Association of Crash Potential of Powered Two Wheelers (PTW) with the State of Traffic Stream

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1 Introduction

Powered two-wheelers (PTWs) are widely used in low- and middle-income countries for short-distance trips. PTWs are faster than other modes in densely populated cities due to their smaller size and higher flexibility. Despite these benefits, PTWs pose a higher crash risk due to their inherent design, especially in mixed, weak lane-disciplined traffic conditions. Previous research on PTW safety has primarily relied on historical crash data to discern the unique characteristics of PTW crashes. However, historical crash reports are known for their limitations, including a lengthy data collection period, inconsistent and limited availability of crash data, a lack of information about the traffic conditions at the time of the incident, and crash propagation (Arun et al. 2021; Laureshyn et al. 2017; Theofilatos and Yannis 2017; Venthuruthiyil and Chunchu 2022). Surrogate Safety Measures (SSMs) are commonly employed to circumvent these constraints and are viable for proactively determining crash contributing components. Proactive safety analysis primarily relies on traffic conflicts, which are more frequent than crashes, and provides information related to pre-crash dynamic events (Guido et al., 2011). The objective of the present study is to perform a proactive safety assessment of PTWs, capturing the conflict types and overall crash risk associated with the mixed traffic conditions existing on the urban arterials of Indian cities. Further, this study investigates how traffic stream states impact the PTW crash likelihood, exposure, and severity for different conflict types.

2 Literature Review

The existing surrogate safety metrics like Time to Collision (TTC), Post-Encroachment Time (PET), and others have been criticized for being restricted to homogeneous traffic circumstances and specific conflict types like rear-end or angled. It is to be noted that, based on crash data, the most frequent collision types of PTWs were side-swipe collisions (Carmai et al. 2018), which cannot be captured by the existing conflict indicators widely used for safety assessment. In fact, the conflict type is a useful indicator for crash risk quantification and for employing proper mitigation strategies. The conventional SSMs are not capturing several types of conflicts observed in the traffic stream. Therefore, a meaningful conflict indicator must combine time proximity and evasive actions (Arun et al. 2021) and provide crash-type information. Furthermore, several researchers found that the conflict frequency is positively related to the crash frequency (Jiang et al. 2020; Zheng, Sayed, and Essa 2019).

3 Data Collection

This study correlates the traffic states with crash risk for PTWs. The traffic states and crash surrogates were estimated from the vehicle trajectory data collected from a 4-lane, divided, urban mid-block road located in Dispur, Guwahati, India. The vehicle trajectory data were extracted from the recorded traffic videos over a 60-m road length using SAVETRAX, a semi-automated trajectory data extraction tool (Suvin and Mallikarjuna, 2022, 2020).

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The extracted trajectories were reconstructed to remove the noise added at several stages of data collection and extraction using a trajectory smoothing technique (Venthuruthiyil and Chunchu 2018, 2020). A total of 4723 vehicle trajectories were extracted for the analysis. The traffic stream mainly consisted of 37.95% Powered Two-Wheelers (PTW), 9.15% Motorized Three-Wheelers (MThW), 46.57% Light Motor Vehicles (LMV), and 6.33% Heavy Motor Vehicles (HMV).

4 Methodology

It is debatable whether traditional traffic flow characteristics (Flow, Density, and Speed) meant for homogeneous and lane-disciplined traffic conditions can be used for mixed and non-lane-disciplined traffic (Mallikarjuna and Rao 2006; Suvin and Mallikarjuna 2018). In light of this, the traffic flow characteristics proposed by Suvin and Mallikarjuna (2018) for mixed, weakly lane-disciplined traffic scenarios, known as Area-Density (AD), Area Flow (AF), and Road-space-Freeing-Rate (RFR), are used in this study. These measures consider the lateral dimensions of both vehicles and the road space to capture the heterogeneity and weak-lane disciplined driving behavior. The traffic entities are represented as Traffic Units (TU) in this definition. For more details about AD, AF, and RFR, the readers can refer to Suvin and Mallikarjuna (2018).

The traffic flow variables were determined for each 5 min interval from the extracted trajectory data. Figure 1 presents the AD-AF and AD-RFR relationship. The maximum area flow (MAF) and critical area density (CAD) were 2043 TU/hr/lane and 59.9 TU/km/lane, respectively.

