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DOI
10.1016/j.iatssr.2023.11.004

Publication date
2023

Document Version
Final published version

Published in
IATSS Research

IATSS Research 47 (2023) 526–534

Contents lists available at ScienceDirect

IATSS Research

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

Research Article

Receptiveness angle: A new surrogate safety measure for monitoring traffic safety

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ARTICLE INFO

Keywords:
Receptiveness angle
Trajectory data
Mixed traffic
Construction zone
Monitoring
Traffic-flow levels

ABSTRACT

This paper presents a framework for monitoring highway traffic-stream measures using quality trajectory data of mixed (heterogeneous) traffic. The framework includes a new measure that reflects the attentiveness of the follower driver, called receptiveness angle, in the vehicle-following process. This measure is integrated with the traditional measures (distance gap between the leader and follower vehicles and their speeds) to model the probabilistic rear-end collision interactions between the two vehicles. To verify the proposed framework, two road sections in India with mixed traffic conditions, located along the same road, were used. One section has no construction activity (base section) and the other has construction activity. The verification consisted of two tasks. First, to trace the movements of the vehicles, trajectory data over the study sections were developed for three traffic-flow levels, where two flow levels between the two sections were comparable. Second, the trajectory data were used to verify the proposed framework which was evaluated for the traffic streams of the two sections at the three traffic-flow levels. The results showed that smaller vehicles in the traffic stream exhibited a higher receptiveness angle (paid less attention) compared to other vehicle classes. Interestingly, the study revealed variations in safety among the three traffic-flow levels. It was observed that the traffic stream was safer at stop-and-go conditions than at other flow conditions. Furthermore, due to the pre-cautioning measures for the construction section, vehicles in this section were more attentive than those in the base section.

1. Introduction

Road safety is one of the major problems in the transportation sector since its inception. Even in modern days with the advent of high-speed automobiles along with efficient road geometric design, road safety problems remain. To address this issue and understand road safety over a road network, initially researchers focused on past collision records in assessing safety [1–3]. To certain extent, these studies supported practitioners and engineers in understanding the critical elements over the road network. Based on the availability of historical collision data, researchers applied numerous mathematical concepts in modeling collisions, including time series modeling [4,5], regression modeling [6], Bayesian analysis [7], hierarchal clustering [8], street-pattern analysis [9], and support vector mechanism [10]. These methodologies have proven to be valuable in quantifying safety and identifying collision black spots over the network. The methodologies have aided authorities in understanding critical collision zones and allocating funds for road improvements. To better understand safety over road sections, the U.S. Federal Highway Administration started the Strategic Highway Research Program (SHRP2) [11] and developed various traffic datasets. Based on SHRP2 datasets, researchers analyzed various safety measures related to naturalistic driving phenomenon, including drivers anger [12], driving errors and violations [13,14], behavior at curves [15], lane changing on collisions [16], and risk prediction [17–19]. In those studies, researchers were able to identify the key influencing factors and causes of collisions and model collision rates. Clearly, the preceding strategies represented a reactive approach in assessing safety.

On another approach, researchers realized the importance of proactive measures to assess safety elements well before the occurrence of collisions. The safety measures included deceleration rate to avoid collision (DRAC) [20], potential index for collision with urgent deceleration (PICUD) [21], collision potential index (CPI) [22], time to collision (TTC) [23], and post encroachment time (PET) [24]. It is noted that the preceding proactive measures have their own advantageous and

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https://doi.org/10.1016/j.iatssr.2023.11.004
Received 21 February 2023; Received in revised form 28 October 2023; Accepted 27 November 2023
Available online 9 December 2023

disadvantageous in evaluating road safety. For example, in the case of TTC, the time gap between the leader and follower vehicles (referred to herein as leader and follower) defined as the ratio of distance gap to relative speed. Consider two scenarios: two vehicles with distance gap of 30 m and relative speed of 15 m/s, and two vehicles with distance gap of 10 m and relative speed of 5 m/s. The TTC in both cases is 2 s, indicating similar probabilities of collision. However, in a realistic sense, the probabilities of collision in both scenarios are different, indicating erroneous definition. Still TTC has been used as a safety measure in numerous studies, including work zone safety [25], collision frequency in urban tunnels [26], and collision risk on freeways [27,28]. It is noted that most studies used a single safety measure in assessing rear-end collisions.

At the same time, from the literature, most of the surrogate safety measures suggest that congested traffic conditions are the most unsafe. This is likely due to the underlying formulations of the surrogate safety measures (SSMs), which are more sensitive to the changes in traffic conditions that occur in congestion, such as reduced time gap and decreased following distance.

On the other hand, the empirical studies on traffic safety emphasize that the speed of vehicles is a key factor in causing accidents. Notably, the Swedish traffic conflict technique [29], identifies 30 kmph as a critical speed threshold for safety assessment along with time gap. Additionally, research by [30–32] indicates that fatal crashes are more likely to happen under free-flowing traffic conditions compared to congested ones.

Most proactive safety studies have used vehicle trajectory datasets to understand driving behavior related to rear-end collisions. Based on the literature, it was inferred that most studies have assessed safety using individual measures, such as distance gap and follower speed. Such safety measures can gauge the attention of the drivers in the traffic stream. However, besides these measures, the attentiveness stage of the follower vehicle in a traffic stream plays a key role in understanding safety. However, none of the previous studies has quantified this measure.

