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Original research article

Development of a Simple Tool to Enhance Driver Identification in Motorcycle Accidents, Covering both Collision and Non-collision Subtypes

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ABSTRACT

In Lampang province, Thailand, motorcycle-related road traffic collisions are common, and the differentiation between drivers and passengers is crucial for legal proceedings. This study aimed to develop and validate two multivariable predictive models that differentiate between motorcycle drivers and passengers based on demographics and fracture patterns. Retrospective data from patients involved in motorcycle accidents from January 2014 to December 2017 at Lampang Hospital were used to construct models. Model 1 focused on motorcycle collisions with other vehicles, while Model 2 focused on non-collision motorcycle accidents. Predictor selection was done through multivariable logistic regression using a stepwise backward elimination method. A total of 1,816 patients with fractures from motorcycle accidents were included, with 1,583 categorized as drivers and 233 as passengers. The final model identified six significant predictors: age categories, gender, pelvis and lumbar spine fractures, wrist and hand level fractures, femur fractures, and lower leg fractures. Both models demonstrated acceptable discriminative abilities, indicating their potential as user-friendly tools for medical and legal adjudication following motorcycle accidents.

Keywords: Driver; Forensic; Fracture; Motorcycle accident; Prediction model; Traffic

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1. Introduction

Investigations into the epidemiology of road traffic collisions (RTCs) in Thailand have elucidated that motorcycles are the predominantly involved, comprising approximately 80% of all involved vehicles [1, 2]. Contributing factors to this prevalence include excessive speeding, driving under the influence, and negligence [2]. Legal ramifications for such infractions are stringent, with The Protection For Motor Vehicle Victims Act B.E.2535 (1992) stipulating that families of deceased passengers receive significantly higher compensations than drivers, accounting for organ loss and sustained disabilities [3]. Thus, the precise distinction between drivers and passengers post-collision is essential for equitable treatment.

Post-RTC, individuals may experience conditions like unconsciousness or amnesia, or in more severe cases, death, which impedes their capacity to impart crucial information. Without witnesses or video evidence, determining the identity of the driver is challenging. This uncertainty may lead to disputations over liability. Therefore, it is imperative for medical professionals to conduct detailed examinations of injuries to accrue substantial evidence, which is crucial in legal contexts [4].

Research has demonstrated that motorcycle drivers sustain injuries predominantly in the head, neck, hands, chest, and abdomen, which reflect the mechanisms of injury [5]. Collisions with other vehicles tend to result in more fatalities among drivers, whereas passengers are more vulnerable to fatal injuries from falls or ejections. Notably, head injuries are a significant factor in mortality rates [5]. In regions with high helmet usage, the disparity in head injuries between drivers and passengers is negligible [6]. However, in areas with low helmet utilization, like Cameroon or Thailand, drivers suffer more head injuries, including skull and facial fractures, compared to passengers [5, 7]. Drivers also exhibit a higher frequency of fractures in regions such as the hand, elbow, forearm, and foot [7], while lower limb injuries are common to both drivers and passengers [6, 8]. Furthermore, injury patterns and severities have been noted to vary with age and gender [9, 10], which may serve as predictive indicators for motorcycle-related accidents [6, 7].

This context provides an opportunity to delve into the diagnostic potential of fracture patterns relative to anatomical sites and demographic attributes for differentiating between drivers and passengers in collisions. Notably, motorcycle accidents, both with and without other vehicles, are prolific in Thailand [11], and discerning injury patterns between these two accident types is imperative [10]. Consequently, the goal is to develop predictive models that leverage fracture distributions and demographic data to distinguish between drivers and passengers in Thai motorcycle accidents, inclusive of both collision and non-collision scenarios.

2. Materials and Methods

2.1 Study design and setting

This research entailed a retrospective cross-sectional predictive study, focusing exclusively on patients who sustained bone fractures from motorcycle accidents (excluding those involving scooters and mopeds). We retrieved data from electronic medical records at Lampang Hospital, an urban tertiary care center in Lampang province, over a period spanning January 2014 to December 2017. Registered with the Thai Clinical Trials Registry (TCTR20230111011), our methodology complied with the TRIPOD guidelines [12] and the CONSORT 2010 statement. The Lampang Human Research Ethics Committee granted ethical clearance (Approval No: 51/64) and waived the requirement for informed consent given the study's observational nature. All data collection from electronic medical records was authorized and conducted in accordance with relevant guidelines and regulations.

