0.171
MUP	Start of turn	0.789	1.245	0.225
	During turn	0.845	1.952	0.105
	End of turn	1.184	2.512	0.219
LICENSE	Start of turn	−0.381	−1.121	0.102
	During turn	−0.512	−1.415	0.135
	End of turn	−0.809	−1.862	0.159
S.D.Gender	Start of turn	0.466	2.251	0.156
	During turn	0.377	1.951	0.117
	End of turn	0.763	2.592	0.204
EDUCATION	Start of turn	0.912	2.452	0.099
	During turn	0.352	1.295	0.120
	End of turn	0.821	2.021	0.111
D.CONV	Start of turn	−1.478	−4.152	0.129
	During turn	−1.184	−3.015	0.078
	End of turn	−1.351	−3.292	0.108
	Start of turn	−1.762	−4.125	0.135
	During turn	−1.455	−3.256	0.093
	End of turn	−1.830	−4.963	0.074
PLT	Start of turn	0.190	2.152	0.082
	During turn	0.442	2.952	0.090
	End of turn	0.796	3.15	0.084
	Start of turn	1.214	1.148	0.117
	During turn	0.319	0.625	0.144
	End of turn	0.725	0.945	0.153
LV	Start of turn	1.306	1.596	0.156
	During turn	0.998	1.221	0.192
	End of turn	1.090	0.952	0.189

R^2			Degree of freedom			*F*			*p*-value		
Start of turn	During turn	End of turn	Start of turn	During turn	End of turn	Start of turn	During turn	End of turn	Start of turn	During turn	End of turn
0.785	0.812	0.716	4	4	4	217.518	172.174	192.545	0.001	0.002	0.001

* Significance at level of 5 % (*p*-value < 0.05).

Kolmogorov-Smirnov test was initially conducted to determine whether the dependent variable was normally distributed; the test values were acceptable for all three phases of the manoeuvre (significance value above 5 %). Furthermore, the Pearson correlation and the Chi-square test were also performed before starting the modelling process to identify any possible variables with a high linear correlation between them.

In addition, all three stages of the right turn had Durbin-Watson statistic values between 1.5 and 2.5, indicating independent errors. Significant values of the *F*-test indicated that the final model was statistically significant and acceptable.

The variables relating to the time for obtaining a driving license, number of pedestrians, talking between drivers and passengers, leadership of the vehicles, collective movement of vehicles, driver's education, gender of the second vehicle's driver, gender of the pedestrian and location where the pedestrian were correlated to other variables. To avoid multicollinearity issues, these variables were eliminated from the modelling process. Then, all the remaining variables (except those being correlated) were examined for model estimation. The variables that had a weak effect on the dependent variable (i.e., the significance level was above 5 %) were excluded from the model, namely, the type of pedestrian crossing, pedestrian's request from the approaching driver to cross, driver's vision limitation, driver's rush, and pedestrian's behavior before crossing. The variables included in the best model specification are presented in Table 5; overall, the factors determining safe speeds for preventing V-P conflicts are similar to those identified for preventing V-V conflicts, with the difference that the V-P model also includes characteristics of pedestrian behaviors as explanatory variables.

The unstandardized model coefficients are provided in the column β_i. However, with the use of the β_i values, it is not possible to identify the magnitude of the effect of the independent variables, due to the use of different measurement units. To compare the effects of the variables, the standardized beta coefficients are used.

