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Evaluation of motorized two-wheeler rider responses towards jaywalking pedestrians through mockup control studies for urban streets

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ABSTRACT

This study aims to model the motorized two-wheeler (MTW) riders' evasive-action behavior towards jaywalking pedestrians using a mockup study. The brake reaction times (BRTs), approach speeds, decelerations, headings, and yaw rates were analyzed for two surprise scenarios (scenarios 1 and 3), one stationary scenario (scenario-2), and one expected scenario (scenario-4). In total, 50 riders participated in the mockup study. The results revealed that the 90th percentile BRT for the expected and surprise scenarios were 3.6 and 1.6 s, respectively. Further, repeated-measures ANOVA was performed followed by mixed effect modeling to ascertain the effect of conflict severity (two groups: group-1 with Time to Collision (TTC) $<$ 1.5 s and group-2 with TTC $>$ 1.5 s) and scenario type (three groups: scenarios 1, 3 and 4) on BRT. The results indicated that the main effects were significant while the interaction effect was not significant. The positive and significant coefficient (0.32) of TTC group-2 indicated higher BRTs than TTC group-1. Considering scenario-1 as the base scenario, the coefficient of scenario 3 (-0.02) indicated that scenario-1 and scenario-3 had a similar effect on BRT, while the coefficient of scenario-4 (1.47) indicated higher BRTs compared to scenario-1. The analysis of evasive action behavior revealed that 32% of riders performed hard braking in surprise scenarios. Further, yaw rate values at the crossing point indicated a loss of control of MTW in 90% of surprise events. The observations from this study provide a basis for developing countermeasures to improve pedestrian and MTW rider safety.

1. Introduction

The world road-fatality statistics by World Health Organization (WHO) indicates that 93% of fatalities occur in low and middle-income countries (LMICs), though these countries have 60% of the world's vehicles (WHO, 2018). The mortality rate (number of fatalities per 100,000 population) is less than 9 in high-income countries (HIC), whereas it averages around 20 in LMICs (Wegman, 2017). Besides, road crash statistics by the WHO indicate that more than half of all global road-user deaths involve vulnerable road users (VRU) (WHO, 2018). Pedestrians and cyclists alone contribute to 26% of all road-user fatalities worldwide, while motorized two and three-wheelers comprise another 28%. In India, the Ministry of Road Transport and Highways (MoRTH) statistics revealed that pedestrian fatalities increase yearly. In 2018, the total pedestrian fatalities were 22,656, and this number increased to 25,858 in 2019,

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with a 17% share in total road fatalities in India (MoRTH, 2019a, 2020). Considering the need to improve pedestrian safety, previous researchers focused on identifying the factors affecting pedestrian-vehicle conflicts and modeling them (Lee & Abdel-Aty, 2005; Spainhour et al., 2006; Pulugurtha & Sambhara, 2011; Dai, 2012; Chen & Zhou, 2016; Vedagiri & Kadali, 2016, Pawar et al., 2016; Pawar & Patil, 2016).

In India, pedestrian signal violation and jaywalking (illegal crossing at unmarked mid-block sections) are common in most cities. Pedestrians choose to cross the roads at locations they desire, mainly if the designated crosswalks are not conveniently located due to the absence of engineering measures and enforcement measures such as barriers to deter pedestrians, on-street parking, and longer signal cycle lengths (Mukherjee & Mitra, 2020). Studies have shown that pedestrian crashes increase due to jaywalking compared to the crossing at marked locations (Shaaban et al., 2018). Further, increased mobile phone usage while crossing streets leads to unsafe behavior resulting in road accidents (Pešić et al., 2016). Such undesirable behavior of pedestrians demands additional attention of interacting road users to prevent crashes resulting in serious injuries and fatalities.

Although several studies have explored the driver's reaction time and standards have been established for the design and the assessment of roads, these standards are sometimes critiqued for their ineffectiveness (Hooper & McGee, 1983a, 1983b; Green, 2000). Limited studies have analyzed driver's reaction time and evasive behavior towards non-standard road user behavior such as pedestrians crossing at unauthorized locations. However, these limited studies were conducted in developed countries with established traffic disciplines (Bella & Nobili, 2020; Cherry et al., 2012). In India, motorized two-wheelers (MTW) contribute a significant share in motorized vehicles (73.5%), followed by cars, jeeps, and taxis (MoRTH, 2018). Furthermore, MTW contributed to 8 to 25% of pedestrian fatalities in six Indian cities (Mohan et al., 2016).

This research aims to understand the MTW rider behavior towards illegal pedestrian crossings without restricting the rider's choice of evasive action. The proposed study designed four scenarios: two surprise scenarios, one expected scenario, and one stationary scenario representing illegal pedestrian crossings using human dummies as pedestrians. Riders' reaction time, choice of speed, deceleration, and yaw rates were analyzed to model riders' behavior towards designed crossing events.

2. Literature review

MTW or powered two-wheelers (PTW) riders are categorized as VRU due to lower safety offered by the vehicle to its riders. Moreover, human error in negotiating traffic conflicts adds to the vulnerability of MTW, leading to a higher number and severe crashes. Further, ease in affording MTW leads to their higher presence in LMICs. In India, share of MTW increased from 8.8% in 1951 to 73.86% in 2017 (MoRTH, 2019b). Many researchers conducted studies to analyze the human error in crashes involving MTW, cars, and pedestrians (Parker et al., 1995, Fuller, 2005, West et al., 1993). Penumaka et al. (2014) studied PTW - car crashes and identified that PTW riders typically make perception and execution failures, while car drivers make perception and comprehension failures. To understand the driver/rider behavior in naturalistic conditions, van Nes et al. (2019) used UDRIVE data, a Cross-European naturalistic study data. The authors inferred that the speed and acceleration choices varied across riders while making a full stop. They also identified that pedestrians' sudden, unexpected appearance is one of the most important conflict types. The following subsection deal with the effect of illegal pedestrian crossings on driver/rider behavior.

2.1. Effect of illegal pedestrian crossings on driver behavior

Road user interactions, specifically near-miss traffic events, are of particular interest to researchers as they can be used as predictors of crash rates (Hayward, 1972). Illegal pedestrian crossing interactions with other road users were examined in several studies. Jurecki and Stańczyk (2014) studied driver behavior in response to pedestrians entering from the right and left sides of roads through a mockup study. The authors found that drivers are more prone to apply brakes when a pedestrian mockup appears from the right side (considering the right-hand driving environment). Bella et al. (2018) analyzed driver behavior during the interactions with a pedestrian crossing during legal and illegal crossings using a driving simulator. The results showed that drivers adopted abrupt braking maneuvers towards illegal pedestrian crossings compared to legal crossings. In another study, researchers used an instrumented vehicle to understand pedestrian-vehicle interactions in the field (Bella & Nobili, 2020). The findings revealed that the average yield rate was lower, while average deceleration rates were higher for jaywalking than permissible crossings.

2.2. Effect of various stimuli on Brake-Reaction Time (BRT)

2.2.1. BRT of MTW riders

Several studies have focused on determining the BRT of MTW riders to expected situations with temporal uncertainty. Thom et al. (1985) recruited 80 participants and recorded their response times to an amber light signal positioned on the motorcycle. The results revealed that the mean response times of experienced and inexperienced riders were 0.40 s and 0.45 s, respectively. Ecker et al. (2001a) used a red traffic light as a stimulus to capture BRTs of 300 MTW riders and found that BRTs for front and rear brakes were almost similar (0.42 s and 0.46 s). Promocycle (2003) analyzed the BRTs of 1181 riders in response to a signal provided on a large screen. The volunteers sat on static motorcycles and applied front and rear brakes in response to a randomized light, and BRTs were captured. The results showed that the average BRT for combined usage of front and rear brakes was 0.54 s. Davoodi et al. (2011) studied the BRTs of 59 participants in response to activating the tail lights of a parked car. The mean BRT for all the participants was found to be 0.44 s. Davoodi et al. (2012) conducted a study to compare the BRTs for 89 MTW riders in expected events (roadside light signal) and 16 MTW riders in unexpected events (using flicked over banner). The mean BRTs for expected and unexpected events were found to be 0.71 and 1.25 s, respectively.