2.2 Participant selection and data collection

We identified motorcycle accident cases that were brought to the emergency department, distinguishing collisions (involving subsequent impacts with other vehicles) from non-collision incidents. We included cases involving interactions with various vehicle types and excluded non-relevant collision scenarios. We gathered baseline data including age, sex, fracture specifics, patient outcomes, and discharge status. Helmet use and location of accident (urban vs. rural) were omitted due to documentation deficiencies. We employed the ICD-10 coding system for classifying injuries and accidents. Eligibility criteria required an official radiographic report confirming bone fractures. Exclusion criteria included ambiguous documentation regarding the patient's position on the motorcycle or inconsistent reports across hospital departments. This study did not involve corpses.

2.3 Potential predictors and study outcome

We identified ten fracture sites and two demographic variables (gender and age, categorized as <15, 15-40, and >40 years) as potential predictors based on prior research [6–10]. Our objective was to discern between drivers and passengers using these predictors. Primary data were obtained from patient self-reports, complemented by accounts from witnesses and medical personnel.

2.4 Statistical analysis and sample size estimation

Baseline characteristics were quantified using appropriate statistical measures. Fisher's exact and independent t-tests assessed the distinctions between drivers and passengers. For non-normal distribution, we employed Mann-Whitney test. A p-value of <0.05 was considered statistically significant. We used Stata version 16.0 for statistical analyses. To determine the required sample size for a binary outcome prediction model, we applied Richard D. Riley's formula [13], accounting for an expected C-statistic of 0.8 and 12 predictors, yielding a minimum sample of 652 patients and at least 555 driver-related incidents.

2.5 Development of prediction model

Initial univariable analysis was conducted using binary logistic regression. Predictors with over 50% missing data were excluded from further analysis. We derived two models using multivariable logistic regression with stepwise backward elimination, targeting collision and non-collision events. The elimination threshold was set at a p-value above 0.05. The final models were generated by integrating predictors from both elimination processes, evaluating logit coefficients to compose the final prediction algorithm.

2.6 Performance measures

The models' discriminative capabilities and calibration were scrutinized. Discrimination was gauged by the C-statistic (AuROC), with thresholds for performance stratified as per Hosmer and Lemeshow [14]. Calibration plots graphically represented the correlation between predicted and actual outcomes. Internal validity and model optimism were evaluated via bootstrapping with 500 iterations, with lower optimism correlating with greater validity.

3. Results

3.1 Baseline characteristics

A total of 1,816 patients sustained fractures resulting from motorcycle accidents, with 1,583 being drivers and 233 being passengers (see Fig. 1). Among these accidents, 1,098 were due to collisions with other vehicles, while 718 were non-collision incidents. A comparison of baseline characteristics between drivers and passengers is presented in Table 1. Males comprised the majority of drivers, whereas over half of the passengers were female. The mean age of drivers, at 37.9 years, was significantly higher than that of passengers. The proportion of drivers tended to increase with age, in contrast to the declining proportion of passengers. In terms of severity, our study found similar distributions in disposition status, number of fractures, hospital stay duration, and recovery rates [see Table 1. Mortality rates were 2.6% for drivers and 1.7% for passengers.

3.2 Fracture distribution between drivers and passengers (stratified by accident type)

Table 2 compares fracture distribution between drivers and passengers based on ten anatomical locations. In collision accidents, statistically significant differences in fracture sites between drivers and passengers were observed, including the pelvis and lumbar spine, wrist and hand, femur, and lower leg (including the ankle). Passengers were more likely to have sustained fractures in the femur, lower leg (including ankle), pelvis, and lumbar spine, while the remaining fractures were more common among drivers. For non-collision accidents, significant differences in four fracture sites were found between drivers and passengers: cervical spine and neck, rib(s), sternum and thoracic spine, pelvis and lumbar spine, and femur. Similar proportions of drivers and passengers experienced fractures in the shoulder, upper arm, wrist, and hand, with larger disparities seen in collision accidents. Most fracture sites exhibited consistent patterns between accident types, except for the forearm, which was more frequent in drivers involved in collision accidents (see Table 2).

3.3 Potential predictors

Twelve factors were initially considered as potential predictors for driver and passenger discrimination. (see Table 3). The cervical spine and neck fractures were excluded from non-collision accidents due to insufficient data. After conducting univariable analyses using logistic regression, age, sex, and fractures of the pelvis and lumbar spine were statistically significant for both accident types (see Table 3). Collision accidents indicated significant of fractures of the wrist and hand (p = 0.001), femur (p = 0.001), and lower leg (including ankle) (p = 0.001). Conversely, non-collision accidents showed significant fractures of the rib(s), sternum, and thoracic spine (p = 0.009), and femur (p = 0.003). All potential predictors listed in Table 4 were included in the comprehensive multivariable prediction model, irrespective of their statistical significance. Age and gender consistently demonstrated statistical significance for both accident types. In collision accidents, only fractures of the forearm (p = 0.028) and wrist and hand (p = 0.003) were statistically significant. In contrast, non-collision accidents identified significant fractures in the pelvis and lumbar