The purpose of this paper is to present a framework for monitoring highway traffic stream measures using trajectory data of mixed (heterogeneous) traffic to identify probable rear-end collisions using trajectory data. The framework includes a new safety measure that captures the attentiveness level of the driver in vehicle-following situations. The new measure is integrated with traditional measures (distance gap and vehicle speeds) to predict the probability of rear-end collisions. The study consists of five main tasks, as shown in Fig. 1. First, a new safety measure that quantifies driver attentiveness, called herein receptiveness angle, is conceptualized. Second, a safety framework for rear-end collisions that integrates the new measure with two traditional measures is developed. The framework can monitor traffic stream distance gaps and speeds and identify probable rear-end collisions. Third, vehicle trajectory data are collected for two different highway sections at three traffic-flow levels: one section has no construction activity (base section) and the other has construction activity. The data were collected using video graphic survey with the help of a semi-automatic tool. Fourth, trajectory data were used to analyze the study sections using the proposed framework. The framework is applied to the study sections and probable rear-end collisions are evaluated. Since the data involve mixed traffic conditions with numerous vehicle categories and complex interactions between them, it was necessary to develop an algorithm to analyze the data. Finally, based on the analysis of the trajectory data, the monitoring framework for rear-end collisions is verified and implementation areas are identified.

The next section presents the monitoring framework, including the new driver attentiveness measure and its integration with other traditional measures. The following sections present data collection and preparation and the application of the framework to the study sections. Analysis of the results is then presented, followed by concluding remarks.

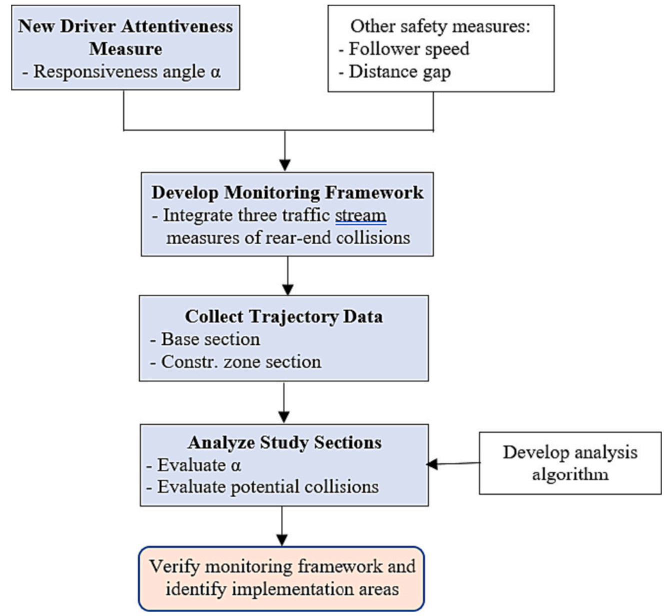


Fig. 1. Tasks of developing the monitoring framework for traffic stream variables.

2. Monitoring framework

2.1. New driver attentiveness measure

Based on the literature, it was noted that the attention of the follower toward the leader in a traffic stream plays a critical role in understanding potential rear-end collisions. For example, due to some random disturbances in the traffic stream, the leader (as a follower of another vehicle) may slow to avoid a rear-end collision with its leader. Then, the subject follower obeys the leader by reducing its speed and tries to match its leader's speed. Further, the time lag between the decisions of the leader and the follower represents the level of attentiveness of the follower.

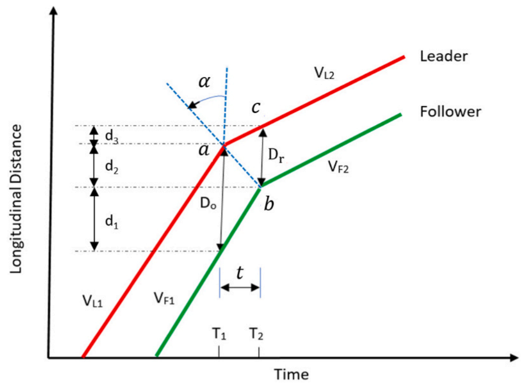
The time-space diagram of the follower and leader are examined, as shown in Fig. 2a. As noted, the leader travels at speed V_{L1} and reduces its speed to V_{L2} at time T_1 (Point a). The follower travels at a speed V_{F1} and responds to the speed reduction of the leader at time T_2 (Point b) by reducing speed to V_{F2}. Note that the time T_2 implicitly includes the perception-reaction time of the follower. Furthermore, d1, stands for the physical distance traveled by the follower along their trajectory while remaining unnoticed to any actions or movements initiated by the leader. On the other hand, d2, denotes the spatial separation or gap between the timing and positioning of the leader's actions and those of the follower. Lastly, d3, signifies the distance covered by the leader along their path up to the moment when the follower acknowledges and responds to the leader's actions.

The original distance gap between the two vehicles is D_o and the distance gap at the follower response is D_r. Clearly, due to the lag in the follower's response, the distance gap decreases. To quantify the attentiveness of the follower, a new safety measure ‘receptiveness angle (α) is defined as the angle measured from the vertical line at a to the line connecting the decision points of the leader and the follower. The angle is positive if it is anti-clockwise and negative otherwise. The angle α depends, to a large extent, on both the distance gap and the level of attentiveness of the follower, reflected by the time lag t.