2.2.2. Evasive action behavior of MTW riders

Evasive actions during critical conflicts consist of either braking, swerving, or both. Ecker et al. (2001b) studied MTW rider braking behavior in straight path emergency braking maneuvers. More than half of riders used only 56% of the study vehicle's theoretically achievable maximum deceleration (11.00 m/s^2). The distance-averaged and time-averaged decelerations were found to be 6.19 m/s^2 and 6.38 m/s^2, respectively. Bokare and Maurya (2017) analyzed the deceleration behaviors of car, two-wheeler, three-wheeler, and truck drivers. The drivers were instructed to accelerate from a stopped condition to desirable maximum speeds, cruise, and decelerate to complete stop in the shortest possible time. The observed maximum deceleration rates for MTW riders were 1.60 m/s^2, 1.33 m/s^2 and 0.59 m/s^2 with maximum approach speeds ranging between 40–50 km/h, 50–60 km/h, and 60–65 km/h respectively.

Lubbe (2017) analyzed BRTs and riders' braking behavior in response to various pedestrian forward collision warning systems. Results indicated that brake jerk and decelerations were independent of warning types. Further, they identified that 90% of the drivers exceeded maximum deceleration of 3.6 m/s^2 and a jerk of 5.3 m/s^3. Huertas-Leyva et al. (2019) studied the MTW rider braking behavior in response to real car turning left across the path (LTAP) through a real-life mockup experiment. In the study, the riders were asked to brake and abstain from performing other evasive maneuvers. The study revealed that the effective decelerations varied from 3.83 m/s^2 to 8.03 m/s^2, and peak decelerations varied from 5.03 m/s^2 to 9.82 m/s^2 for novice to expert riders. Nugent et al. (2019) studied the MTW rider steering responses in a car pop-up paradigm using an MTW simulator. For a time-to-collision (TTC) of 1.5 s, the authors observed that the riders were consistent and eight times more likely to produce a successful virtual swerve than in situations with a TTC of 1.0 s.

Further, literature review shows that the evasive action behavior of the riders can be used to indicate conflict severity. Gettman and Head (2003) have used evasive action-based indicator, namely, initial deceleration rate, apart from other proximity based indicators such as TTC, post-encroachment time (PET) to describe severity and extract conflicts from the traffic simulation trajectories. Guo et al. (2018) compared the use of TTC and evasive action-based indicators (deceleration, jerk, and yaw rate ratio) to define conflict severity. The authors concluded that yaw rate ratio was efficient in measuring conflict severity for e-scooters, motorcycles, and bicycles while TTC was efficient for e-bikes, and bicycles, respectively. As there are multiple indicators in use to define severity of conflicts, Johnsson et al. (2018) studied the suitability of indicators for vulnerable road users. The authors concluded that no indicator reflects all the aspects of the conflicts and context-dependent suitability of the indicator has to be checked before using it to ascertain the severity of conflict. Vlahogianni et al. (2014) identified that behavior-based parameters such as PTW front and rear brake activation, wheel speed, throttle and steering can be used to identify incident's criticality. The authors observed that magnitude of deviation from average driving behavior indicates incident's criticality in naturalistic driving data. Tageldin et al. (2015) studied the use of deceleration, jerk and yaw rate as evasive action-based SSMs to explain the severity of MTW-MTW conflicts. The authors concluded that because not all the conflicts include swerving; deceleration and jerk had stronger correlation with conflict severity. The study results also indicated that proximity based indicators yielded more number of conflicts when compared to evasive action-based indicators in mixed traffic environment that may not have high severity. However, evasive action-based indicators possess some limitations in explaining the conflict severities (Guo et al., 2018). In some collision events, the drivers did not employ any evasive actions. Further, in some events with high decelerations and jerks, the drivers performed precautionary evasive measures to decrease the potential risk.

Many factors such as riders' emotional conditions, weather and environmental factors, vehicle related factors affect the riders' reactions and evasive actions performed towards traffic conflicts. As data pertaining to all the factors is impossible to be captured by any one or a combination of instruments, modelling techniques were developed to cater to the unobserved heterogeneity that might arise due to factors that are not considered. Mannering et al. (2016) discussed the various modelling techniques available to cater to unobserved heterogeneity such as latent class (finite mixture) models, latent class models with random parameters within class, markov switching models to model the crash likelihood and injury severity. Further, a study by Waseem et al. (2019), addressed unobserved heterogeneity while modelling motorcyclists' injury severity using random parameters logit model. Similarly, Saeed et al. (2017), Volovski et al. (2017), Saeed et al. (2020), Yamany et al. (2020), used random effects models to cater to unobserved heterogeneity in various use cases pertaining to pavements, bridges and autonomous vehicles. However, due to the complexity involved in random parameters models, researchers still rely upon relatively homogeneous set of participants to model their responses to varying stimuli and draw optimal inferences.

To summarize the literature, limited studies analyzed the BRT of two-wheeler riders. Moreover, the reported studies used banners or flashing lights to understand the riders' BRTs and evasive actions, which may not accurately represent the field conditions. Some studies also restricted riders' evasive maneuvers to either braking or swerving, which do not represent the full spectrum of evasive actions as riders may adopt a combination of braking and swerving simultaneously. Further, evasive action-based indicators were preferable in mixed traffic environments for defining conflict severity. Therefore, this study aims to understand the MTW riders' BRTs and evasive action behavior in real-life situations through a mockup study designed using human dummies to replicate crossing pedestrians. MTW rider behavior (approach speed, acceleration/deceleration, heading, and yaw rate) is captured using a high-end data logger approaching a crossing pedestrian in surprise, expected, and stationary scenarios.

3. Methodology

3.1. Participants

55 male riders were recruited using the convenience sampling technique for participating in the mockup study. The participants

were recruited through personal contacts and University (Indian Institute of Technology Hyderabad (IITH)) mailing lists. Further, the participation was voluntary, and the participants were required to have a valid MTW driving license with a minimum driving experience of 2 years. Participants' mean age was 28 years with a standard deviation of 6.75 years. Participants were not given any monetary rewards; however, they were offered non-financial incentives to participate in the study. Due to loss in global positioning system (GPS) signal for five riders, data of 50 riders was considered for final analysis.

3.2. Equipment and data collection

Honda Unicorn (150 cc), a commonly used motorcycle in India, was used in this study. The vehicle had a five-gear manual transmission system with a disc brake for the front wheel and a drum brake for the rear wheel. The motorcycle did not have any additional safety assistance systems, such as an antilock braking system (ABS) or a combined braking system (CBS).

A high-end GPS data-logger (video VBOX HD2) was used to capture the vehicle kinematics and rider behavior towards the crossing events. The system can record vehicle position (GPS) data at 10 Hz and time-synchronized videos at 1080-pixel resolution. Two cameras were used to collect video data, both facing front. The camera placement and field of view are depicted in Fig. 1. Care was taken while placing the cameras so that no obstruction or discomfort is caused to the rider. Camera-1 was fixed to the MTW's front windshield to capture the front view and validate yaw movement with information collected from the data logger. Camera-2 was fitted to riders' helmets and positioned to capture the riders' field of view and head movements.