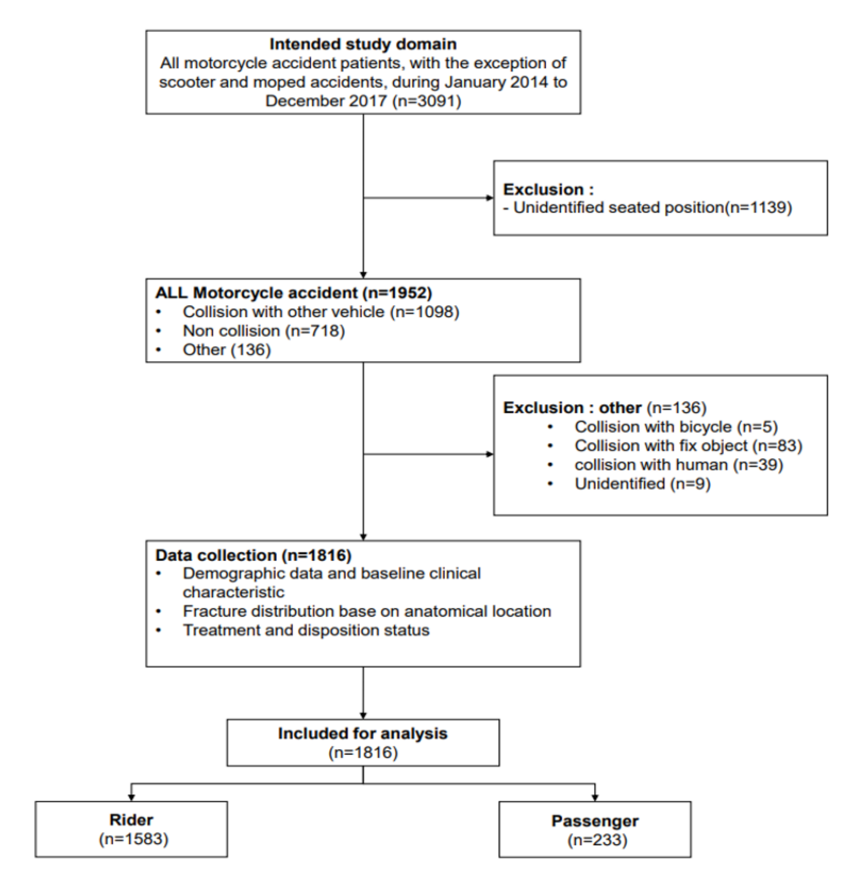

Fig. 1. Study flow diagram.

spine ($p = 0.006$) and femur ($p = 0.030$) (see Table 3).

3.4 Final predictors

Six final predictors were identified for predicting drivers in non-collision accidents [see Table 4]. The backward elimination method revealed four predictors: age 15-40 years (Odds Ratio [OR] 6.90, 95% Confidence Interval [CI] 3.26 - 14.6, $p < 0.001$), age > 40 years (OR 17.53, 95% CI 7.62 - 40.34, $p < 0.001$), male (OR 4.05, 95% CI 2.41 - 6.81, $p < 0.001$), fracture of the pelvis and lumbar spine (OR 0.1, 95% CI 0.02 - 0.48, $p = 0.006$), and fracture of the femur (OR 0.32, 95% CI 0.15 - 0.71, $p = 0.005$). Two additional predictors were incorporated into the final model through the merging method, as they showed significance in the collision accident model: fracture of the wrist and hand (OR 0.82, 95% CI 0.40 - 1.69, $p = 0.600$) and fracture of the lower leg (including ankle) (OR 0.72, 95% CI 0.36 - 1.44, $p = 0.352$) (see Table 4). For predicting drivers in collision accidents, the backward elimination method yielded five final predictors: age 15-40 years (OR 8.61, 95% CI 4.65 - 15.96, $p < 0.001$), age > 40 years (OR 20.32, 95% CI 10.20 - 40.48, $p < 0.001$), male (OR 4.64, 95% CI 3.09 - 6.99, $p < 0.001$), fracture of the femur (OR 0.48, 95% CI 0.29 - 0.79, $p = 0.001$), fracture of wrist and hand (OR 2.73, 95% CI 1.21 - 6.18, $p = 0.001$), and fracture of lower leg

Table 1. Comparison of characteristics between driver and passenger.