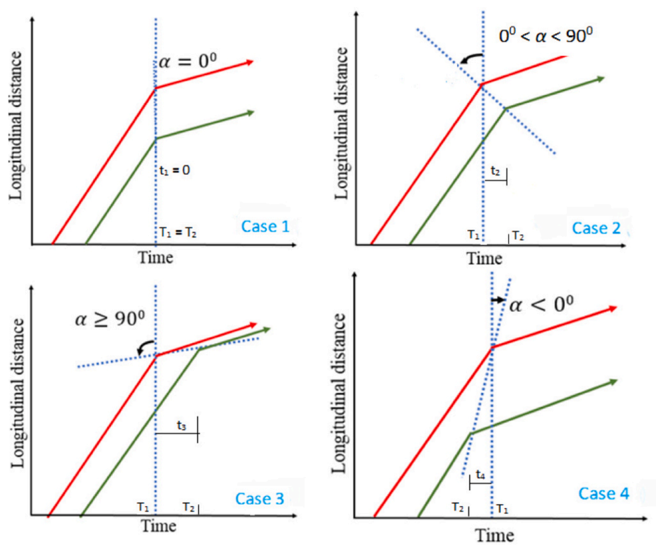
From the geometry of Fig. 2a, the receptiveness angle can be derived as follows. The lag time is given by

$$t = T_2 - T_1 \tag{1}$$

where:



(a) Time-space diagram



(b) Boundary conditions of receptiveness angle

Fig. 2. Time-space diagram and different cases of the receptiveness angle.

t = lag time (s).
T_1 = time at which the leader reduces speed (s)
T_2 = time at which the follower reduces speed (s)
where D_o is original distance gap (m). Since $\tan\alpha = t / d_2$, then the receptiveness angle α can be written as

$$\alpha = tan^{-1}\left(\frac{t}{d_2}\right) \tag{2}$$

The D_o, original distance gap (m), and D_r, clear distance during the lag time, the leader travels a distance d_3 and therefore the clear distance D_r between the leader and the follower at time T_2 is $(d_2 + d_3)$. Thus,

$$D_0 = d_1 + d_2 \tag{3}$$

$$D_r = d_2 + d_3 \tag{4}$$

Adding Eqs. (3) and (4) yields

$$2d_2 + d_1 + d_3 = D_0 + D_r \tag{5}$$

$$2d_2 + 0.278V_{F1}t + 0.278V_{L2}t = D_0 + D_r \tag{6}$$

Rearranging the terms, then d_2 is given by

$$d_2 = \frac{D_0 + D_r - 0.278(V_{F1} + V_{L2})t}{2} \tag{7}$$

Substituting for d_2 from Eq. 2 into Eq. 7, then

$$\alpha = tan^{-1}\left(\frac{2t}{D_0 + D_r - 0.278(V_{F1} + V_{L2})t}\right) \tag{8}$$

where:
α = receptiveness angle (degrees),
D_0 = clear distance between the leader and the follower at time T_1 (m),
D_r = clear distance between the leader and the follower at time T_2 (m),
V_{F1} = original speed of the follower at time T_1 (km/h),
V_{L2} = reduced speed of the leader at time T_2 (km/h), and
t = lag time of the follower (s).
Various possible cases of the receptiveness angle (degree) are shown in Fig. 2b.

In Case 1 ($\alpha = 0$), the follower took the decision immediately when the leader decreased its speed with zero lag time $t_1 = 0$, indicating that the follower is fully attentive to the leader (full attention). In Case 2 ($0 < \alpha < 90$), the follower responded with some time lag $t_2 < D_o/0.278V_F$, indicating that the follower is displaying partial attentive to the reader (partial attention). It can be noted that in "case 1," to convey the concept of the receptiveness angle more effectively. Simultaneously, given the ongoing advancements in vehicle connectivity, it is likely that "case 1" could transition from a mere hypothetical to a tangible reality at different points in time. Within the revised manuscript, we depict "case 1" as an interconnected environment, while "case 2" serves as a representation of standard behavior. In Case 3 ($\alpha \geq 90$), the follower responded with a time lag corresponding to the original distance gap, $t_3 \geq D_o/0.278V_F$, indicating that the follower is not attentive at all to the leader (no attention). In Case 4 ($\alpha < 90$), the follower reduced the speed before the follower's action, indicating also that the follower is fully attentive. Conversely, in "case 4," the primary objective of the authors is to illustrate a scenario where the follower vehicle remains unresponsive to its leading counterpart. This situation typically arises during lane changes or in various other circumstances driven by the preferences of the follower vehicle, thereby highlighting instances where the follower's actions do not align with those of the leader. Note that the distance gap in Case 1 does not change, while it decreases in Cases 2 and 3 and increases in Case 4 (opening process). Clearly, an increase in the lag time of the follower depicts the inattentiveness of the follower. Thus, the boundary conditions of α are defined as follows,

$$\alpha = \begin{cases} 0, (\textit{full attention}) \\ 0 < \alpha < 90^0, (\textit{partial attention}) \\ \geq 90^0, (\textit{no attention}) \\ < 0, (\textit{opening process}) \end{cases} \tag{9}$$

Note that Fig. 2b shows Case 3 for $\alpha \geq 90$ which is the boundary for this case since $\alpha > 90$ represents a worse situation. Clearly, the receptiveness angle represents the rate of shift in the vehicle-following process.

2.2. Integrating three safety measures

The stage at which the follower pays attention toward the leader plays a key role in having a rear-end collision. For example, consider two scenarios. In Scenario 1, the follower perceived its leader at $\alpha = 15^0$ while moving at 100 km/h at a distance gap of 30 m from its leader. In Scenario 2, the follower perceived its leader at $\alpha = 15^0$ while moving at 75 km/h at a distance gap of 15 m from its leader. Clearly, even though the receptiveness angles in both scenarios are equal, the probabilities of rear-end collisions in the two scenarios should be different, given the variation in speed and distance gap. Therefore, it can be concluded that in addition to the receptiveness angle, the follower speed and distance gap play a vital role and forms a strong probability scheme among the three variables in assessing the rear-end collision. Such a scheme should generate a high probability for rear-end collision between the follower and the leader when all variables are at their extreme limits.

