Modeling Vehicle-Pedestrian Interactions Using a Non-Probabilistic Regression Approach

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ABSTRACT

Understanding how vehicle drivers and pedestrians interact is key to identifying countermeasures to improve the safety of these interactions. Furthermore, there is a need to identify techniques that can be used to evaluate the effectiveness of safety countermeasures and traffic control devices without the need to wait for crash data. Using video, interactions between right-turning vehicles and conflicting pedestrians were documented by logging the timestamps associated with key vehicle positions during right turn maneuvers and corresponding key conflicting pedestrian positions. Interactions documented were purposely limited and narrow in scope to provide a controlled dataset. Logged timestamps enabled the calculation of values such as time to complete a right turn and time for a pedestrian to reach a critical conflict point when a vehicle initiated a right turn.

A non-probabilistic regression model explaining the relationship between the calculated values was created. The model described the expected right turning behavior: when drivers perceive the possibility of pedestrian reaching a critical conflict point at the same time as them, they will modify their behavior even if not coming to a stop. The behavior is not a surprise and has been previously documented in the literature. The main contribution of this paper is demonstrating that by analyzing a narrow set of interactions, a clean and simple model that explains the interaction of right-turning vehicles and pedestrians can be developed using a non-probabilistic regression approach. An argument is made that the model parameters can be used to evaluate the effectiveness of traffic control devices.

Keywords: Safety, Pedestrians, Interaction Modeling, Data Collection

INTRODUCTION

Evaluating the safety effects of using traffic control devices for new applications, e.g., the use of Flashing Yellow Arrows (FYA) for right turns, is a task that too often relies on the availability of crash data. The traditional approach to evaluating the safety of a new transportation infrastructure involves comparing crashes before and after the installation date of the new infrastructure. Such an approach to safety evaluations is not only slow but also does not account for scenarios in which safety improvements are not manifested as a reduction in crashes, especially since crashes are rare events in the transportation system. Regardless, crashes have been and continue to be the "gold standard" used to evaluate the safety of transportation infrastructure even when alternatives exist.

If a city transportation agency decides to install a new safety countermeasure meant to improve the safety of the interactions between right-turning vehicles and pedestrians, as has been happening with the use of FYA for right turns (*1*), the countermeasures could be installed on intersections that have no crash history but for which there are constant complaints of near misses and reckless drivers. Under such a scenario, since there is no crash data, evaluating the effectiveness of the countermeasure deployed is not possible with traditional before-and-after techniques. However, an evaluation of the countermeasure based on the concept of surrogate safety measures is possible. This idea of using detailed field observations to obtain a model that explains the interaction of transportation users to rank the safety of infrastructure has been previously proposed from the perspective of left-turning maneuvers (*2*).

The Potential of Surrogate Safety Measures

Arguably, most users of the transportation system are in a continuous collision path with other users. Most of the time, users adjust their trajectories to avoid a collision. Surrogate safety measures can be described as quantifiable measurements of how close users were to a collision (measured in multiple forms) at some point in time. Examples of surrogate safety measures include time to collision (*3*) which is abbreviated in the literature as TTC and post encroachment time (*4*) which is abbreviated in the literature as PET. The PET value is of importance to the hypothetical scenario described because, while mostly discussed from the perspective of two vehicles, PET describes how close users came to a collision. For example, if a right-turning vehicle and conflicting pedestrian crossed the same point in the crosswalk 100 milliseconds apart, that situation would certainly trigger a safety flag to an observer.

Surrogate safety measures require detailed observations of the behavior of transportation system users on the field, a concept that is not new and that in fact was mentioned in the literature as early as in the 1960s (*5*). Therefore, one method to evaluate the safety benefits of the hypothetical countermeasure mentioned is to document the average PET value observed between conflicting pedestrians and right-turning vehicles before and after the installation of a countermeasure. However, one limitation of such an approach is that it does not convey the entire story of how the interactions between right-turning vehicles and pedestrians unfold.

Time to Complete a Right Turn as a Safety Surrogate

A driver that approaches an intersection and starts the process of completing a right turn when a conflicting pedestrian is present must decide if the trajectory they would normally follow is safe. Safety, from a binary perspective in the aforementioned scenario, means whether continuing the trajectory unchanged will result in a collision with the conflicting pedestrian. From a theoretical perspective, if the driver does not hit the pedestrian, then the interaction was safe. However, the decision for the driver is more complex as the driver must determine if maintaining the trajectory they would normally follow provides a sufficient level of comfort in achieving the goal of avoiding a collision with the pedestrian. A safer driver would arguably adjust their trajectory more than a less safe driver. Since the time to complete a right turn will be variable and depend on the position of the pedestrian, the rate at which adjustments to the time to complete a right turn are made by the driver population of an intersection arguably describes the level of "respect" that drivers have for pedestrians and can be used as a type of surrogate safety measure.

OBJECTIVES

The objective of the research effort described is to evaluate the feasibility of establishing a simple non-probabilistic regression model that explains the attitude of right-turning drivers at a specific intersection towards the presence of conflicting pedestrians. The attitude of drivers was quantified in a regression model using the time to complete a right turn which, as suggested, acts as a surrogate safety measure. The research team made no attempt, or claims, to explain the general attitude of drivers towards pedestrians, but instead focused on the feasibility of creating a model through narrow and detailed field observations for a specific intersection. If a model like the one described is created for an intersection prior to the installation of a countermeasure or traffic control device, the model creation process can be repeated with data collected after deployment to evaluate the safety effects of the new countermeasure or traffic control device deployed.