VBOX provides speed data with a resolution of 0.01 km/h, with an error of 0.1 km/h (averaged over 4 samples) and acceleration/deceleration values with a resolution of 0.01g with an error of 1%. The heading angle captured by VBOX has a resolution of 0.01° with an error of 0.1° (Video VBOX Technical Specifications, 2018). The derived quantity, namely, yaw rate has an error of 0.2°. Further, the speed recorded using VBOX was validated using the speed values obtained through the speedometer of the MTW and was found to be in close proximity to each other.

3.3. Experimental setup

Data collection was carried out on a two-lane undivided road of 4.75 km in length. The service roads of the IITH's campus were selected for the experimentation. The study site was selected such that the traffic can be regulated and regular traffic does not hinder the experimental setup or the riders' behavior towards the planned experiment. Fig. 2**(a)** shows the experimental route and the location of pedestrian crossing scenarios using Google earth image. Since the experiment was designed to understand riders' behavior, we limited our study to daylight and dry weather conditions. Human dummies were used to represent the crossing pedestrians. The dummies were dressed and placed in such a way that they closely represented human pedestrians. Parallel tracks were laid on the pavement surface, and dummies were glided over the tracks using a trolley system. The trolley and the tracks were colored grey to match the pavement surface and make it inconspicuous to prevent anticipation of the events and avoid riders' attention. The dummies were pulled manually at a rate of 1 to 1.2 m/s. Fig. 2**(b)** shows the mechanism used to create the crossing events. It is essential to point out that, as the image was photographed from a close view, the tracks are noticeable in the pictures. The triggering setup was in the participants' field of view from 80 to 100 m for scenarios 1, 2, and 3, and 40 m for scenario-4. However, while the riders were in motion, they overlooked the tracks/triggering mechanism as the mechanism was hidden behind banners made using pictures of the natural location. Therefore, riders could not foresee the events, and the evasive actions were in response to moving dummies, as stated by the participants in the post-experiment survey.

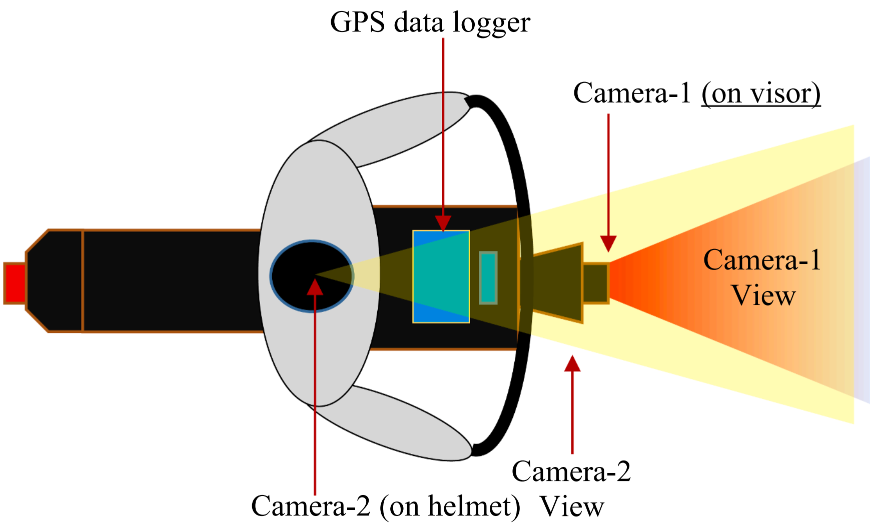

Fig. 1. Pictorial representation of the instrumented vehicle.

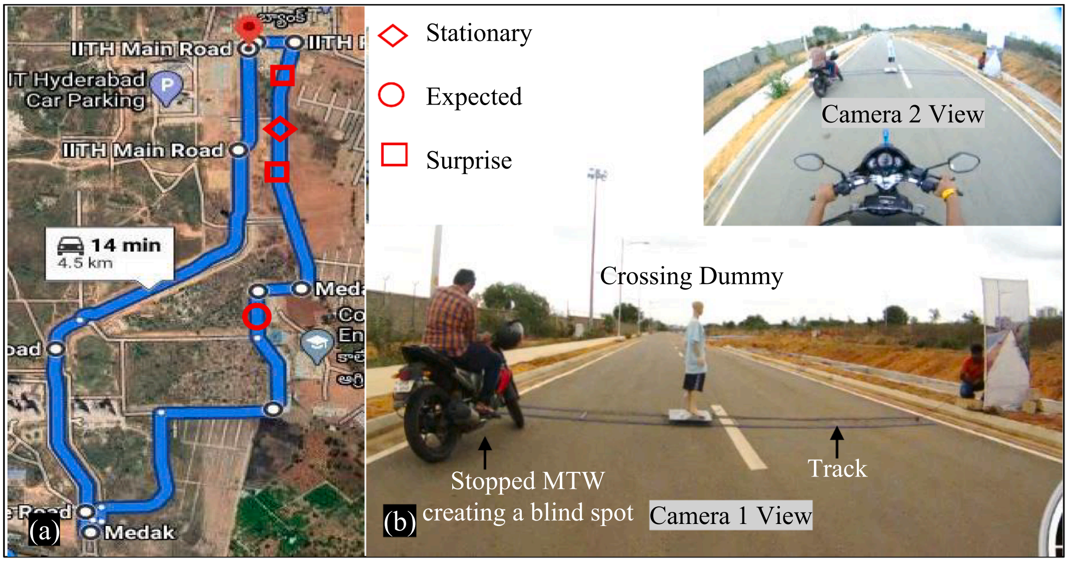

Fig. 2. (a) Selected route with event locations and (b) Dummy triggering mechanism.

3.4. Designed scenarios

Four scenarios were designed to understand and analyze rider behavior towards jaywalking pedestrians. The scenarios were designed on straight roads free from curves, speed breakers, and intersections where the stipulated speed was achievable. Scenario-1 was designed to replicate a pedestrian suddenly appearing from a blind spot formed due to a roadside-parked auto-rickshaw (Fig. 3**(a) and** Fig. 4**(a)**) and is classified as a surprise event. The dummy was triggered when the MTW reached a predetermined point corresponding to a planned time to collision (TTC) of 3 s with an expected average approach speed of 40 km/h (11.11 m/s). Scenario-2 was designed to replicate a stationary and yielding pedestrian waiting for the MTW rider to pass (Fig. 3**(b) and** Fig. 4**(b)**). Dummy in scenario-2 was visible from 80 to 100 m before the scenario location, and the riders expected the dummy to move. However, the

Fig. 3. Designed scenarios with (a) Scenario-1 – surprise event, (b) Scenario-2 – stationary pedestrian, (c) Scenario-3 – surprise event, and (d) Scenario-4 – expected event.

dummy was not moved, thus creating a stationary scenario. This scenario was created to prevent riders from becoming more alert towards possible crossing events ahead. Scenario-3 was designed to replicate a pedestrian suddenly appearing from a blind spot formed due to a roadside-parked two-wheeler with a designed TTC of 3 s and is classified as a surprise event. An MTW was used as a parked vehicle instead of an auto-rickshaw (as in scenario-1) to create a blind spot **(**Fig. 3**(c) and** Fig. 4**(c))** and avoid anticipation of the crossing event in Scenario-3. In Scenario-4 **(**Fig. 3**(d) and** Fig. 4**(d))**, the pedestrian dummy was visible to the rider 40 m ahead of the crossing track. The dummy first appears to be waiting for the two-wheeler to pass. However, it then starts crossing when the two-wheeler is close to the crossing track with a designed TTC of 2.5 s (triggering distance = 20 m) according to the expectation of the riders, thus creating an "expected" event.