The proposed safety framework requires values of the critical speed, critical receptiveness angle, and critical distance gap with respect to rear-end collisions. Let P(V_{F1}) be the probability that the follower speed is greater than the critical speed, P(α) be the probability that α is greater than its critical limit, and P(D_0) be the probability that the distance gap is less than the critical distance gap for rear-end collision. Let P(V_{F1}^c), P(α^c), and P(D_0^c) be the complementary probabilities of the respective events. As such, the probability of rear-end collision event occurrence is given by P($V_{F1} \cap \alpha \cap D_0$), as shown in Fig. 3. To evaluate this probability, the probabilistic concepts are applied to the rear-end collision events, as follows

$$P(V_{F1} \cup \alpha \cup D_0) = P(V_{F1}) + P(\alpha) + P(D_0) - P(V_{F1} \cap \alpha) - P(V_{F1} \cap D_0) - P(\alpha \cap D_0) + P(V_{F1} \cap \alpha \cap D_0) \quad (10)$$

Rearranging the terms, the probability of rear-end collision is given by

$$P(V_{F1} \cap \alpha \cap D_0) = P(V_{F1} \cup \alpha \cup D_0) - P(V_{F1}) - P(\alpha) - P(D_0) + P(V_{F1} \cap \alpha) + P(V_{F1} \cap D_0) + P(\alpha \cap D_0) \quad (11)$$

Further, the probability of no rear-end collision is given by.

$$P(\text{no rear} - \text{end collision}) = 1 - P(\text{rear} - \text{end collision}) \quad (12)$$

3. Data collection and preparation

3.1. Description of study sections

Testing of the proposed safety framework warrants high-quality trajectory data, such that vehicle movements should be traced over the road space with at a microscopic level. Two study sections on the western expressway, Mumbai, India (an intra-urban multilane high-speed road) were selected, as shown in Fig. 4a. The first section (base section) is a 5-lane road with width 17.5 m (each lane 3.5-m wide) and traps length of 100 m. Further, along the same road, construction work was ongoing, where road width was narrowed from 17.5 m to 10.5 m (5-lanes to 3-lanes) for about 500 m. With this as an opportunity, a construction section was considered with a trap length of 100 m, exactly near the mid-portion of the construction zone. Note that the study sections were selected in such a way that the construction section is situated on the upstream and the base section on the downstream of the traffic stream (2.5 km apart) so that the impact of construction work on the base section would be minimal.

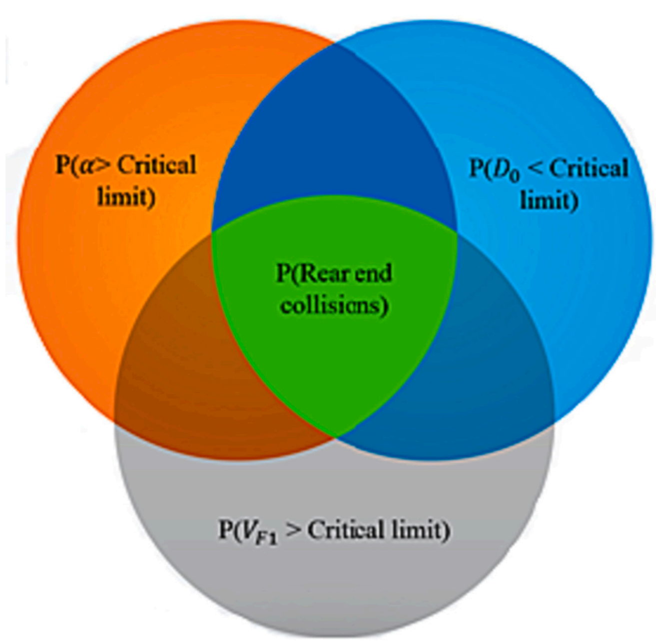


Fig. 3. Illustration of the probability of rear-end collision using Venn diagram.

3.2. Trajectory data development

Traffic observed on the study sections was found to be heterogeneous in nature and with weak-lane disciplined movements. Due to the complex vehicular movements and interactions, automation in traffic data collection and vehicle tracking is difficult under heterogeneous traffic conditions. Even the well-established image processing tools failed and exhibited a mediocre performance in trajectory development. To overcome these difficulties in the present study, video graphic surveys were initially performed, and then traffic movements were recorded over a wide range of traffic flow, ranging from free to congested flow. This data primarily comprises longitudinal and lateral vehicle positions for each time point along the study section. The tracking primarily focuses on the vehicle centre, including the vehicle's length and width.