Previous Work and Contribution

The idea of studying the interactions of vehicles and pedestrians is not a new concept. Countless researchers have made contributions in the field. The academic literature is filled with examples that include analysis of pedestrian and vehicle conflicts (*6*), pedestrian behavior models (*7*), yield/gap behavior (*8*, *9*), and impact of pedestrians on capacity (*10*) just to name some examples. A review of existing literature and analysis of modeling procedures reveals that most modeling approaches used are focused on returning the probability of an event happening or describe an event in "binary form" such as efforts to quantify conflicts. These existing models are key to developing simulations and understanding safety. However, these models are often difficult to communicate to transportation stakeholders; thus, the focus of the research team on exploring the use of non-probabilistic regression under narrow conditions and making the argument throughout the paper that even while simple, the underlying model parameters could be used as the foundation to evaluate the safety of countermeasures and traffic control devices.

DATA COLLECTION

The data collection process followed to complete the research described involved obtaining video recordings from a signalized intersection to document the behavior of right turning vehicles with and without the presence of a conflicting pedestrian on the crosswalk. Documenting the behavior involved a frame-by-frame analysis of the video to obtain the timestamps associated with the key positions of right turning vehicles and conflicting pedestrians. Using the timestamps, additional measurements were derived which were then used to model the impact of a conflicting pedestrian on the time to complete a right turn which, as previously mentioned, can be treated as a surrogate of the safety of a vehicle and pedestrian interaction.

Video Recording

Video from the intersection of North Randall Avenue and West Dayton Street (Latitude = 43.071114 and Longitude = -89.409040) in Madison, WI was obtained by installing a handheld camera next to the intersection. The position of the camera varied by day; regardless, the camera position allowed observing/documenting the moment when the front axle of a vehicle crossed the P_0, P_1, and P_2 positions shown in **FIGURE 1**. The position of the camera also allowed documenting the moment when a conflicting pedestrian crossed P_4 and P_5 which are also shown in **FIGURE 1**.

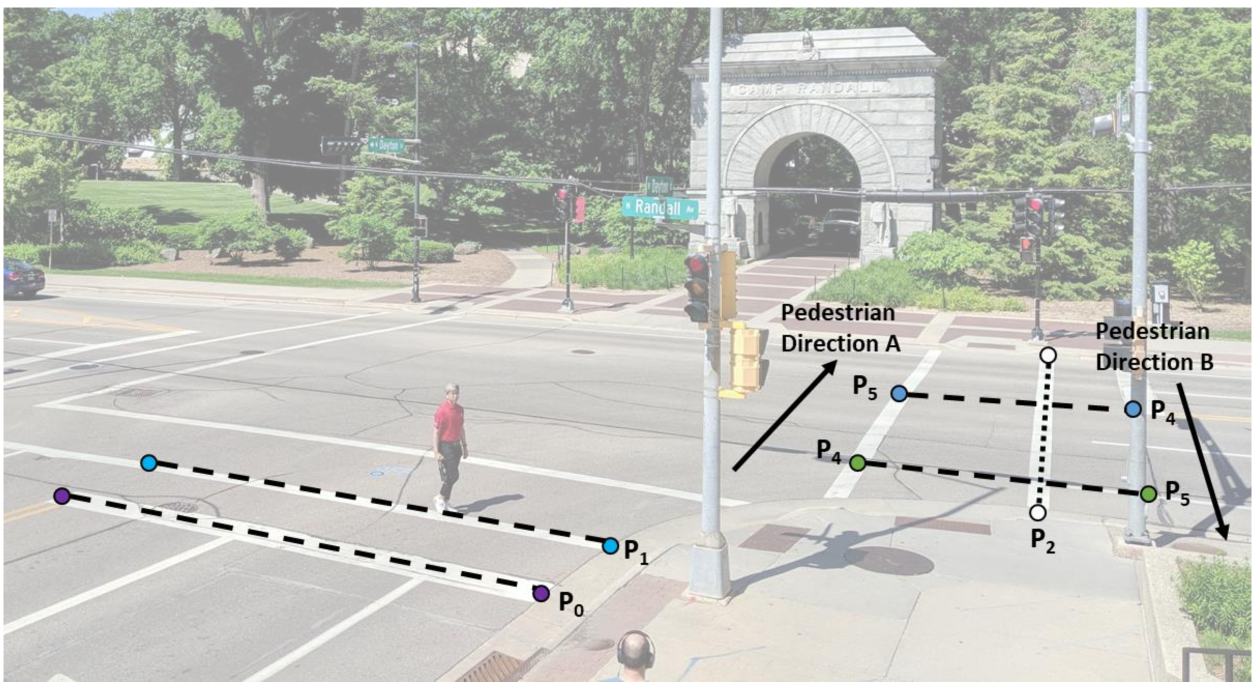

FIGURE 1 Visual Representation of Timestamps Documented

As shown in **FIGURE 1**, P_0 represents the stop bar of the entering approach, P_1 represents the most upstream bar of the crosswalk in the entering approach, and P_2 represents the most downstream bar of the crosswalk in the exiting approach for vehicles making a right turn from West Dayton Street onto North Randall Avenue. Finally, P_4 and P_5 represent the boundaries of the lanes that the right turning vehicle can use during the completion of the maneuver. P_4 is the boundary that the conflicting pedestrian crosses first (determined by the direction of travel) and P_5 is the last boundary that the conflicting pedestrian crosses.