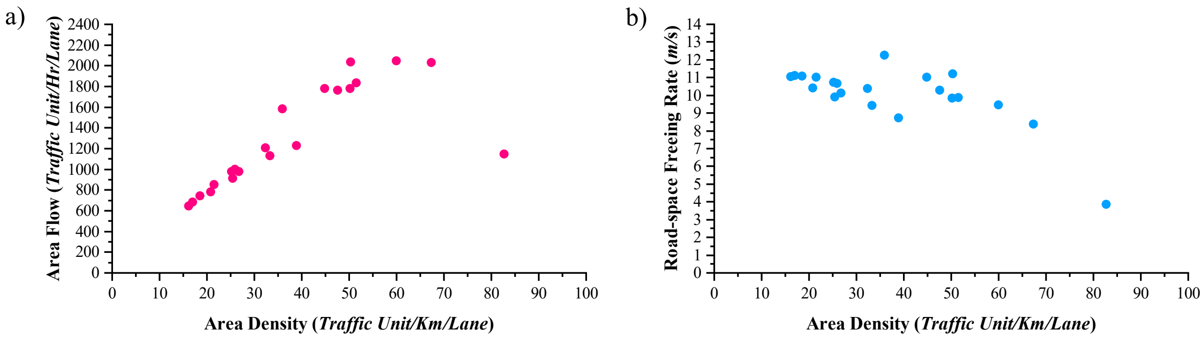

Figure 1: Observed traffic data; a) AD-AF plot; b) AD-RFR plot

For the analysis purpose, the traffic states were divided into 5-states based on AD at an interval of 20 TU/km/lane. The number of vehicles of different classes in each 5 min interval was calculated and averaged for each traffic state. The traffic states where AD ranges from 40-80 TU/km/lane indicate near capacity and capacity, and 80-100 indicate congestion. It is to be noted that when AD is below 40 TU/km/lane, PTW proportion was lower than LMVs, whereas it was the opposite when AD was above 40 TU/km/lane.

The crash risk for the traffic was evaluated using the surrogate safety indicator, Anticipated Collision Time (ACT), and its derivatives Time-of-Evasive-Action (TEA), Time-Exposed ACT (TEACT), and Time-Integrated ACT (TIACT), which were proposed by Venthuruthiyil and Chunchu (2022). All these measures can capture all dimensions of crash risk, including crash likelihood, crash exposure, crash severity, and evasive actions. The inputs for *ACT* estimation are the vehicle's position, speed, and acceleration in the longitudinal and lateral direction, heading angle, and yaw rate. The details of the estimation of these indicators can be found in Venthuruthiyil and Chunchu (2022).

5 Results and Discussion

The correlation of crash risk for PTWs at different traffic states was evaluated using all the measures. The PTW conflict frequency increased with the AD, indicating that the crash frequency is positively correlated with the AD. Further, the conflict frequency was evaluated for a range of threshold values (1s to 4s) to determine whether the threshold value has any effect on this correlation. It was found that a positive association between AD and conflict frequency exists regardless of the threshold value. By taking the 1s threshold value, the average PTW proportion at AD above 80 TU/km/lane is 23.7%, and their conflicts are 41.63%. In contrast, when AD is between 40 and 80 TU/km/lane, the observed PTW proportion is 58.44%, which results in 50.24% of the conflicts, and when AD is below 40 TU/km/lane, only 8.13% of PTW conflicts caused by 17.86% of PTWs. Notably, the increased crash likelihood at higher AD ranges could be attributed to the PTW rider's close moving attitude and higher relative speed in those conditions. These results match past studies based on real-time traffic data (Theofilatos and Yannis, 2017), which found that PTW crash involvement was high when the traffic flow was high.

The conflict-type-specific frequency analysis was performed to know the most prominent crash type for a PTW. The crash types observed in this study are the rear-end and the side-swipe crashes. The results show that side-swipe and rear-end conflicts account for 83% and 17% of all PTW conflicts. It is evident from Figure 2 that, irrespective of the conflicting vehicle type, the PTW crashes are mainly side-swipe crashes, and their frequency increases with AD. In contrast, for the PTW-PTW conflict situation, the side-swipe collision becomes less at higher density conditions, and the likelihood of rear-end collision becomes relatively higher. This could be attributed to the filtering behavior of PTWs, where other PTWs will follow the filtering PTW, resulting in a higher potential of rear-end collision than a side-swipe. The increased side-swipe collision likelihood of PTWs with other vehicle types during higher AD conditions can also be attributed to the filtering behavior of PTWs. Remarkably, the findings of this analysis closely match those of previous research (Carmai et al. 2018; Hyun et al. 2021; Theofilatos 2017), which found based on historical crash data that the most common type of PTW collision is a side-swipe collision. Another interesting finding is that the PTW-PTW conflicts (46.78%) are higher compared to other vehicle classes, where the share of PTW-LMV, PTW-MThW, and PTW-HMV conflicts are 32.43%, 7.25%, and 13.54%, respectively (Figure 2). The peculiar attitude of PTW riders to follow another PTW can be ascribed to the relatively higher proportion of PTW-PTW collisions.