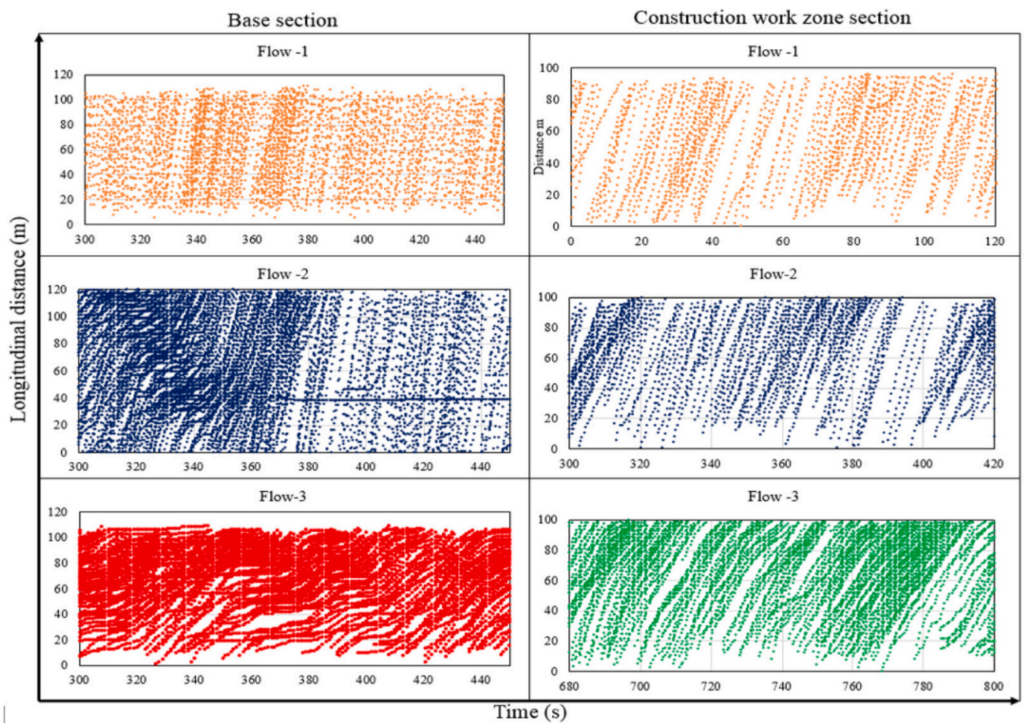
In line with the literature [33], in this study a traffic data extractor, which is a semi-automated image processing tool [34], was used in developing the trajectory data, using computer mouse clicks for an update interval of 0.2 s to track a particular vehicle. Trajectory data were developed for each section at three flow levels: free flow, medium flow, and congested flow, as shown in Table 1. Further, to address the noise in the trajectory datasets different smoothening techniques were applied [35]. The trajectory data were depicted in terms of time-space plots, as shown in Fig. 4b. To develop the macroscopic plots the volume counts of the vehicles are standardized in the form of passenger car units [36], based on the developed macroscopic plots from the study sections, clustered in six states, the trajectory data were classified with respect to the specified flow thresholds. It was noted that for Flows 1 and 2 of both sections corresponded to flow regimes II and IV, and Flow 3 in flow regimes VI and V for the base and construction sections, respectively. Considering this in the present work, driving behavior is comparable among the matching Flows 1 and 2 between the study sections. Whereas Flow 3 of the base section corresponded to stop-and-go conditions and Flow 3 of the construction section was near capacity conditions. A total of 6900 vehicles are tracked for a duration of 85 min for both sections and six different vehicle categories were observed on the two sections: Motorized Two Wheelers (MTW), Motorized Three Wheelers (MThW), Bus, Cars, Trucks, and Light Commercial Vehicle (LCV).

4. Analysis of trajectory data

4.1. Algorithm development

It is obviously difficult to capture the receptiveness angle manually from the huge trajectory data. Therefore, an algorithm was developed and scripted in python 3.7.2 to compute the receptiveness angle automatically from the trajectory data. The logic of the algorithm is presented in Table 2. The flow of the algorithm is as follows. Initially, trajectory data are loaded as a data frame. Then, for the subsequent vehicles over the road space, the lateral overlaps among them are computed. If the vehicular pairs are found to have a lateral overlap, those pairs will be considered as leader-follower pairs. After evaluating the receptiveness angle, the extracted leader-follower pairs are thoroughly investigated. To compute the receptiveness angle, initially the leader trajectory data is scrutinized and the instant at which leader dropped its speed is identified. Then, the follower action, particularly speed drop is examined. A threshold of 1 m/s within a given time step has been adopted as the criterion for identifying points of inflection. On this basis, follower responses are organized with leader instincts. Later, the angle between the line joining the action of leader and follower actions is computed as the receptiveness angle. Using this algorithm, the receptiveness angle is computed for all pairs from the available

(a) Snapshots of the study sections



(b) Time-space plots of the vehicles at three flow levels

Fig. 4. Snap shots and time-space plots of the vehicles at study sections.

Table 1
Details of the trajectory data of the study sections.

Section	Dominant Vehicles	Trap length (m)	Road Width (m)	Traffic Flow Classification (V/C Ratio)[a]	Average speed (KMPH)	Traffic Composition (%)[c]	Flow Level	No. of Vehicles Tracked	Duration of Trajectory Data
Base	MTW, cars and trucks	120	17.5	Flow 1 (0.35)[c]	52.1	15,35,5,40,2,3	II	1080	15 min
				Flow 2 (0.71)	36.8	20,29,2,45,1,3	IV	1715	15 min
				Flow 3[b]	5.2	17,25,5,45,3,4	VI	660	10 min
Const. work	MTW, cars and trucks	100	10.5	Flow 1 (0.42)	51.8	15,27,8,42,5,3	II	870	15 min
				Flow 2 (0.68)	37.3	13,30,6,45,3,3	IV	1218	15 min
				Flow 3 (0.91)	21.4	10,35,5,45,2,3	V	1312	15 min

[a] V/C = volume to capacity.
[b] Stop-and-go conditions.
[c] Traffic composition: MThH, MTW, buses, cars, trucks, LCV.

trajectory data for both study sections.

4.2. Evaluation of receptiveness angle

Based on the scripted algorithm, using trajectory data over the study sections, python runs were carried out and the receptiveness angles between vehicles were evaluated. As previously mentioned, the distance gap at which subject follower perceived its leader plays a key role in understanding driver behavior. To understand this, the receptiveness angle is correlated with the distance gap. Further, based on the vehicle categories and their sizes, the data are segregated such that MTW is in one class, MThW and Cars are in another class, and buses, trucks, and LCV are in a third class. Based on the type of road section as shown in Fig. 5 and the descriptive statistics of Table 3. From Fig. 5, it is observed

Table 2
Flow of algorithm for calculating receptiveness angle (Scripted in python).

```
Input: vehicular trajectory data
For (Given subject vehicle)
        Identify the subsequent vehicles and compute lateral overlap
        If (subsequent vehicles having lateral overlap)
           Compute longitudinal distances
           Assemble them as leader-follower pairs
        End If
End For
For (Given leader-follower pair)
   Compute distance gap, relative speed for leader-follower pairs
         If (leader reduces speed) # Computing receptiveness angle
            Identify the time stamp as T1; measure the distance gap Do;
           Identify the speed of the follower VF1;
               If (the follower reduces speed after the leader's action)
                   Identify the time stamp as T2
                   Compute lag time t (Equation 1)
                   Clear distance between leader and follower at T2 is Dr
                   Calculated distance d2 (Equation 7)
                  Calculate α (Equation 8)
               End If
        End If
        Report α, VF1, and D0 to carry out safety analysis.
End For
Output: Leader-follower pairs and their receptiveness angles
```

that there is a wide variation in data patterns with respect to the change in vehicle class, traffic-flow level and road-section type.