A total of 18 hours of intersection video recorded at 30 frames per second were analyzed. The 18 hours of video were recorded over multiple days during periods of low pedestrian and vehicle activity to support the goal of having a narrow analysis dataset with minimal influencing factors. The timestamps associated with positions P_0, P_1, P_2, P_4, and P_5 were obtained from the video using a frame-by-frame analysis that relied on the *mpv* video player shown on **FIGURE 2** displaying video from the data collection site.

FIGURE 2 Screenshot of Timestamp Extraction Process

Type of Interactions Documented

The final dataset used to model the vehicle-pedestrian interactions contains right turn observations limited to leading right-turning vehicles. A leading right-turning vehicle is defined as a vehicle that completed the right turn at least 5 seconds after another vehicle completed the same right turn. Furthermore, right turn observations analyzed were also limited to right turns made when no pedestrians were present (Group 1) or to right turns made when 1, 2, or 3 pedestrians that entered the crosswalk at the same time and in the same direction were present in the crosswalk (Group 2). For each right turn observation included in Group 1 and Group 2, additional variables were documented such as the number of conflicting pedestrians, the right turn signal status, and if the right turning vehicle came to a complete stop prior to initiating the right turn maneuver.

Examples of Group 2 vehicle-pedestrian interactions included and not included in the analysis dataset are shown in **FIGURE 3**. Narrowing the type of interactions included in Group 2 made it possible to obtain an analysis dataset that limits the influence of other variables in the model that explains the behavior of vehicles completing a right turn when a pedestrian is present within the crosswalk. In other words, the narrow conditions used provide scenarios that are closer to a naturalistic field experiment without the associated complexities. The sections ahead the type of data extracted from Group 1 and Group 2 and how the corresponding data will be used to model the vehicle-pedestrian interactions using a linear regression model.

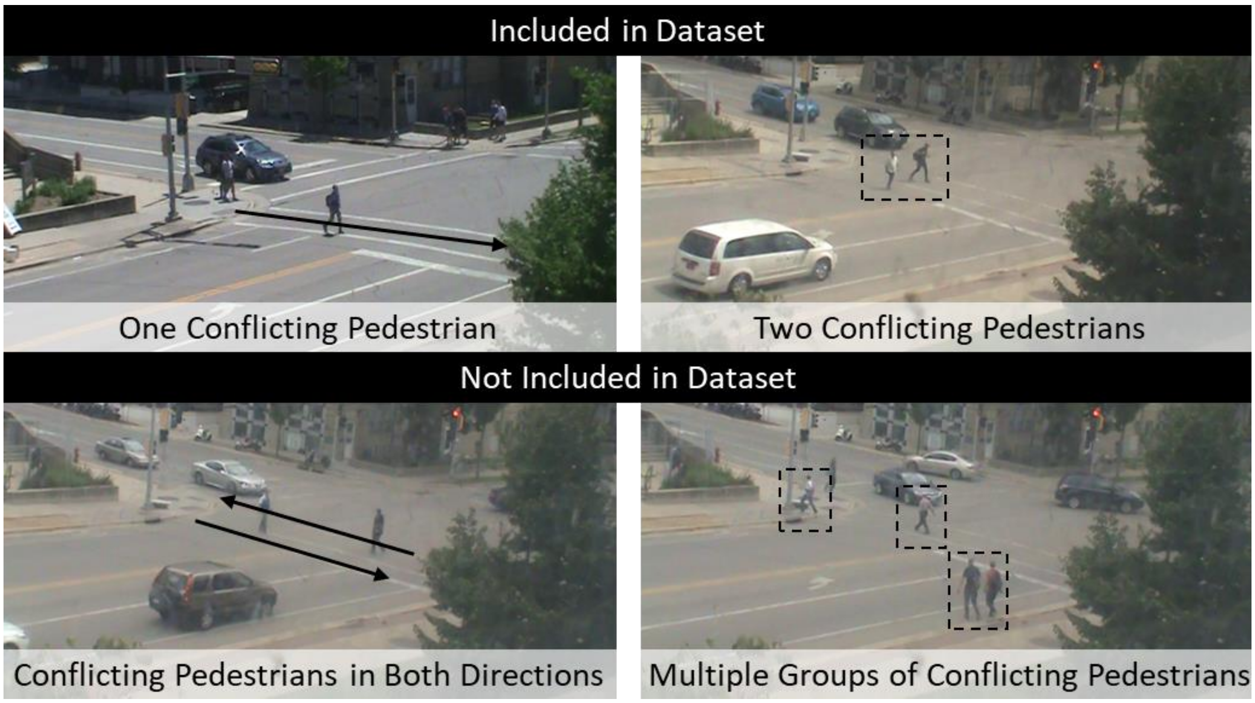

FIGURE 3 Sample Vehicle-Pedestrian Interactions Included and Not Included in Analysis Dataset

Group 1: Expected Behavior of Right Turn Movement

Using the video, the timestamps associated with P_1 and P_2 were documented for vehicles making a right turn when there were no conflicting pedestrians present. The documentation of the timestamps was also limited to leading vehicles that arrived at the stop bar when the right turn signal was permissive green and that also completed the maneuver when the right turn signal was permissive green. The difference in time between the timestamps associated with P_2 and P_1 of 26 passenger cars was calculated and will be referred to as the unobstructed right turn time (U_{RTT}). A visualization of the U_{RTT} values is shown in **FIGURE 4**.