4. Discussion

4.1. Traffic conflicts

The logistic regression models showed similar patterns in V-V and V-P conflicts. Therefore, drivers' behaviors seem to exhibit consistent patterns for both conflict types, with the results highlighting that risky driving behaviors increase the likelihood of collisions, either with other vehicles or pedestrians. Specifically, the model for V-V conflicts showed that the distance between the approaching vehicles significantly affects the conflict occurrence probability. Lower distances between approaching vehicles increase the potential for conflicts, which can lead to collisions if drivers do not take proper evasive actions. This result is consistent with the findings of previous studies examining the interactions between vehicles at right-turn movements (Ahmed et al., 2016; Chai et al., 2017). In addition, the driver's aggressive behavior, expressed through excessive speeds and driver distraction, increases the likelihood of conflicts and, possibly, collisions between vehicles. Similar results have also been reported in previous studies (Qu et al., 2014; Zhao et al., 2018). The model for V-P conflicts also showed that pedestrians distracted by a secondary task, such as texting while crossing, increase the potential for collision, which is also corroborated by previous evidence (Mwakalonge et al., 2015; Raghuram Kadali et al., 2014). Furthermore, the model results highlight the effects of vehicle speed, distance to pedestrians, and driver distraction on the occurrence probability of V-P conflicts, which are factors that previous studies have also identified. However, these studies focused on more than just the right-turn movement of the vehicle (Hunter et al., 2015; Salamati et al., 2014).

The results also showed that speed and distance are the two dominant factors determining the probability of conflicts. Although the magnitudes of their effects were not the same, both factors significantly affected the likelihood of road users being involved in a conflict. Particularly, the impact of speed was greater – in magnitude – than that of distance, which subsequently leads to an overall more pronounced effect on the behaviors of road users. Therefore, our study suggests that speed is the most important driving factor leading to the occurrence of a conflict. The dominant role of speed constitutes a novel finding, considering that previous studies have discussed the role of both factors in pedestrian safety (Salamati et al., 2014; Sheykhfard and Haghighi, 2019; Zhang et al., 2017), but highlighting the distance as the major factor (Hunter et al., 2015; Salamati et al., 2014). However, these studies were focused on through movements and not on right turn manoeuvres. It seems that the limited space available to the driver throughout the right-turn movements may be the reason that the distance factor has an inferior role compared to those in previous studies. In addition, lower speeds in right-turn manoeuvres give more time to drivers to assess possible unexpected situations and react properly, whereas higher speeds can contribute to an easier loss of control, considering also the role of the centrifugal force, which is not present in through movements. Furthermore, the effects of other determinants of conflicts, which have been reported as significant in previous studies, were identified as insignificant in the present study, including the pedestrian speed (Zhang et al., 2017), waiting time (Salamati et al., 2014), high-risk crossing styles, such as running (Habibovic et al., 2013) or rolling gap (Serag, 2014), pedestrian gender (Brosseau et al., 2013), and pedestrian age (Sheykhfard et al., 2021; Toran Pour et al., 2018). This finding may also imply the major role of vehicle speeds for the generation of conflicts in right-turn movements, suggesting that the risk stemming from pedestrian-specific characteristics or behaviors is significantly inferior compared to the risk induced by excessive vehicle speeds. As such, possible measures towards enhancing the safety of right-turn manoeuvres should be targeted at reducing vehicle speeds.

4.2. Safe speeds and policy implications

The linear regression models of safe speeds showed that the appropriate speed required for a safe manoeuvre, regardless of the type of the user the driver encounters (i.e., either pedestrian or other vehicle), varies at different stages of the manoeuvre. The results revealed that 92 % of V-V conflicts and 73 % of V-P conflicts occurred at speeds of above 30 km/h at the start of the turn. On the other hand, about 50% of V-V conflicts and 49% of V-P conflicts occurred at speeds above 30 km/h at the during-the-turn stage. Given the speed limit of 40 km/h on the study sites, it seems that setting a new, yet lower speed limit

Table 5
Results of the linear regression models for V-P conflicts.