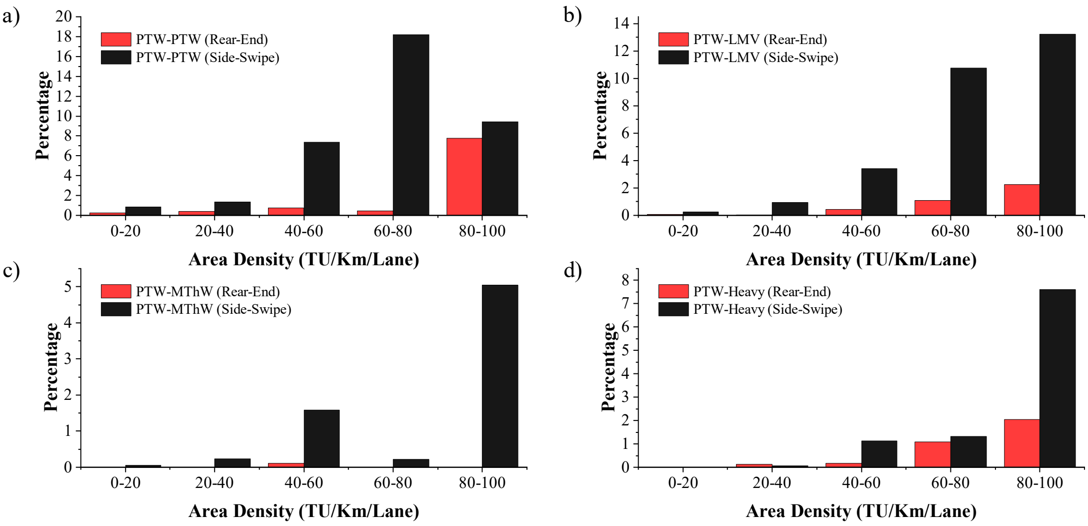

Figure 2: Distribution of conflict types between different vehicle types (a) PTW-PTW (b) PTW-LMV (c) PTW-MThW (d) PTW-Heavy

The correlation of PTW conflict exposure, severity, and percentage of PTWs exposed to crash risk with AD are evaluated by Pearson and Spearman correlation coefficients and presented in Table 1. The ACT threshold value considered while estimating $TEACT_P$ and $TIACT_P$ was 1 s. The Pearson correlation coefficient is higher than the Spearman correlation coefficient, indicating a significant positive linear correlation between AD and PTWs conflict exposure, severity, and percentage of PTWs exposed to crash risk.

Table 1: Correlation between AD and crash exposure, severity, and percentage of PTWs exposed to crash risk

Variables	Pearson cc	p-value	Spearman cc	p-value
AD, $TEACT_P$	0.85	0.00	0.77	0.00
AD, $TIACT_P$	0.88	0.00	0.76	0.00
AD, Percentage of PTWs exposed to crash risk	0.84	0.00	0.74	0.00

It was demonstrated that there is a relationship between the percentage of PTWs exposed to crash risk and AD. The one-way ANOVA [$F(4,16) = 11.25$, $p\text{-value} < 0.05$] results show that AD substantially impacts the percentage of PTWs exposed to crash risk. The fraction of PTWs exposed to crash risk increases as AD increases, but there is a sharp rise when AD exceeds CAD (Figure 3a). Figure 3b proves that crash exposure and severity are positively correlated with AD. Additionally, the one-way ANOVA shows that AD has a significant impact on conflict exposure [F(4,16) = 50.68, p-value < 0.05] and conflict severity [F(4,16) = 15.83, p-value < 0.05]. This could be attributed to the PTW's unique riding behaviors, such as filtering, weaving, tailgating, and maintaining a shorter headway when aligning to the lateral edge of the preceding vehicle (Lee 2007), which leads to frequent extreme near-miss conflicts.

The vehicle's speed is the primary factor that affects the severity of a crash in both single and multivehicle crashes (Theofilatos and Yannis, 2015). The relationship between the average speed of PTW and conflict severity and the coefficient of variation (CV) of PTW speed and conflict severity was investigated. The total sample of PTWs was 1805, out of which 298 PTWs were exposed to an unsafe situation. The average traffic speed is 9.96 m/s. One-way ANOVA shows that the average speed of PTW has no significant impact on PTW conflict severity [F(3, 295) = 0.71, p-value > 0.05]. However, the CV of PTW speed has a significant impact on conflict severity [F(5, 295) = 2.95, p-value < 0.05]. Figure 4 presents the variation of PTW conflict severity with its average speed and CV of speed. No significant change exists in PTW conflict severity when the CV of PTW speed is below 0.25. Crash severity is higher when the CV of PTW speed is more than 0.25. These results reveal that average speed is not a significant factor that causes a severe conflict. It is the variation of speed that causes more severe conflicts.