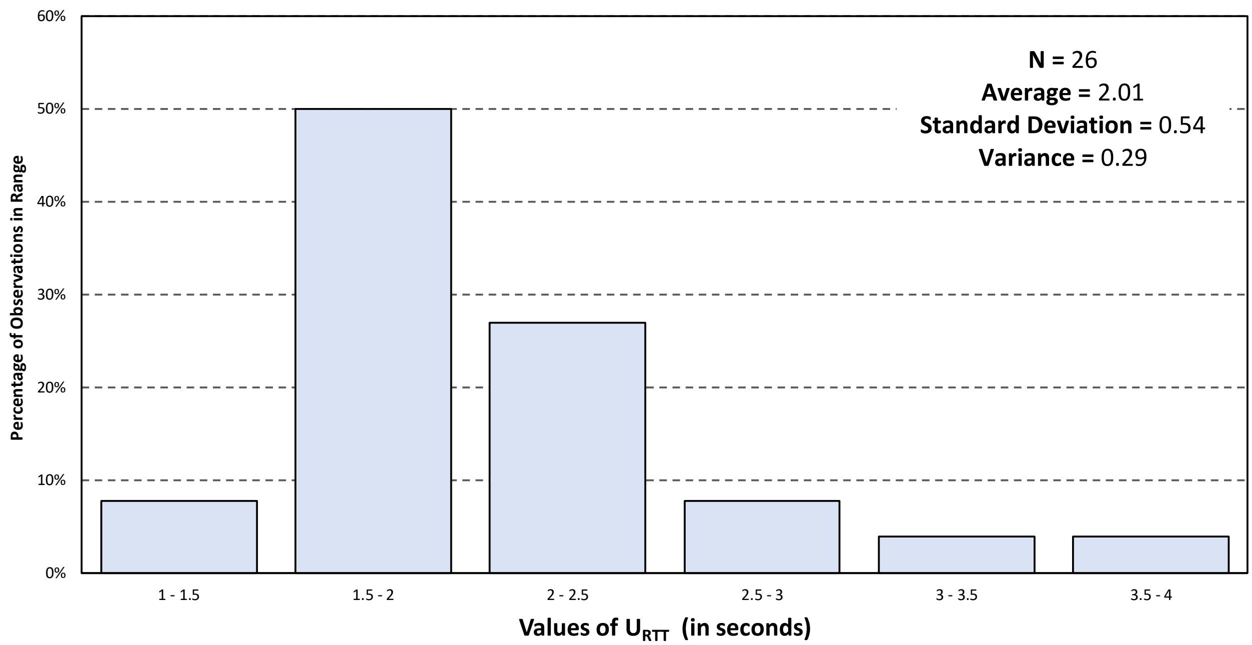

FIGURE 4 Histogram of U_{RTT} Values

The average U_{RTT} value ($\overline{U_{RTT}}$) was found to be 2.01 seconds. Due to the narrow conditions associated with the collection of U_{RTT} values, the average value represents the expected behavior of right-turning vehicles at the intersection under an ideal scenario. As previously suggested, values higher than 2.01 seconds can be considered a safer maneuver while values lower than 2.01 seconds can be considered more aggressive maneuvers.

Group 2: Deviation from Expected Right Turn Behavior

For observations associated with vehicles that arrived at P_0 when a conflicting pedestrian was present, the difference between the corresponding P_2 and P_1 timestamps was calculated and is referred to as obstructed right turn time (O_{RTT}). For each O_{RTT} observation, the timestamps when the conflicting pedestrian crossed P_4 and P_5 were also documented along with the right turn signal status (R_S), the number of conflicting pedestrians (CP_{NO}), the pedestrians travel direction (P_{TD}), and whether the vehicle stopped prior to initiating a right turn (V_S). A total of 52 O_{RTT} observations were made using the 18 hours of video.

Using the timestamps associated with conflicting pedestrians crossing P_4 and P_5, and by assuming a uniform walking speed, the theoretical time for the moment when the pedestrian arrived at the midpoint between P_4 and P_5 was calculated. The midpoint is referred to as P_{45} and can be treated as the physical point within the crosswalk where pedestrians are the most vulnerable. The difference between the timestamps associated with P_{45} and P_1 were then used to calculate the time it would take each of the conflicting pedestrians associated with an O_{RTT} observation to reach P_{45} and is referred to as TT_{45}. The difference between the observed O_{RTT} value and $\overline{U_{RTT}}$ was also calculated and is referred to as the deviation from expected behavior (D_{EB}). **TABLE 2** shows a breakdown of the number of observations per corresponding categorical variable (V_S, P_{TD}, CP_{NO}, and R_S) and **TABLE 2** shows descriptive statistics for O_{RTT} and TT_{45} which are continuous variables.