Moreover, all the riders faced the scenarios in the same order, and randomization of the order was not carried out as the dummies were triggered manually. The study was designed as a quasi-experimental study with triggered dummies as interventions. A quasi-experimental traffic study has limited interventions such as the usage of traffic control devices for ethical, jurisdictional, and liability reasons. Besides, in a quasi-experimental study, only gross correlates of the rider's behavior are observed (Koppa et al., 1996). In the current study, only gross correlates such as speed, acceleration, and yaw-rate profiles were captured using a VBOX instrument.

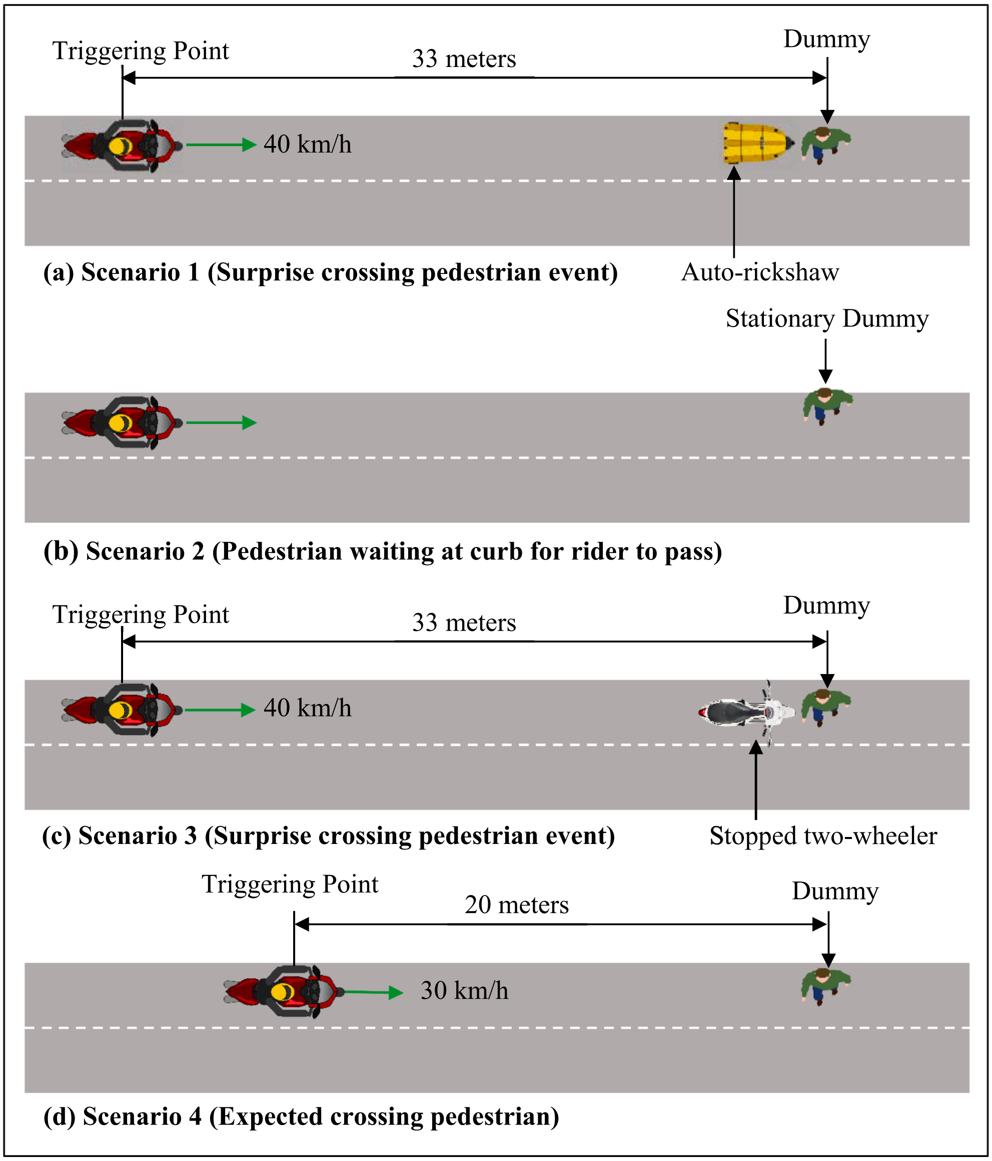

Fig. 4. Pictorial representation of the designed pedestrian crossing events.

3.5. Experimental procedure

The experiment was divided into three stages. The participants' demographic details, including age, gender, MTW riding experience, driving license details, and driving frequency, were collected in the first stage. In this stage, the participants were informed about the experiment route and duration. Participants were not informed about the designed events and were asked to ride as they would do during routine driving without exceeding the posted speed limit of 40 km/h. Participants were also asked to sign an informed consent form for their voluntary participation. The proposed study methdlology was approved by the Indian Institute of Tecnology Hyderabads's Ethics Committtee (IEC Protocol No. IITH/IEC/2020/10/08). In the second stage, participants were asked to take trial rides on a different route to acquaint themselves with the test vehicle. In the third stage, the experiment was conducted on the actual route having the experimental setup. No particular type of evasive action was instructed; therefore, participants chose to perform braking, swerving, or both, which they deemed was appropriate to avoid possible collision with the dummies.

4. Data analysis

4.1. Approach speed profiles

Fig. 5**(a)** shows the speed profiles of the MTW riders when encountering Scenario-1 (surprise event: pedestrian crossing from blind spot due to parked auto rickshaw). The dummy triggering distance for the scenario was 33 m (TTC of 3 s for approach speed of 40 km/h) before the crossing. The steep downward slopes of the speed profiles indicate relatively high decelerations exhibited by riders. Further, it was observed that in 17% of surprise events, riders came to a complete halt. A generalized profile indicating the variations (minimum, maximum, and average values) in speed for all riders while approaching surprise Scenario-1 is shown in Fig. 5**(b)**. It can be observed that speeds were lowest within 5 s from the appearance of the dummy.

Fig. 6**(a) and 6(b)** depict the speed profiles in Scenario-2 (stationary human dummy waiting for riders to pass). It was observed that some MTW riders expected the pedestrian dummy to move and therefore yielded by gradual braking. The findings revealed a reduction of 6 km/h between the 85th percentile approach speed and 85th percentile speed at the tracks. The analysis also revealed that 96% of riders reduced their speeds in response to the stationary human dummy waiting for riders to pass, indicating that riders were generally alert and noticed the waiting pedestrians.

Fig. 7**(a)** shows the speed profiles of MTW riders in response to the dummy at Scenario-3 (surprise event: pedestrian crossing from blind spot due to parked two-wheeler). The speed profiles show that the decelerations were sudden, indicating that riders did not notice the crossing pedestrian. The results revealed that 24% of the MTW riders performed hard-braking (maximum decelerations greater than 3.4 m/s^2) towards Scenario-3. Similar to Scenario-1, Fig. 7**(b)** shows that minimum speeds were observed within 5 s from the appearance of the dummy.

Fig. 8**(a) and 8(b)** show the speed profiles of the MTW riders towards Scenario-4 (Expected event). The road leading to the scenario had a horizontal curve, and its effect on the speed profiles of the MTW riders is shown in the figure. However, care was taken to set up the dummy away from the curve (40 m) such that the decelerations can be attributed purely to the designed scenario. The speed profiles indicated that the riders accelerated after traversing the curve and then reacted to the dummy by deceleration and swerving.