Variable	Stage	Unstandardized coefficient (β_i)	Standardized coefficient (β)	*p*-value
Constant	Start of turn	−3.25	-	0.01*
	During turn	−1.77	-	0.01*
	End of turn	−1.02	-	0.01*
Distance	Start of turn	1.43	4.23	0.005*
	During turn	1.52	4.99	0.008*
	End of turn	2.13	6.51	0.01*
Distraction	Start of turn	−0.225	−4.51	0.015*
	During turn	−0.355	−5.68	0.015*
	End of turn	−0.217	−2.11	0.015*
Music	Start of turn	−0.284	−6.93	0.003*
	During turn	−0.376	−6.21	0.003*
	End of turn	−0.269	−3.55	0.003*
D. Gender	Start of turn	−0.309	−7.15	0.01*
	During turn	0.401	−6.34	0.01*
	End of turn	−0.261	−3.46	0.01*
SPEED	Start of turn	−4.060	−5.552	0.482
	During turn	−3.324	−4.804	0.482
	End of turn	−3.621	−4.045	0.482
P.SECWORK	Start of turn	−0.698	−11.21	0.01*
	During turn	−0.515	−9.55	0.01*
	End of turn	−0.476	−5.18	0.01*
MUP	Start of turn	2.187	4.125	0.152
	During turn	2.540	4.856	0.152
	End of turn	1.845	3.485	0.152
LICENSE	Start of turn	−2.170	−3.515	0.372
	During turn	−2.745	−2.854	0.372
	End of turn	−1.985	−2.452	0.372
P.C.L	Start of turn	−0.824	−14.37	0.02*
	During turn	−0.614	−11.84	0.03*
	End of turn	−0.551	−6.05	0.03*
	Start of turn	−2.325	−6.515	0.086
	During turn	−2.476	−5.145	0.086
	End of turn	−3.111	−4.258	0.086
P.BEH	Start of turn	5.752	3.582	0.196
	During turn	3.196	2.965	0.196
	End of turn	4.756	3.142	0.196
P.GENDER	Start of turn	4.154	2.125	0.108
	During turn	3.069	2.005	0.108
	End of turn	2.159	1.634	0.108
S.D.Gender	Start of turn	3.175	2.596	0.152
	During turn	4.256	3.313	0.152
	End of turn	3.45	2.745	0.152
P.SEEN	Start of turn	3.125	3.259	0.097
	During turn	2.856	3.021	0.097
	End of turn	2.985	2.632	0.097
EDUCATION	Start of turn	2.451	1.975	0.361
	During turn	2.201	1.865	0.361
	End of turn	1.582	1.505	0.361
D.CONV	Start of turn	−3.602	−4.866	0.273
	During turn	−3.158	−4.004	0.273
	End of turn	−2.562	−3.626	0.273
	Start of turn	−3.600	−5.879	0.130
	During turn	−3.245	−5.551	0.130
	End of turn	−2.514	−4.9654	0.130
PLT	Start of turn	1.362	0.958	0.207
	During turn	1.610	1.1252	0.207
	End of turn	1.202	1.001	0.207

(continued on next page)

Table 5 (*continued*)

Variable	Stage	Unstandardized coefficient (β_i)	Standardized coefficient (β)	*p*-value
	Start of turn	1.070	1.652	0.115
	During turn	1.255	1.862	0.115
	End of turn	1.711	2.001	0.115
LV	Start of turn	−1.850	−1.595	0.085
	During turn	−2.056	−1.869	0.080
	End of turn	−2.245	−2.113	0.080
ALLOW	Start of turn	2.070	3.296	0.295
	During turn	2.081	3.545	0.295
	End of turn	2.593	3.995	0.295

R^2			Degree of freedom			*F*			*p*-value		
Start of turn	During turn	End of turn	Start of turn	During turn	End of turn	Start of turn	During turn	End of turn	Start of turn	During turn	End of turn
0.721	0.768	0.842	4	4	4	199.251	162.527	205.485	0.000	0.002	0.001

* Significance at level of 5 % (*p*-value < 0.05).

could potentially reduce the likelihood of conflicts, and subsequently, collisions. Interestingly, 20 % of V-V conflicts and 42 % of V-P conflicts occurred in the speed range of 30 km/h to 40 km/h. As a result, a lower speed limit could encourage drivers to choose lower speeds during manoeuvring. In fact, the establishment of a 30 km/h (or 20 mph) speed limit has proven a successful pathway towards achieving lower vehicle speeds, and subsequently fewer collisions (Popov et al., 2021).