TABLE 1 Number of O_{RTT} Observations by Value of V_S, P_{TD}, CP_{NO}, and R_S

Stopped (V_S)			Pedestrian Direction (P_{TD})	
Yes	No		A	B
17	35		36	16
Number of Conflicting Pedestrians (CP_{NO})			**Right Turn Signal (R_S)**	
1	**2**	**3**	**Green**	**Red**
27	15	10	46	6

TABLE 2 Descriptive Statistics for O_{RTT} and Associated Values

Statistic	O_{RTT}	D_{EB}	TT_{45}
Mean	4.161	1.0699	-0.1541
SD	2.136	1.063	2.490
Median	3.395	0.6891	-0.1753
Min	1.184	-0.4109	-4.9715
Max	10.845	4.3955	6.057

As **TABLE 1** shows, most O_{RTT} observations were associated with a green indication. Furthermore, those associated with a red indication can be treated as effectively green due to the field conditions. For instance, the fact that an O_{RTT} observation was made implies that the observation is associated with a "right turn on red" scenario and since a corresponding conflicting pedestrian was present that means that the pedestrian was willing to cross the crosswalk outside the walk period. Therefore, the observations were during an "effectively green" right turn phase caused by the safe conditions perceived by the pedestrian and the driver of the right turning vehicle. **TABLE 2** shows that the average O_{RTT} value is approximately 2 times (4.16 seconds compared to 2.01 seconds) the average U_{RTT} value suggesting that, as expected, the presence of a pedestrian causes the driver of a right-turning vehicle to take longer to complete the right turn. The average value of TT_{45} indicates that, on average, conflicting pedestrians crossed the critical P_{45} mark 0.15 seconds after the right turning vehicle arrived to P_1.

DATA ANALYSIS AND RESULTS

Regression analysis was used to explore the relation between O_{RTT} and the TT_{45}, V_S, P_{TD}, CP_{NO}, and R_S predictor variables. The dependent variable O_{RTT} was found to be not normally distributed. Normality of residuals was inspected visually using QQ-plots. As a result, the analysis was then performed with the values of O_{RTT} logarithmically transformed. A simple linear regression was first used to show the relationship between the O_{RTT} response and the single predictor variable TT_{45}. Multiple linear regression was then used to assess the influence of the five previously mentioned predictor variables on O_{RTT}. Error! Reference source not found. shows a visual representation of the data. A linearly increasing relationship between O_{RTT} and TT_{45} can be seen with a strong positive correlation of 0.8.

As Error! Reference source not found. shows, when pedestrians were far from the critical conflict point (represented as $TT_{45} = 0$) in the figure, vehicles completed the right turn maneuver in a short time with a minimal deviation from $\overline{U_{RTT}}$. The linear relationship between O_{RTT} and TT_{45} is likely to be maintained near TT_{45} values close to zero. The slope of a linear fit for this region can be considered an indicator of "respect" for pedestrians because when drivers felt that pedestrians were going to be approaching the critical conflict point during the right turn maneuver, vehicles slowed down and took more time to complete the right turn. Arguably, the higher the slope near the $TT_{45} = 0$ region the higher the "respect" exhibit towards pedestrian at the location; thus, the argument made that model parameters derived from the dataset shown can be used as a form of surrogate safety measure.