4.2. Brake reaction times (BRT)

BRT is commonly used to assess the stopping sight distance (SSD) and determine road design requirements for a particular design speed. In this study, the BRT was measured as the time elapsed between the instant the crossing pedestrian dummy becomes visible to the rider and the instant the rider starts decelerating the vehicle by applying the brakes. Fig. 9 illustrates a typical rider's speed and acceleration profiles approaching a crossing pedestrian in scenario-1 (surprise event). In the figure, t_1 represents the time instant at

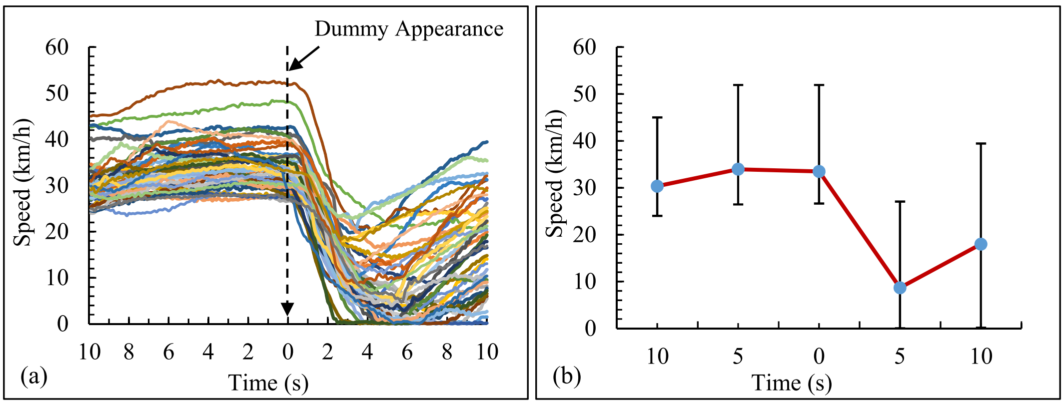

Fig. 5. (a) Riders' speed profiles and (b) Speed distribution for Scenario 1.

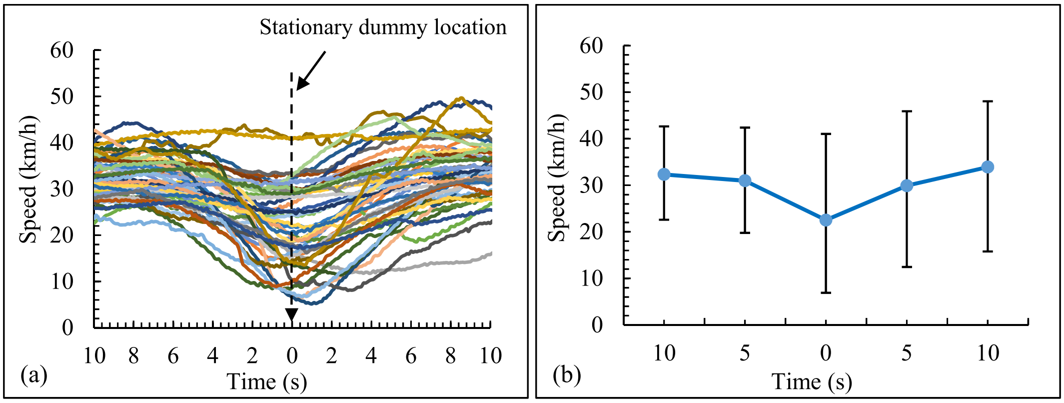

Fig. 6. (a) Riders' speed profiles and (b) Speed distribution for Scenario 2.

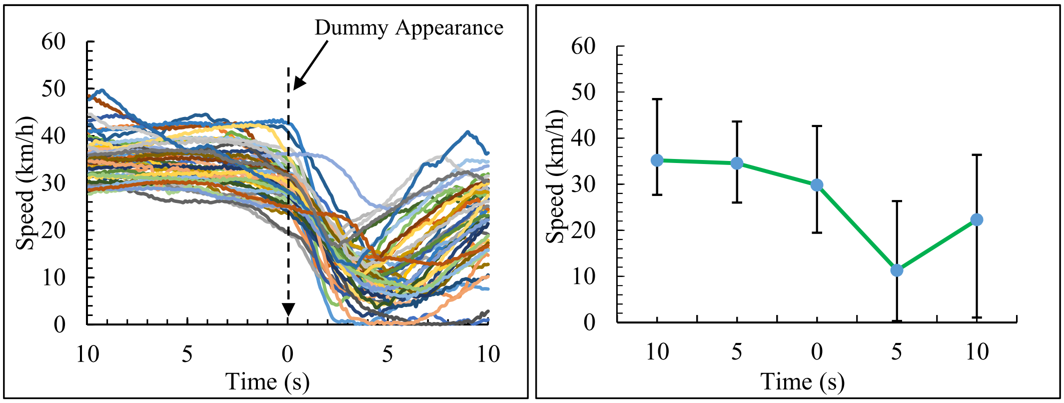

Fig. 7. (a) Riders' speed profiles and (b) Speed distribution for Scenario 3.

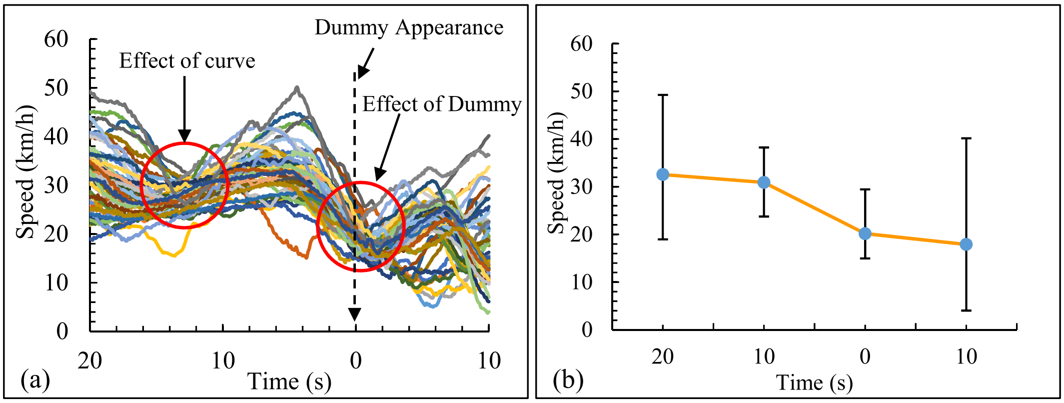

Fig. 8. (a) Riders' speed profiles and (b) Speed distribution for Scenario 4.

which the dummy was visible to the rider, and t_2 represents the instant at which the rider responded by applying brakes. The time difference $(t_2 - t_1)$ gives the BRT of the rider.