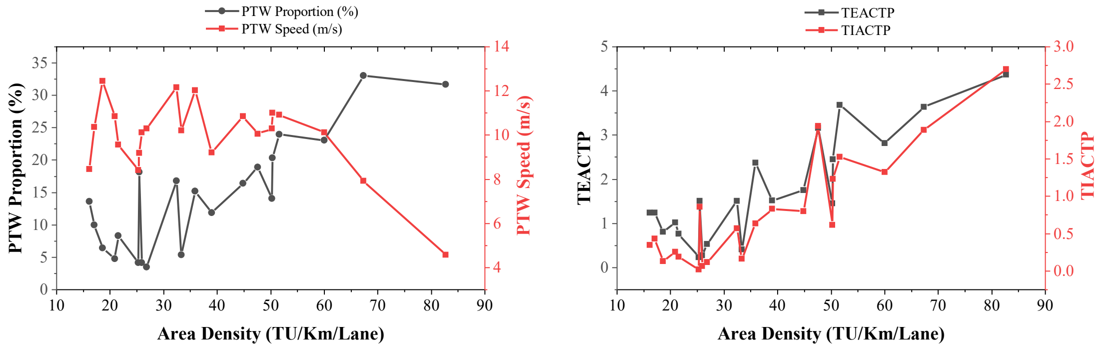

Figure 3: a) Relation between AD, and PTW proportion and PTW speed; b) Relation between AD, and $TEACT_P$ and $TIACT_P$

For the practical design of a warning mechanism to alert the users before the unsafe situation with a sufficient buffer to respond, it is essential to know how early drivers respond to a potential conflict situation under different traffic conditions. Therefore, the relation between the response time of PTW riders under different AD levels was determined and compared with car drivers using TEA. One-way ANOVA shows that AD has statistically significant impact on the TEA of PTW riders [F(4, 100) = 3.43, p-value < 0.05], whereas for car drivers, it is not [F(4, 43) = 0.96, p-value > 0.05]. However, the pairwise comparison shows that only TEA of PTW riders under AD range (80-100 TU/km/lane) is statistically different from AD ranges (40-60 TU/km/lane and 60-80 TU/km/lane) (p-value < 0.1). The mean TEA of PTW riders (3.8 s) is lower than cars (4.5 s), which indicates the late response of PTW riders than car drivers to a potential conflict situation. However, they are statistically insignificant by a two-sample t-test (p-value > 0.05).

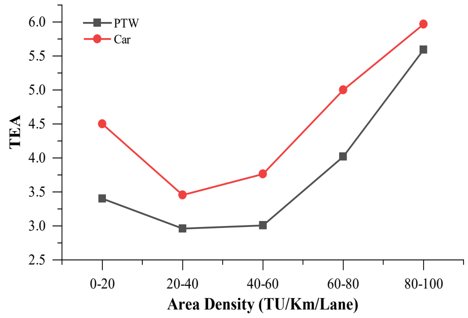

Figure 4: Average response time of drivers at different traffic states

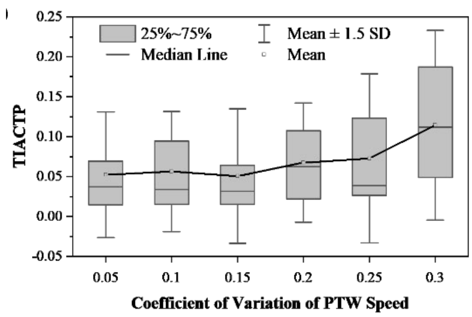

Figure 5: Distribution of conflict severity with CV of PTW speed

Interestingly, at capacity conditions, the response time of the PTW and cars is shorter (Figure 5), implying that the vehicles are less vigilant in responding to risky situations. However, for both cars and PTWs, the response time consistently increases above CAD. This indicates that when traffic is crowded, drivers are more cautious.

Drivers have also exhibited a reasonably early response in free-flow conditions, which can be related to the higher speed of the vehicles and the realization that the severity of the crash could be more significant.

6 Conclusions

The results indicate that the frequency, exposure, and severity of PTW crashes are positively correlated with AD. Moreover, the proportion of PTWs involved in an unsafe situation increases with AD. The CV of PTW speed was found to be significantly impacting the conflict severity. However, the average PTW speed does not explain the conflict severity. The mean PTW conflict severity was found to increase with the CV of speed. PTW riders and car drivers' response time to a potential conflict was found using TEA and compared. The response patterns of the PTW riders were also found to vary depending on the traffic states. The response times at higher AD levels were found to be higher compared to the lower AD levels. This indicates that drivers are more cautious during congested than the free-flow conditions. Moreover, it was found that the difference between response times to an unsafe situation for car drivers and PTW riders was statistically insignificant. The findings provide an insight into the risk-taking behavior of PTW riders and the response patterns toward unsafe situations. This understanding would help the concerned authorities and implementing agencies to perform targeted road safety interventions and campaigns. Nevertheless, safety assessment corresponding to several mid-block sections and covering more time periods is needed for further assessment of the safety of PTWs.

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