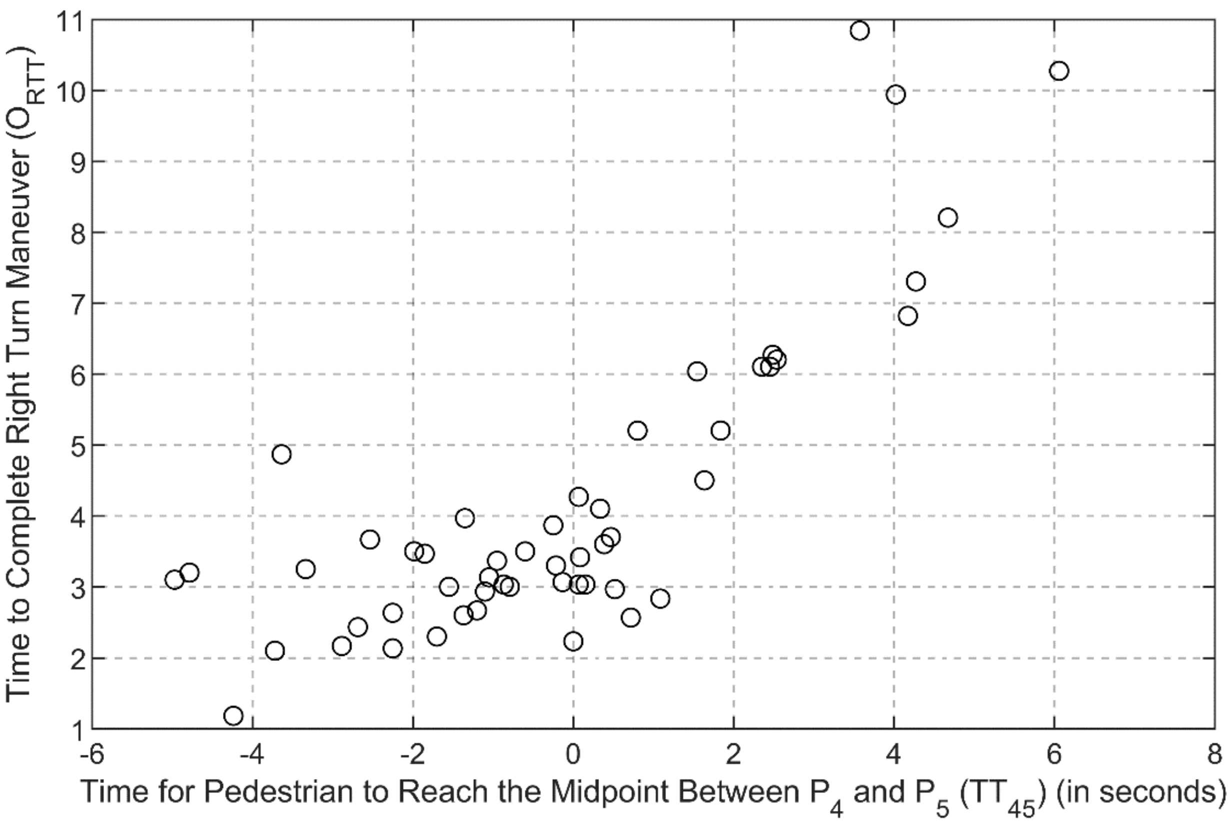

FIGURE 5 Scatter plot of O_{RTT} as a function of TT_{45}

Based on the high correlation coefficient, a linear model of O_{RTT} as a function of TT_{45} was built. A visual representation of the model is shown in Error! Reference source not found.. The output of the simple linear regression model is shown in **TABLE 3** and the model is represented by **Equation 1**.

$$Log - O_{RTT} = 1.3427 + 0.1432 * TT_{45} \quad (1)$$

When pedestrians are present at the conflict point (TT_{45} = 0), vehicles need 3.83 sec (= $e^{1.3427}$) to complete the right turn maneuver. A time of *t* seconds for pedestrians to reach the conflict point corresponds to $3.83e^{0.1432t}$ seconds to complete the right turn maneuver.

TABLE 3 Simple Linear Regression Model

	Estimate	Std. Error	p-value
Intercept	1.34272	0.03788	< 2e-16
TT_{45}	0.14316	0.01533	1.52e-12
Multiple R-squared: 0.6357, Adjusted R-squared: 0.6284			
F-statistic: 87.24 on 1 and 50 DF, p-value: 1.519e-12			

A closer look at Error! Reference source not found. (a) shows that the plot can be split into 2 regions at TT_{45} = 0. Segmented regression, also referred to as piecewise regression, was used to fit two separate-but-connected lines for each region as shown in Error! Reference source not found. (b). The output of the segmented linear regression model is shown in **TABLE 4** and the model is represented by **Equation 2**.

$$Log - O_{RTT} = \begin{cases} 1.1916 + 0.0589 * TT_{45}, & TT_{45} < 0 \\ 1.2024 + 0.2168 * TT_{45}, & TT_{45} \geq 0 \end{cases} \quad (2)$$

As previously mentioned, the change in slope between the 2 regions can act as an indicator of the "respect" exhibited towards the presence of conflicting pedestrians. In other words, higher values of O_{RTT} are exhibited when there is a possibility of pedestrians within the critical conflict point described by TT_{45} = 0. The model shown suggests that when pedestrians are present at the critical conflict point, vehicles need 3.33 sec to complete the right turn maneuver.

TABLE 4 Segmented Simple Linear Regression Model

	Estimate	Std. Error	p-value
Intercept	0.80424	0.23909	0.00154
TT_{45}	0.21677	0.02867	1.16e-09
TT_{45} < 0	0.38743	0.25284	0.13321
TT_{45} > 0	0.39820	0.25020	0.11819
TT_{45}:TT_{45} < 0	-0.15794	0.04441	0.00087
Multiple R-squared: 0.7366, Adjusted R-squared: 0.7142			
F-statistic: 32.86 on 4 and 47 DF, p-value: 4.439e-13			