Fig. 10**(a)** presents BRT distribution using a box plot for all riders corresponding to scenarios 1, 3, and 4. In the figure, lower and upper quantiles represent the 15th and 85th percentile BRTs. Braking observed in scenario-2 was purely due to anticipation and not in response to a moving pedestrian stimulus; so, BRTs for scenario-2 were not reported. The BRTs in scenarios 1 and 3 were compared to identify whether the riders became more alert after facing scenarios 1 and 2. The mean and median values for scenarios 1 and 3 were 0.86 and 0.8, respectively. Kolmogorov-Smirnov test (KS test) was performed to verify whether the BRTs of both the scenarios belong to the same population distribution. The results (p-value = 0.12) indicated that the null hypothesis could not be rejected at a 5%

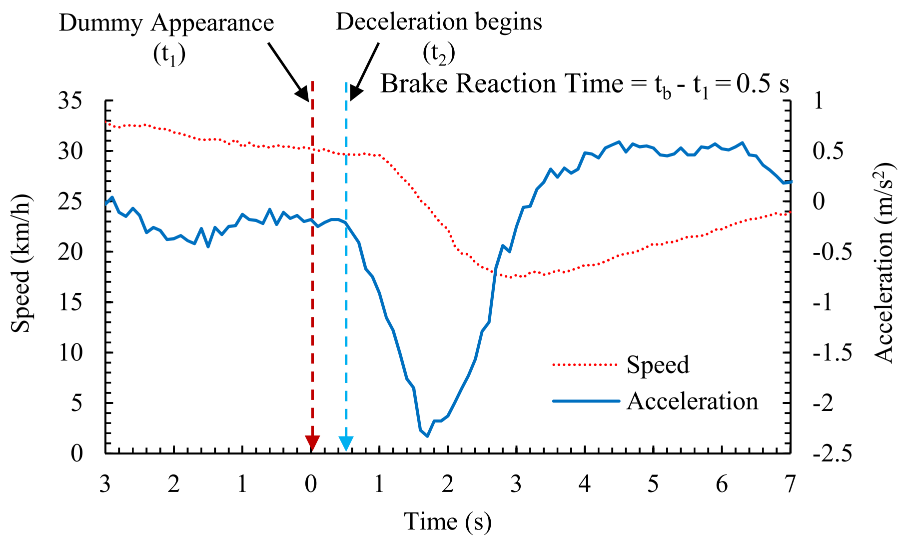

Fig. 9. Typical speed and acceleration profile of a rider when facing surprise event.

significance level, confirming that the BRTs follow the same distribution. Therefore, BRTs of scenarios 1 and 3 were combined, and the 15th, 50th, and 85th percentile BRTs for surprise events were found to be 0.35 s, 0.77 s, and 1.25 s, respectively. The study also reports the 90th percentile value as it is prominent in calculating SSD (AASHTO, 2011). The 90th percentile BRT of MTW riders in case of surprise scenarios was found to be 1.52 s.

The riders' BRTs to expected conflicts (Scenario-4) were studied using a dummy waiting to cross the road at the curb. The riders responded to the dummy in its close spatial proximity. The 15th, 50th, 85th, and 90th percentile BRT values for Scenario-4 were 1.70, 2.10, 3.16, and 3.62 s, respectively. Higher BRTs for Scenario-4 were observed as riders optimized their reaction by responding in close proximity of the crossing dummy. A summary of BRTs in surprise and expected scenarios is given in Table 1.

The study also analyzed the effect of TTC on the BRTs of riders. The BRTs were averaged for every 0.5 s interval of TTC, and a positive linear relationship was established between BRT and TTC (Fig. 10**(b)**). The averaging was done to prevent clustering of the data. The coefficient of determination was 0.85, while the correlation coefficient was 0.92. Further, the effect of MTW riders' distances at triggering instances on riders' BRTs was also evaluated. Fig. 11**(a)** depicts the relationship, and it can be inferred that irrespective of the approach speeds, a linear relationship exists between the initial distances and the BRTs. In addition, an inverse relationship exists between BRTs and approach speeds, as shown in Fig. 11**(b)**.

4.3. *Effect of conflict severity (TTC) and scenario type on BRT*

As all riders drove the same four scenarios, individual rider's responses for any scenario are subjected to the rider's learning capabilities and may not be considered independent. Therefore, repeated measures ANOVA (RM-AMOVA) is chosen to identify whether scenario type and conflict severity (defined by TTC value) have statistically significant effects on the BRTs of riders. The conflict severity for the analysis was divided into two groups based on a threshold TTC of 1.5 s. Events with TTC less than 1.5 s are considered

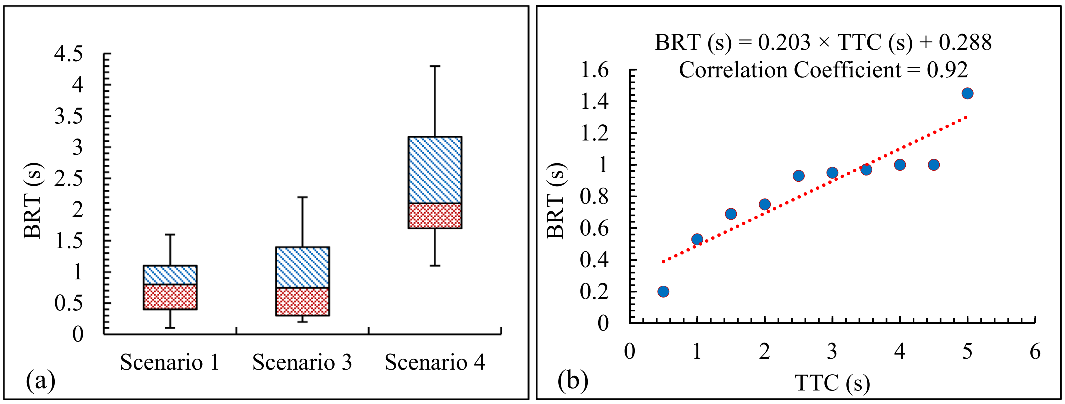

Fig. 10. (a) Distribution of MTW riders' BRT (b) Relationship between BRT and TTC.

Table 1
Summary of Brake Reaction Times for surprise and expected scenarios.

Scenario (Type)	15th Percentile	50th Percentile	85th Percentile	90th Percentile
Scenario 1 (Surprise)	0.40	0.80	1.10	1.42
Scenario 3 (Surprise)	0.30	0.75	1.40	1.62
Scenario 4 (Expected)	1.70	2.10	3.16	3.62

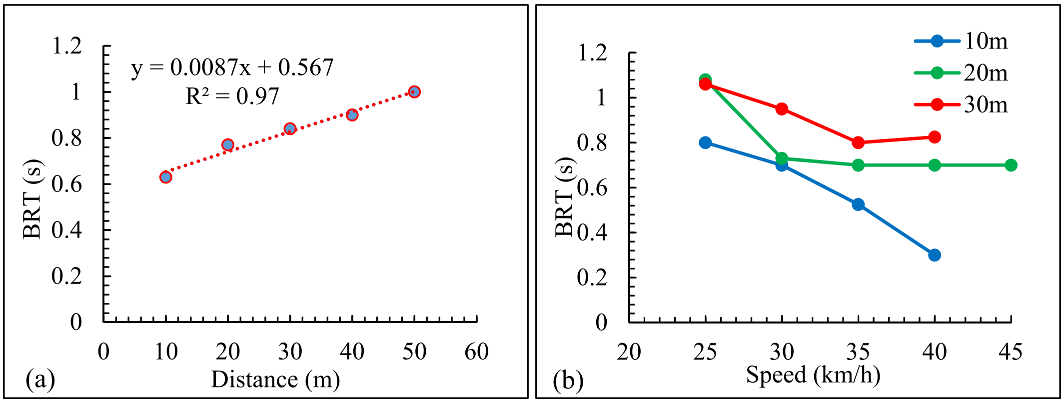

Fig. 11. (a) Relationship between distance and BRT and (b) Variation of BRT with speed.

serious conflicts, according to Hydén (1987). Therefore, in this study, events with TTC less than 1.5 s were classified as high severity conflicts, and those with TTC greater than 1.5 s were categorized as low severity conflicts for the analysis.