Previous evidence also shows that channelization can also affect right-turn speeds (Fitzpatrick et al., 2006). Therefore, the implementation of channelization and signalization of the right-turn lane could work synergistically with the setting of a lower speed limit. Specifically, both channelization and signalization of the right-turn could improve lane discipline, primarily by separating drivers who intend to turn right from those who want to continue onto the through movement. These interventions could also encourage drivers to reduce their vehicle speeds while merging with the traffic flow of the intersected road at the end of the turning manoeuvre. However, the implementation of these measures is subject to other factors, such as the radius of the intersection (Fitzpatrick et al., 2021; Khasawneh et al., 2019). For instance, a previous study (Fitzpatrick et al., 2021) indicated that right-turn speeds increase slightly with increasing radii if the preceding vehicle proceeds through (rather than turning right) at the intersection. More comprehensive studies on other factors should also be considered, such as the geometric characteristics of the interventions.

Over the recent decades, the United States, European, and other countries have been growingly implementing roundabouts, to reduce the number and severity of conflicts in intersections. The primary reason for this arises from the demonstrable benefits roundabouts offer in terms of traffic flow and safety. A roundabout slows down traffic, reduces the potential conflict points, reduces delays, and is more aesthetically appealing than a traditional intersection. Therefore, the replacement of existing configurations with roundabouts could be considered as a remedial measure to upgrade safety at unsignalized intersections in suburban areas of Babol.

In addition, user training and awareness countermeasures, such as safety awareness campaigns, could be also leveraged for increasing safety at unsignalized intersections. Such campaigns could focus on possible driving manoeuvres during the turning movements that can be potentially hazardous not only for other vehicles, but also for pedestrians crossing the road. To better alert drivers about the specific points where they should take an action, it is vital to clearly mark stop lines on the pavement and ensure the conspicuity of these markings over the years. In addition, drivers can be better informed about the potential presence of pedestrians on the turning road by using highly visible pavement markings for the pedestrian crossings. Interestingly, previous researched demonstrated that the implementation of high visibility crosswalks (HVCs) has evidently resulted in lower vehicle speeds and conflicts between pedestrians and vehicles (Pantangi et al., 2021; Sarwar et al., 2017).

5. Conclusion and further research

A significant portion of crashes at unsignalized intersections in suburban areas are caused by collisions between turning-right vehicles and other vehicles or pedestrians. Therefore, the present study attempted to investigate drivers' behaviors while performing a right turn manoeuvre to better understand which driving attributes or patterns enhance the risk of collisions in suburban areas. Specifically, we analyzed the occurrence probability of traffic conflicts, which constitute a surrogate measure of collisions, at suburban, unsignalized intersections in Babol, Iran. To do so, we conducted an instrumented vehicle study using in-vehicle cameras, thus collecting naturalistic driving study data. The behaviors of drivers and pedestrians were analyzed using video-recorded footages, whereas the factors affecting the occurrence of V-V and V-P conflicts were identified through statistical models. The binary logistic regression models showed similar causal patterns of factors determining the probabilities of V-V and V-P conflicts. Overall, high vehicle speeds and drivers' distraction while making a right-turn manoeuvre increase the probabilities of V-V- and V-P conflicts. Moreover, the distraction of pedestrians while crossing the road, because of cell phone use or talking with another pedestrian, also increases the probability of a V-P conflict. Furthermore, short distances between right-turning vehicles and other vehicles and/or pedestrians increase the probability of both V-V and V-P conflicts. Additionally, the linear regression models of safe speeds showed that similar speed selection patterns were exhibited by the participating drivers across the three different stages of a right-turn manoeuvre to avoid V-V and V-P collisions.