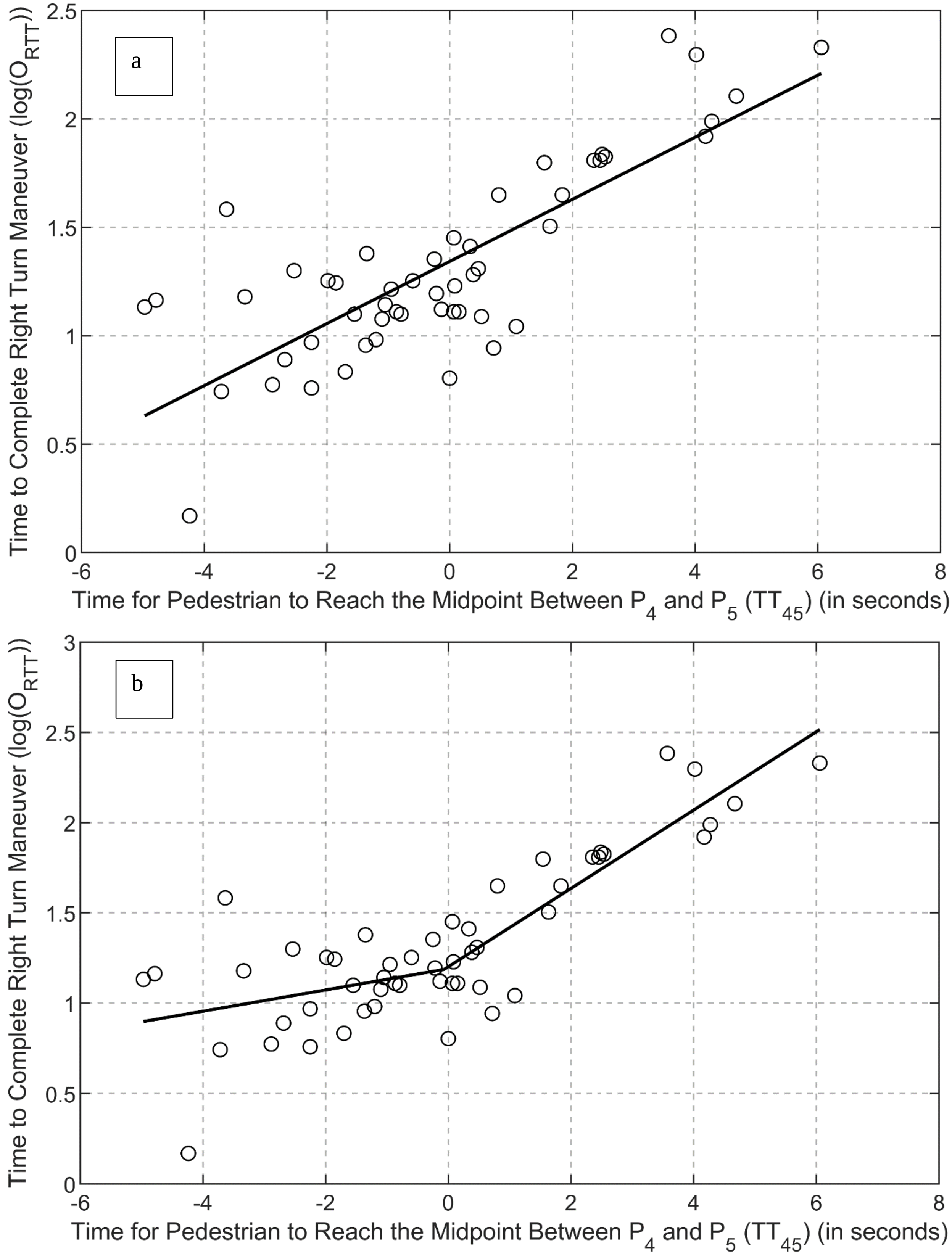

FIGURE 6 Linear Regression Model (a) and Segmented Regression Model (b)

Multiple linear regression was then performed and included the 5 dependent variables and the possible interactions. The categorical variables were first recorded in a set of binary variables as shown in **TABLE 5**. The p-value was used to determine the variables that statistically fit the model. The best model which had the best statistical results was developed. A p-value of less than 0.01 was used as the criterion to select the dependent variables. The output of the multiple linear regression model is shown in **TABLE 6** and the model is represented by **Equation 3**.

$$Log - O_{RTT} = 1.185 + 0.1067 * TT_{45} + 0.2883 * Vs + 0.188 * P_{TD} \quad (3)$$

TABLE 5 Dummy Variables Coding

Stopped (V_S)		Pedestrian Direction (P_{TD})		Right Turn Signal (R_S)	
Yes	**No**	**A**	**B**	**Green**	**Red**
1	0	0	1	0	1

TABLE 6 Multiple Linear Regression Model

	Estimate	Std. Error	p-value
Intercept	1.18500	0.04991	< 2e-16
TT_{45}	0.10671	0.01611	2.76e-08
Stopped (V_S)	0.28834	0.08302	0.0011
Pedestrian Direction (P_{TD})	0.18798	0.07309	0.0133
Multiple R-squared: 0.7343, Adjusted R-squared: 0.7177			
F-statistic: 44.21 on 3 and 48 DF, p-value: 7.441e-14			

Segmented regression was performed to consider the break point at $TT_{45} = 0$. The output of the segmented multiple linear regression model is shown in **TABLE 7** and the model is represented by **Equation 4.**

$$Log - O_{RTT} = \begin{cases} 1.1496 + 0.0671 * TT_{45} + 0.2191 * Vs + 0.1538 * P_{TD}, & TT_{45} < 0 \\ 1.084 + 0.1787 * TT_{45} + 0.2191 * Vs + 0.1538 * P_{TD}, & TT_{45} \geq 0 \end{cases} \quad (4)$$

TABLE 7 Multiple Linear Regression Model using Segmented Regression

	Estimate	Std. Error	p-value
Intercept	0.80424	0.21952	0.000652
TT_{45}	0.17866	0.02902	1.83e-07
$TT_{45} < 0$	0.34544	0.23256	0.144420
$TT_{45} > 0$	0.27981	0.23254	0.235153
Stopped (V_S)	0.21907	0.08243	0.010852
Pedestrian Direction (P_{TD})	0.15379	0.06902	0.030904
$TT_{45}:TT_{45} < 0$	-0.11160	0.04331	0.013316
Multiple R-squared: 0.7874, Adjusted R-squared: 0.7591			
F-statistic: 27.78 on 6 and 45 DF, p-value: 1.354e-13			

To simplify the segmented multiple linear regression model, a binary dummy variable called $V_{BreakPoint}$ was created. $V_{BreakPoint}$ takes the value of -1 if TT_{45} is < 0 and +1 if TT_{45} is ≥ 0. The output of the final model is shown in **TABLE 8** and the model is represented by **Equation 5**.

$$Log - O_{RTT} = 1.09655 + 0.11633 * TT_{45} + 0.22281 * Vs + 0.159438 * P_{TD} - 0.01546 * V_{Break\ Point} + 0.06151 * TT_{45} * V_{Break\ Point} \quad (5)$$