In the majority of instances, the receptiveness angle of the situation remains confined within the relatively safe range of 0 to 90 degrees. However, it is crucial to note that should this angle surpass the 90-degree threshold, it takes on a striking resemblance to a crash scenario, signifying a significantly elevated risk of collision or accident. Analyzing the trajectory data that is currently available, one notable observation emerges: there are no recorded instances of a crash point occurring within the dataset. This observation underscores the significance of adhering to the safe 0 to 90-degree range in the context of vehicle dynamics and behavior. It suggests that, for the most part, vehicle interactions tend to stay within this range, minimizing the potential for hazardous situations and collisions.

To better understand the variation, the plots and data in Table 3 were examined throughly. It was found that most of the time nearly free-flow conditions the receptiveness angle was larger. Even the 50th percentile value of the receptiveness angle ranged from 49.3^0 to 71.2^0 (Flow 1), from 39.8^0 to 56.3^0 (Flow 2), and from 12.9^0 to 34.9^0 (Flow 3) for all vehicles over both study sections. The receptiveness angle tended to decrease with the increase in flow levels, which clearly signifies that vehicle attention level increased with the increase in traffi flow level. Similar findings are observed with distance gap, where the distance gap tended to decrease as the flow level increases.

The receptiveness angles of the base and construction sections were compared for all vehicles at comparable traffic flow conditions, as shown in Table 3. For the construction section, the angles of the base section are comparatively smaller, indicating that vehicles are comparatively inattentive in the base section. Similarly, for the distance gap, vehicles in the construction section are moving closer compared to those in the base section, indicating better attention. Whereas in the base section, even though vehicles are maintaining larger distance gaps When the vehicle class data are compared between the base and construction sections, it is noticed that vehicles are moving closer with their leaders in the construction section. Further, it is observed that vehicles in the construction section are moving uniformly with less decrease in the speed instincts. As a result, very few data points were registered, compared with the base section.

4.3. Evaluation of potential collisions

In the literature, there are no clear findings related to critical speed, critical receptiveness angle, or critical distance gap with respect to rear-end collisions. However, based on Shi et al. [37], the critical thresholds set for distance gaps is 5, 10, 15, and 20 m which and that for follower speed is 70, 50, 30 km/h. For the receptiveness angle five threshold values are considered in this study as 90, 72, 54, 36, 18 deg. Based on the sensitized thresholds using the Python code, safety analysis is performed for each possible combination of the preceding thresholds sets. In this study, the critical threshold combination of $V_F \geq 30$ km/h, $D_r \leq 10$ m, and $\alpha \geq 72^0$ (as an example) is considered in the analysis of probable rear-end collisions.

In line with the conceptualized safety framework, the probable and non-probable rear-end collision instincts are mapped over the space of the study sections for all flow levels, as shown in Fig. 6. Further, the number of probable rear-end collision points are segregated based on the leader-follower combinations as shown in Table 4. In comparing the two study sections, for Flows 1 and 2, the number of probable rear-end collision points is 23 and 29, respectively, for the base section and 55 and 22, respectively for the construction section. This clearly shows that at Flow 2, the ongoing construction work activity has alerted the behavior of drivers who tend to pay attention comparable with that of the base section. As a result, the number of rear-end collision points dropped by 60% (22 compared with 55).

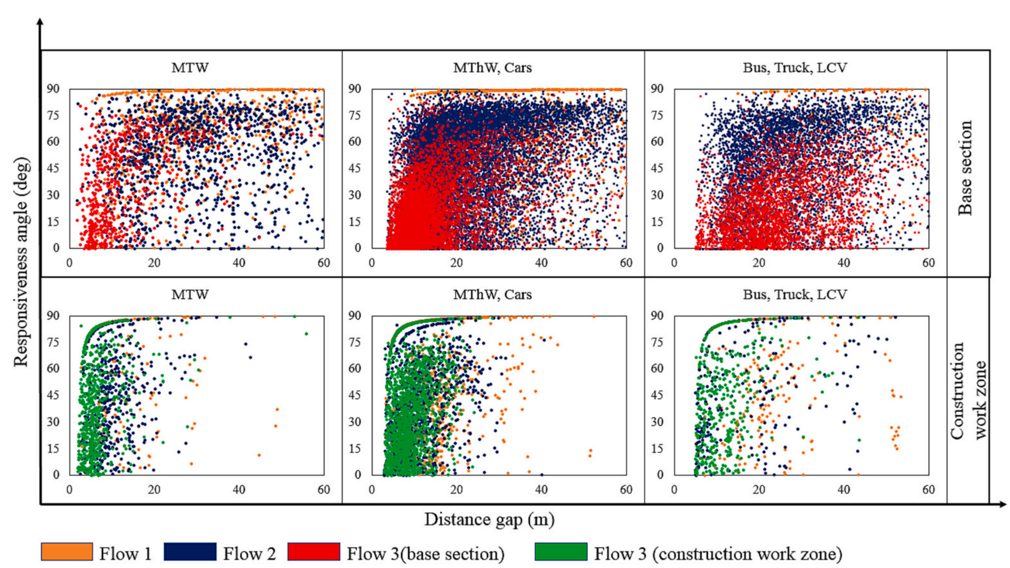


Fig. 5. Receptiveness angle vs. distance gap for vehicle classes at different traffic-flow levels (both sections).