As RM-ANOVA is a parametric method, the assumptions of no significant outliers, normality, and sphericity were checked for and met before performing RM-ANOVA. Extreme outliers were checked and removed. Shapiro-Wilk's test for the normality was performed along with a q-q plot check, and the results validated normality. Mauchly's test of sphericity was also conducted, and the results indicated homogeneity of variances. In the RM-ANOVA, the interaction between the scenario type and TTC group was also checked for a significant effect on BRT. However, the results indicated that the main effects due to scenario type and TTC group significantly influence the BRT, while the interaction did not have significant influence. It was found that $F(1,142) = 7.8$, $p < 0.05$ for TTC group variable, $F(2,142) = 103.2$, $p < 0.05$ for scenario type variable.

Mixed-effects models were also developed between BRTs and TTC groups, scenario types while controlling for the within-rider variations. The coefficients of fixed effects are shown in Table 2. The results indicate that TTC group and scenario type have a significant effect on BRT, while their interaction did not significantly affect BRTs. The significant positive coefficient (0.32) of TTC group 2 indicates higher BRTs than TTC group 1. The coefficients of scenario-3 (-0.02) and scenario 4 (1.47) indicate that scenario-3 and scenario-1 (base scenario for mixed-effects model) had similar effects on BRT, while scenario-4 resulted in higher BRTs compared to scenario-1. The marginal R-squared (R_m^2) and conditional R-squared (R_c^2) were found to be 0.57 and 0.59, respectively.

5. Evasive actions

5.1. Decelerations

The evasive actions performed by MTW riders generally consist of braking, swerving, or both. Each event was classified as a hard or a soft braking event based on the magnitude of deceleration employed. The events with an observed deceleration rate of more than 3.4 m/s^2 were considered hard-braking events. The rest of the events were considered soft-braking events. The threshold for defining hard and soft braking events was based on the threshold for comfortable deceleration of 3.4 m/s^2 by AASHTO (2011) for cars. Fig. 12**(a)** shows the distribution of hard and soft braking events for all scenarios. It can be observed from the figure that hard braking was performed only in Scenario-1 and Scenario-3, with a total share of 34%.

5.2. Swerving

The swerving characteristics during hard-braking events were compared with soft-braking events for the surprise scenarios using two parameters. The first parameter denoted by "Max-Diff" compares the magnitude of swerving between the hard and soft braking events and is determined by calculating the maximum difference between observed heading and expected heading in the absence of a dummy. The second parameter used for comparing the swerving characteristics is the yaw rate, defined as the rate of change of heading with time. For Scenarios 1, 2, 3, and 4, the expected headings without the influence of dummies were 185°N, 180°N, 166°N, and 179°N, respectively. Fig. 12**(b)** depicts the Max-Diff employed by the MTW riders for the hard and the soft braking events for the

Table 2
Results of the Generalized Linear Mixed Model (Fixed Effects Estimates).

	Estimate	Std. Error	DF	t-statistic	p-value
Intercept	0.63	0.125	145.67	5.05	<0.05
TTC group 2	0.32	0.124	143.39	2.57	<0.05
Scenario 3	−0.02	0.122	97.14	−0.20	0.83
Scenario 4	1.47	0.123	97.57	11.94	<0.05

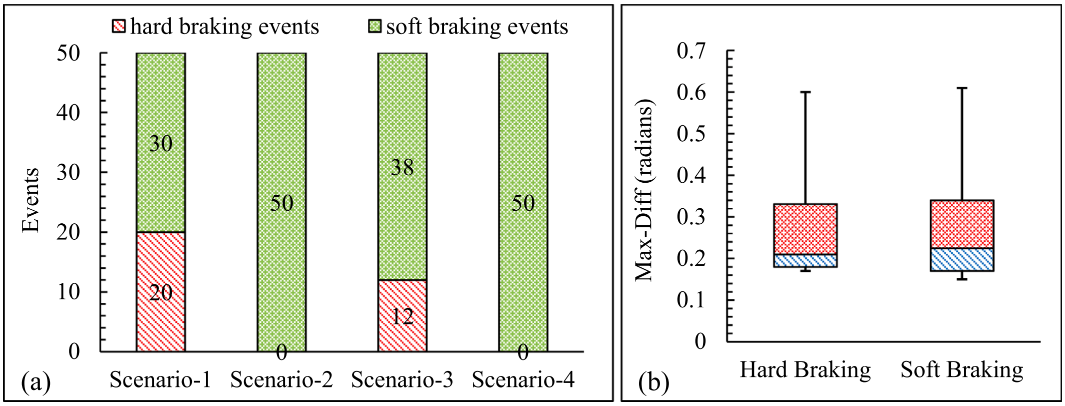

Fig. 12. (a) Distribution of events (b) Max-Diff of hard and soft braking events of surprise scenarios.

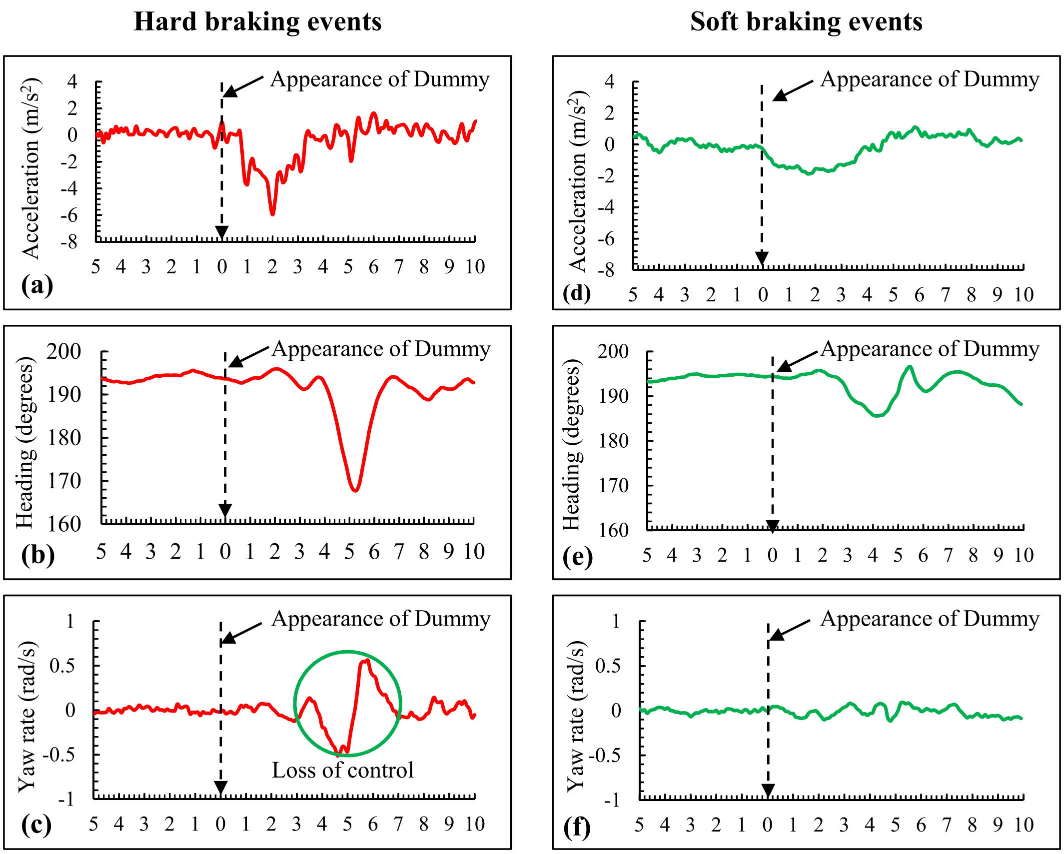

Fig. 13. (a) Acceleration (b) Heading (c) Yaw rate, in hard braking events (d) Acceleration (e) Heading (f) Yaw rate, in soft braking events for surprise scenarios.

surprise scenarios. The minimum and maximum values of Max-Diff for the hard-braking events were 0.17 and 0.60 rad, respectively, and for soft-braking events, they were found to be 0.15 and 0.61 rad, respectively. It was hypothesized that the Max-Diff would be relatively higher for soft-braking events than for hard-braking events. An ANOVA test was conducted. To identify the statistical difference between the means of the Max-Diff. The results ($F = 0.156$, $p = 0.697$) indicated no significant difference between the swerving characteristics of hard and soft braking events, implying that the decelerations were the predominant evasive maneuvers differentiating the severe non-severe conflicts.