By utilizing these research findings, ADAS technologies can be fine-tuned to deliver advanced support and direction to drivers, thus creating a safe driving atmosphere, especially during right turns in suburban areas. This application of research outcomes offers great potential for substantially enhancing driver safety, diminishing the occurrence of conflicts, and lowering the probability of accidents during right-turn maneuvers in suburban settings. The below potential applications, within the context of Advanced Driver Assistance Systems (ADAS), exemplify how the outcomes of the research can be effectively employed to enhance the safety of drivers, alleviate conflicts, and mitigate the probability of collisions specifically during right-turn maneuvers conducted in suburban areas, including:

- Collision detection and warning systems: The research highlights that high vehicle speeds and driver distraction increase the probability of both V-V and V-P conflicts. ADASs can utilize this information to develop collision detection and warning systems. By monitoring vehicle speed and driver behavior, ADASs can detect potentially dangerous situations during right-turn maneuvers and provide timely alerts to the driver, encouraging them to take corrective actions and avoid collisions.
- Pedestrian detection and warning systems: The study emphasizes that pedestrians' distraction while crossing the road increases the probability of V-P conflicts. ADASs can incorporate pedestrian detection technologies, such as cameras or sensors, to identify pedestrians and assess their behaviors. If a distracted pedestrian is detected, the system can issue warnings to the driver, helping them anticipate potential conflicts and take appropriate evasive actions to prevent collisions.
- Intersection assistance systems: ADASs can provide real-time assistance to drivers during right-turn maneuvers at unsignalized intersections. Based on the identified factors affecting conflict occurrence, ADASs can offer visual or auditory cues to promote safe driving behaviors. For example, the system can provide speed recommendations to ensure drivers maintain safe speeds during different stages of the right-turn maneuver. It can also monitor distances to other vehicles and pedestrians and provide alerts if the distance becomes too short, helping drivers make informed decisions and reduce the risk of conflicts.
- Driver monitoring and alertness systems: The research indicates that driver distraction is a significant factor in conflict occurrence. ADASs can employ driver monitoring systems, such as cameras or sensors, to assess driver attentiveness and detect signs of distraction. If the system detects driver distraction during a right-turn maneuver, it can issue alerts to regain the driver's attention, thereby reducing the likelihood of conflicts and improving overall safety.
- Speed adaptation systems: The linear regression models of safe speeds reveal consistent speed selection patterns during different stages of a right-turn maneuver. ADASs can utilize this information to implement speed adaptation systems that automatically adjust vehicle speeds based on the specific stage of the maneuver. By recommending and enforcing safe speeds, ADASs can help prevent conflicts and collisions during right turns.
- Development of driver training programs: The findings can inform the development of driver training programs targeted at right-turn maneuvers. ADASs can incorporate these training materials and provide interactive guidance to drivers, helping them understand the risks associated with specific driving behaviors and encouraging safer driving practices during right turns.

There are several limitations to this study, including limited resources (time and budget), which may affect its generalizability. First, the study was conducted in a specific geographic location (Babol city, Iran) and may not reflect driver behaviour elsewhere. Therefore, caution should be exercised when generalizing the results to other populations. Furthermore, the size of the naturalistic data sample was relatively small, limiting the statistical power of the analysis. Moreover, driving behaviours were recorded only during the day, so it may not fully capture driving behaviors at night or in different weather conditions. Moreover, the naturalistic data may not capture all aspects of driving behaviors since not all traffic conditions or driver actions were observed. Future research can consider larger sample sizes from different geographic locations to increase generalizability. By analyzing variables such as driving experience, future studies should examine the differences in behaviors among drivers. Additionally, future studies could incorporate eye tracking or physiological measures of driver behaviour in addition to naturalistic driving studies; such advanced data collection and analysis techniques can allow in-depth investigations of how different types of distraction (e.g., visual, cognitive, and manual) can affect driving behaviors, especially in cases of interactions with other road users. In addition, the linear regression models focus only on the determinants of appropriate speeds that do not result in traffic conflicts with other road users. Given that the absence of conflicts does not entail elimination of crash risk, future research should explore safe speed patterns in right-turn maneuevers by leveraging more holistic risk indicators, which take into account geometric and traffic conditions, such as the time-to-collision (TTC) or kinematic models that account for turning radius and vehicle acceleration. Lastly, future research can investigate how weather conditions and time of day can affect driver behavior and pedestrian safety. This would provide a more comprehensive understanding of the relationship between driver behavior and pedestrian safety.

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Conflict of Interest

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Declaration of competing interest

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

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