Table 3
Descrpitve analysis of receptiveness angle and distance gaps for vehicles.

Traffic Flow Level	Percentile	Base Section			Construction Section		
		MTW	MThW, Car	Bus, Truck, LCV	MTW	MThW, Car	Bus, Truck, LCV
(a) Receptiveness angle (deg)							
	Min	0.7	0.0	0.1	3.2	0.1	0.1
	25	54.9	46.6	44.5	29.4	26.8	24.9
Flow 1	50	71.2	65.7	62.7	58.7	49.3	47.6
	75	87.8	84.9	81.7	86.3	82.2	77.7
	Max	89.6	89.6	89.6	89.4	89.5	89.4
	Min	0.0	0.0	0.0	0.6	0.0	0.1
	25	30.8	24.9	20.3	26.0	22.2	19.5
Flow 2	50	56.3	50.9	45.3	48.9	46.8	39.8
	75	71.3	67.0	65.3	72.3	74.7	63.5
	Max	89.3	89.3	89.5	89.2	89.0	89.4
	Min	0.0	0.0	0.0	0.0	0.0	0.2
	25	12.2	7.5	4.7	18.5	21.7	16.3
Flow 3[a]	50	33.2	19.9	12.0	22.4	26.9	24.5
	75	56.6	35.0	27.1	70.9	66.4	58.2
	Max	88.3	88.8	88.6	89.5	88.9	89.3
(b) Distance gap (m)							
	Min	3.9	9.9	6.6	3.9	9.2	6.2
	25	18.3	22.8	19.0	7.4	11.6	7.6
Flow 1	50	26.6	28.8	28.6	11.4	11.0	16.2
	75	39.7	37.4	40.9	18.4	14.6	22.3
	Max	59.9	59.9	59.9	47.1	49.4	48.4
	Min	3.5	4.5	5.7	2.5	3.2	4.5
	25	9.0	12.3	18.3	4.7	4.2	11.8
Flow 2	50	19.5	14.6	20.1	8.4	6.5	17.9
	75	38.8	24.8	30.1	15.1	11.2	25.9
	Max	59.7	60.0	60.0	59.4	59.9	59.9
	Min	2.1	3.2	4.2	3.2	3.9	4.5
	25	2.3	3.4	5.8	3.5	5.4	5.8
Flow 3[a]	50	3.5	5.3	6.0	6.5	6.2	8.0
	75	5.2	8.0	9.4	10.2	10.3	18.4
	Max	53.9	25.3	38.7	40.2	37.7	47.2

[a] The volume-to-capacity ratios differ between the base section and the construction work zone section.

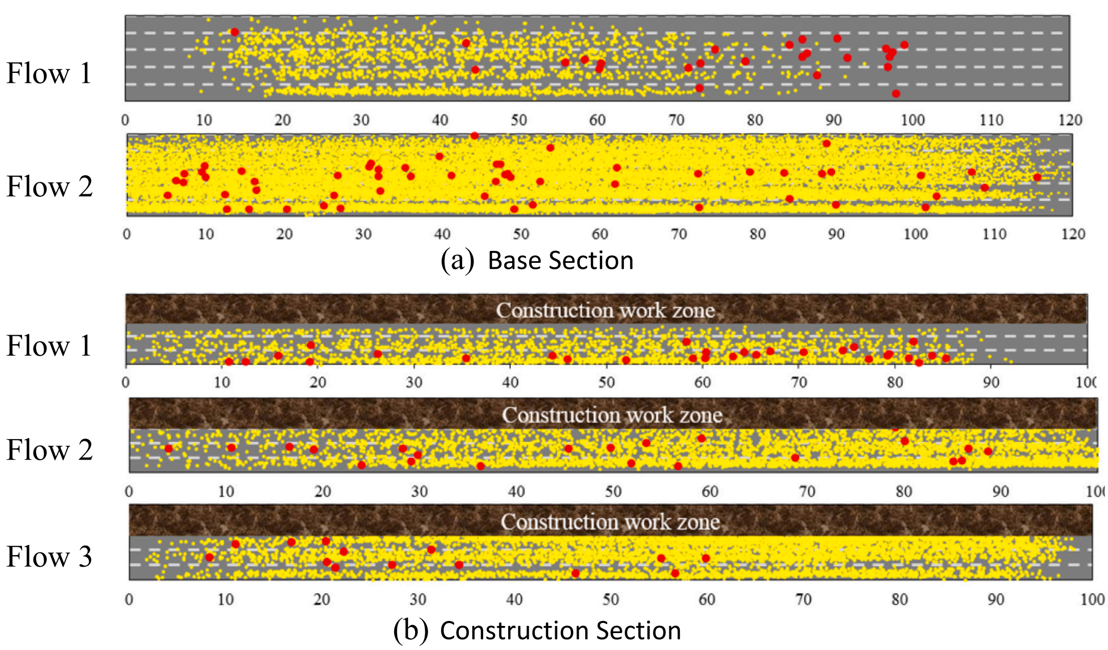


Fig. 6. Positions of vehicles over the road space, explaining the nature of interactions. Red color: P(rear end collision) and Yellow color: P(no rear end collision). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Interestingly in the base section, 23, 55, and 0 rear-end collision points are observed for Flows 1 to 3, respectively. This can be explained as follows. Initially, with the increase in flow level safety deteriorates with the availability of lateral freedom, then after the breakdown of the traffic flow at stop-and-go conditions particularly at Flow 3, no rear-end collision points are observed. It is inferred that at Flow 3, due to the constrained movement and the decrease in speed, vehicles tend to pay greater attention at even smaller distance gaps. As a result, the traffic stream becomes safer, compared with other flow levels. On the other hand, in the construction section, due to the constrained lateral

Table 4
Probable rear-end collisions based on leader-follower combination.