TABLE 8 Multiple Linear Regression Model with $V_{BreakPoint}$

	Estimate	Std. Error	p-value
Intercept	1.09655	0.05540	< 2e-16
TT_{45}	0.11633	0.02078	1.16e-06
Stopped (V_S)	0.22281	0.08346	0.01046
Pedestrian Direction (P_{TD})	0.15943	0.06981	0.02705
$V_{BreakPoint}$	-0.01546	0.05144	0.46514
TT_{45} : $V_{BreakPoint}$ (Interaction)	0.06151	0.02159	0.00653
Multiple R-squared: 0.777, Adjusted R-squared: 0.7527			
F-statistic: 32.05 on 5 and 46 DF, p-value: 6.437e-14			

CONCLUSIONS

Using a frame-by-frame video-based analysis of maneuvers by right-turning vehicles facing conflicting pedestrians from a signalized intersection, timestamps associated with key trajectory points of the pedestrians and vehicles were documented during individual vehicle-pedestrian interactions. Timestamps for the key positions were then used to create measurements that explain the time it takes for a vehicle to complete a right turn when a pedestrian is present (O_{RTT}) and the time for the pedestrian to arrive at a critical conflict point (TT_{45}).

Other variables such as vehicles stopping prior to completing a right turn (V_S) and the pedestrian travel direction (P_{TD}) were also logged for each vehicle-pedestrian interaction. The subset of vehicle-pedestrians interactions documented was limited to right turns completed when only one conflicting pedestrian was present or when a group of up to three pedestrians that entered the crosswalk at the same time were present. The narrow set of conditions documented enabled the creation of linear regression models that explain how right-turning vehicles and the site studied behaved when conflicting pedestrians were present.

A Simplified Approach to Modeling Vehicle and Pedestrian Interactions

Most of the research conducted that looks at vehicle-pedestrian interactions, or simply at vehicle-vehicle interactions, is focused on modeling approaches that calculate the probability of an action such as the acceptance of a gap happening. The research team purposely modeled a narrow set of vehicle-pedestrian interactions from a single intersection using multiple linear regression approaches to predict the value of O_{RTT}. The narrow set of interactions modeled provided a dataset that attempts to resemble what is only possible through controlled experiments by limiting the number of variables that could have a significant impact on driver behavior that manifests as the time for a vehicle to complete a right turn.

Model parameters confirmed what drivers experience daily and what countless research has previously quantified: the presence of a conflicting pedestrian causes the driver of a vehicle to deviate from the expected behavior when no conflicting pedestrians are present. The research team does not expect, or claims, that the model presented is representative of vehicle-pedestrian interactions on right turns, even under similar narrow scenarios. Therefore, the key contribution of the research effort described is demonstrating that by narrowing the scenarios considered, a "simple to understand" model that describes vehicle-pedestrian interactions at an individual site can be created with parameters that can be used to quantify the impact that safety countermeasures or traffic control devices have on vehicle-pedestrian interactions.

Implications for Evaluating the Effectiveness of Safety Countermeasures

The modeling approach presented in this paper can be used as a foundation for evaluating the effectiveness of safety countermeasures deployed at a signalized intersection without having to wait for crashes. This is possible because the model parameters explain the "attitude" of a vehicle (and therefore that of the driver) towards the presence of a pedestrian. Therefore, when multiple models are created for the same location that describes attitudes before and after the deployment of a countermeasure, quantifiable differences between the model can be established to explain the impact the countermeasure had on the attitudes towards the presence of pedestrians.

For example, prior to installing a countermeasure such as a right turn flashing yellow arrow to improve the yielding behavior of vehicle drivers towards pedestrians, a model like the ones shown can be established through field observations. After installation of the countermeasure, the same data collection and modeling procedure can be repeated. A comparison of the two models can then be conducted to explain if the installation of the countermeasure had a positive, neutral, or negative impact on the safety behavior observed through detailed field observations such as the ones described in this paper. Specifically, in the simplest version of the model, the one that describes O_{RTT} as a function of TT_{45}, the difference in the slopes can be interpreted as an indication of "respect" by drivers to the presence of conflicting pedestrians.

FUTURE WORK

While the modeling approach presented is discussed from the perspective of potentially using similar models to evaluate the effectiveness of countermeasures and traffic control devices, the reality is that the type of detailed analysis of vehicle-pedestrian interactions performed is going to be crucial as the transportation field moves forward. Once the transition to autonomous and connected vehicles starts to happen, having detailed models that explain vehicle-pedestrian interactions will be key, especially during the slow market penetration period for autonomous vehicles. Models such as the one described, developed with larger datasets, could be used in the future by autonomous vehicles to better understand how human drivers interact with pedestrians and better resemble that behavior to avoid situations such as rear ends by human drivers due to confusion and violations of expectancy when making permissive or protected left turns.

AUTHOR CONTRIBUTION STATEMENT

The authors confirm contribution to the paper as follows: study conception and design: H. Nassereddine, K. R. Santiago-Chaparro, D. A. Noyce; data collection: H. Nassereddine, K. R. Santiago-Chaparro; analysis and interpretation of results: H. Nassereddine, K. R. Santiago-Chaparro; draft manuscript preparation: H. Nassereddine, K. R. Santiago-Chaparro. All authors reviewed the results and approved the final version of the manuscript.

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