5.3. Acceleration, heading and yaw rate for hard and soft braking events

Fig. 13**(a), 13(b), and 13(c)** indicate a typical rider's acceleration, heading, and yaw rate profiles during a hard-braking event. Similarly, Fig. 13**(d), 13(e), and 13(f)** represent a typical rider's acceleration, heading, and yaw-rate profiles for a soft-braking event. In the case of hard-braking events, deceleration was the primary evasive action observed within 2.5 s of triggering the dummy, followed by swerving between 2.5 s and 6 s of triggering the dummy (See Fig. 13**(a) and 13(b)**). For soft-braking events, riders employed moderate braking and swerving simultaneously between 0 s and 5 s (Fig. 13**(d), 13(e))**. For hard-braking events, sudden and relatively higher yaw rates were observed **(**Fig. 13**(c))** after severe braking indicating near loss of vehicle control. In contrast, the yaw rates for the soft-deceleration events were found to be low and uniform (Fig. 13**(f)**), inferring reasonable control of the vehicle.

6. Discussion

This study first analyzed the MTW riders' BRTs towards surprise illegal pedestrian crossing scenarios (scenario-1 and scenario-3). The mean and median values of BRTs in scenarios 1 and 3 were observed to be the same (0.86 and 0.8 s), and the KS test for BRT indicated similar population distributions for both scenarios. Therefore, in our study, we achieved control for the learning effect in a significant manner. The results also revealed that the mean BRT for surprise pedestrian crossing events (0.86 s) was lower compared to the mean BRT (1.29 s) stated in the study by Davoodi et al. (2011). As the average approach speed in this study was 40 km/h as against 60 km/h in the study by Davoodi et al. (2011), it was expected that the BRT would be higher than 1.29 s due to lower alertness levels. The relatively lower BRT may be attributed to the attentive and cautious nature of the MTW riders accustomed to the surprises in complex, heterogeneous, and less lane-disciplined traffic conditions. The observed 90th percentile BRT for the surprise scenarios was lower than the 2.5 s threshold for cars used for calculating stopping sight distances. According to AASHTO (2011), the threshold BRT of 2.5 s exceeds the 90th percentile BRT of all drivers and is considered adequate for conditions that are more complex than laboratory conditions, but it is not adequate for most complex situations encountered in actual driving. As the designed experimental scenarios in this study were simple surprise events without complex situations such as the presence of surrounding traffic, the 90th percentile BRT in complex real-life surprise scenarios is expected to be relatively higher. The BRTs for expected events were found to be higher compared to surprise events as the MTW riders tried to optimize and delay their reactions to avoid unnecessary decelerations. The relationship established between TTC and BRT for MTW riders was found to be in close approximation to the relation given by Jurecki and Stańczyk (2014) for car drivers. Also, the positive linear relationship observed between the initial distance (distance between MTW and tracks at the start of braking), and BRT irrespective of speed was similar to that obtained for cars by Jurecki and Stańczyk (2014). Moreover, the speed and deceleration behaviors in surprise scenarios indicated that there was a considerable variation in braking among riders as 68% of the surprise events had harsh braking while 34% had soft braking. A similar observation was made by van Nes et al. (2019) for PTW riders towards two scenarios, namely full stop followed by a right turn and full stop followed by a left turn. The authors reported that the magnitude of decelerations varied among riders before and while performing evasive maneuvers. Further, in the current study, the riders' swerving profiles at the end of the manoeuvers indicated the loss of control of the MTW, which indicates an execution failure of the evasive action. A previous study by Penumaka et al. (2014) also observed that PTW riders typically made perception and execution failures while facing different merged accident configurations.

7. Conclusions

This study investigated MTW riders' responses to the conflicts resulting from illegal pedestrian crossings through a mockup study. Four scenarios were designed with two surprise scenarios, one expected scenario, and one stationary scenario. The 50th and 90th percentile BRTs in surprise scenarios (Scenario 1 and 3) were observed to be 0.77 and 1.52 s, respectively. In the case of the expected scenario (pedestrian dummy waiting to cross with temporal uncertainty), the average BRT was observed to be 2.38 s, which was relatively higher because of the lower urgency in the conflict situation. A positive linear relationship was established between TTC and BRT of MTW riders, with an R^2 of 0.85 indicating that as the TTC increases, the BRT of riders increases. It was also observed that irrespective of the approach speeds, the distance at the appearance of the dummy was directly proportional to BRT. Also, an inverse relationship between approach speeds and BRTs was observed. As all riders faced multiple scenarios, the BRTs were also considered as non-independent, and a repeated-measures ANOVA was conducted to ascertain whether there was a significant effect of conflict severity (denoted by TTC group) and scenario type on BRT. The results revealed that the TTC group and scenario type had significant effects on BRT, and therefore, the BRT was modeled through a generalized linear mixed-effects model by controlling for the variation within the rider. The fixed effects due to the independent variables were significant; however, the interaction between the independent variables was found insignificant. Further, the hard braking events (events with max deceleration above 3.5 m/s^2) were analyzed and found to have relatively higher yaw rates at the end of braking, indicating loss of control of the vehicle. To avoid accidents with pedestrians in such cases, MTW with advanced braking systems such as antilock braking systems (ABS) or combined braking systems

(CBS) and motorcycle advanced emergency braking (MAEB) system can help in effectively bringing the MTW to a halt without the loss of control of the vehicle. The insights from this study are useful to understand rider behavior and the development of countermeasures to avoid MTW-pedestrian crashes.

8. Study limitations

The study has some limitations which need to be addressed in future research: a) the study analyzed BRT and evasive actions for 50 male riders. Data for more riders along with female riders will help to develop robust and generalized models and related threshold values. b) This study used human dummies for replicating the crossing pedestrians; however, rider behavior in the naturalistic environment may differ, and therefore data from the naturalistic environment will be useful to strengthen the study findings. c) This study analyzed rider behavior towards simple surprise and expected scenarios; future studies also need to analyze relatively more complex situations observed in mixed traffic conditions d) The study used a manual triggering system to trigger dummies; however, slight variations in the triggering may lead to slight variations in the BRTs. e) Further, other factors such as rider emotional status, vehicle-characteristics affect the BRTs and evasive characteristics of the riders and are not captured in the instrumented data leading to the phenomenon of unobserved heterogeneity in the data. Further studies can address the phenomenon by using statistical techniques such as random parameter models.

CRediT authorship contribution statement

Pradhan Kumar Akinapalli: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Digvijay S. Pawar:** Funding acquisition, Investigation, Methodology, Project administration, Resources, Validation, Visualization, Writing – review & editing. **Hussein Dia:** Funding acquisition, Project administration, Resources, Validation, Visualization, Writing – review & editing.

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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