Flow Level	Leader [a]	Follower MThW	MTW	Bus	Car	Truck	LCV	Total
(a) Base Section [b]								
	MThW	2	4		1			
	MTW	1	5		4	1		
Flow 1	Bus		1					23
	Car		3					
	Truck				1			
	MThW	8	1		4	3		
	MTW	5	10		9			
Flow 2	Bus		3					55
	Car		9					
	LCV		3					
(b) Construction Section								
	MThW	2		1	2			
Flow 1	MTW	4	7		3	1		29
	Bus		2		1			
	Car	2	4					
	MThW	1			1			
Flow 2	MTW	3	8		2			22
	Car	1	5				1	
	MThW	1						
Flow 3	MTW		8		2			14
	Car		2	1				

[a] Vehicle classes not shown have zero entries for all follower classes.
[b] No data points lie in this regime at Flow 3 for the base section.

movement and with the flow level near capacity, vehicles are forced to follow one another and tends to pay good attention, resulting in a drop of the number of rear-end collision points from 29 (Flow 1) to 14 (Flow 3), as shown in Table 4. As noted, for all flow levels over the study sections, only three leader-follower combinations (MTW-MTW, MTW-Car, and Car-MTW) out of all possible combinations are found to be most unsafe with larger number of rear-end collision instincts. It is inferred that, because of their size and dominant proportion in the traffic stream, MTW tends to switch leaders more frequently, compared to other vehicles. As such, MTW drivers pay less attention toward their leaders.

5. Concluding remarks

The attentiveness of the follower in the traffic stream and its instance play a huge role in understanding safety. This paper has presented a new driver attentiveness measure in the vehicle-following process. The measure, represented by the receptiveness angle, was integrated with two traditional measures (speed and distance gap) for safety analysis for assessing potential rear-end collisions. In testing the new measure, the present study has overcome the limitations of trajectory data development under mixed traffic conditions. Based on this study, the following comments are offered:

- The study can be useful in assessing safety of construction zones under mixed traffic conditions. The results showed that pre-cautioning for the construction zone has alerted the drivers to a large extent, as indicated by the smaller number of probable rear-end collision points observed, compared with the base section. In addition, with the possibility of using trajectory data on a real-time basis, the presented methodology can be programmed for developing safety surveillance tools that enable practitioners and enforcement officers to measure safety in a traffic stream. Based on the density of the probable rear-end collision points, black spots over the road space can be mapped well in advance. Furthermore, studies of this nature can be helpful in modeling the safety component (equivalent to attentiveness) in autonomous vehicles to limit rear-end collisions. For example, consider the rapidly evolving landscape of autonomous vehicles, with SAE Level 2 autonomous vehicles being readily available in today's market. These vehicles heavily rely on adaptive cruise control systems, which automatically adjust the vehicle's speed to maintain a safe following distance from other vehicles. By drawing parallels to this advanced technology, the authors propose a similar methodology for SSM implementation. Through careful programming and integration into existing traffic management systems, SSM can play a pivotal role in augmenting road safety. As a result, this approach leads to enhanced surveillance capabilities, ensuring that safety conditions are continuously monitored and evaluated on a regular basis.
- When the receptiveness angle is related to the distance gap, it was observed that the receptiveness angle decreases as the distance gap decreases. The decrease varied for different vehicle classes and road sections, clearly indicating the variation in driving behavior. Further, from the descriptive analysis of the receptiveness angle and distance gap, it is observed that smaller vehicles are less attentive, compared with other vehicles. This can be attributed their better maneuverability (due to their size) which allows them to switch leaders, resulting in larger receptiveness angles with smaller distance gaps.
- From the safety analysis of the base section, rear-end collision points were observed over the road space for Flows 1 and 2. On the other hand, for Flow 3 (stop-and-go conditions), with limited freedom to move, the followers were more attentive toward their leaders and followed them with less relative speeds and distance gaps. As a result, no potential rear-end collisions were observed at this flow level. This clearly exemplifies that safety and efficiency of the traffic stream are inversely related to one another.
- Based on the analysis of the leader-follower combinations, it was observed that smaller vehicles in the traffic stream were the most vulnerable vehicle category from the safety point of view. This can be attributed to their high degree of lateral maneuverability since they can switch laterally to escape delay. For the construction section, it was observed that the pre-cautioning measures have alerted the drivers and in turn caused the vehicles to follow one another with more attentiveness. Such measures showed a huge impact in restoring traffic safety in comparison with the base section. As a result, at comparative flow levels particularly at Flow 2, there is a decrease of 60% in the probable rear-end collisions.
- It can be noted that, in line with the present surrogate safety measures, this research assumes specific thresholds for follower speed, distance gap, and receptiveness angle. However, it is necessary to highlight that these assumed thresholds necessitate further empirical investigation. The establishment of precise thresholds is pivotal for a comprehensive safety analysis. A call for additional studies becomes evident, aiming to solidify these thresholds and enhance the reliability of surrogate safety results. Simultaneously, recognizing the significance of calibration emerges as a key consideration. Calibrating the assumed thresholds has the potential to significantly improve the realism and explicability of surrogate safety outcomes. Considering this the above-mentioned aspect is one of the research gap in this domain and will act as a future scope of the study.

Declaration of Competing Interest

The authors have no affiliation with any organization with a direct or indirect financial interest in the subject matter discussed in the manuscript.

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