Characteristics	Driver -1,583	Passenger -233	p-value
Gender (%)			
male	1,136 (71.8)	103 (44.2)	<0.001
female	447 (28.2)	130 (55.8)	<0.001
Age (mean ± SD)	37.9 ± 18.1	28.2 ± 19.7	<0.001
<15 years (%)	48 (3.0)	51 (21.9)	<0.001
15 - 40 years (%)	826 (52.2)	125 (53.6)	
>40 years (%)	709 (44.8)	57 (24.5)	
Disposition status (%)			0.427
inpatient	1,356 (85.7)	195 (83.7)	
outpatient and emergency room	227 (14.3)	38 (16.3)	
Number of fractures per case (median, IQR)	1 (1,2)	1 (1,2)	0.001
Treatment outcome (%)			0.65
recovery	1542 (97.4)	229 (98.3)	
death	41 (2.6)	4 (1.7)	
Prevalence of motorcycle accidents (%)			<0.001
collision with 2 wheeled motor vehicle	448 (28.3)	29 (12.5)	
collision with car or pickup truck	473 (29.9)	112 (48.1)	
collision with heavy transport vehicle	30 (1.9)	6 (2.6)	
non-collision transport accident	632 (39.9)	86 (36.9)	
Number of passengers			
1	-	233 (100)	
≥ 1	-	0 (0)	

Abbreviation: SD; standard deviation, IQR; interquartile range

Table 2. Comparison of fracture distribution between drivers and passengers based on anatomical location, subgroup analysis according to accident type.

Anatomical location	Collision with another vehicle			Non-Collision		
	Driver -951 No. (%)	Passenger -147 No. (%)	P-value	Driver -632 No. (%)	Passenger -86 No. (%)	p-value
Skull and facial bones	262 (27.6)	30 (20.4)	0.071	180 (28.5)	17 (19.8)	0.095
Cervical spine and other part of neck	23 (2.4)	4 (2.7)	0.775	28 (4.4)	0 (0.0)	0.039
Rib(s), sternum and thoracic spine	97 (10.2)	9 (6.1)	0.134	87 (13.8)	2 (2.3)	0.001
Pelvis and lumbar spine	46 (4.8)	14 (9.5)	0.03	3 (0.5)	4 (4.7)	0.005
Shoulder and upper arm	162 (17.0)	18 (12.2)	0.153	147 (23.3)	19 (22.1)	0.892
Forearm	169 (17.8)	20 (13.6)	0.241	88 (13.9)	18 (20.9)	0.104
Wrist and hand level	150 (15.8)	7 (4.8)	0	85 (13.5)	11 (12.8)	1
Femur	120 (12.6)	34 (23.1)	0.001	33 (5.2)	12 (14.0)	0.007
Lower leg, including ankle	194 (20.4)	48 (32.7)	0.001	79 (12.5)	13 (15.1)	0.492
Foot, except ankle	121 (12.6)	11 (7.5)	0.076	55 (8.7)	4 (4.7)	0.293

(including ankle) (OR 0.49, 95% CI 0.32 - 0.74, p = 0.002). Fracture of the pelvis and lumbar spine (OR 0.59, 95% CI 0.29 - 1.18, p = 0.135) was added to the final model through the merging method (see Table 4). The coefficients presented in Table 4 formulate the estimated probability equations for identifying drivers in collision and non-collision accidents. Regarding the coefficient in Table 4, the equations used for the estimated probability of being a driver in collision and non-collision accidents are shown below.

A value of 1 was used to indicate the presence of fracture sites, while a value of 0 indicated their absence.

The Rider Probability Calculator is available through the link: https://tharathipdevelop.com/rider-prob/form

Table 3. Estimated odds ratios in univariable and multivariable logistic regression model for collision (with another vehicle) and non-collision accidents.

Predicting factor chance of being driver	Collision with another vehicle				Non-collision			
	Univariable analysis		Multivariable analysis		Univariable analysis		Multivariable analysis	
	Odds ratio (95%CI)	p-value	Adjusted Odds ratio (95%CI)	p-value	Odds ratio (95%CI)	p-value	Adjusted Odds ratio (95%CI)	p-value
Age								
<15	Reference		Reference		Reference		Reference	
15-40 years	7.4 (4.2-13.0)	<0.001	8.9 (4.8-16.8)	<0.001	6.6 (3.3-13.2)	<0.001	6.0 (2.8-12.6)	<0.001
>40 years	14.8 (7.9-27.5)	<0.001	21.4 (10.5-43.6)	<0.001	11.2 (5.3-23.7)	<0.001	14.9 (6.4-34.9)	<0.001
Male	3.1 (2.2-4.5)	<0.001	4.4 (2.9-6.6)	<0.001	3.3 (2.1-5.2)	<0.001	3.9 (2.3-6.6)	<0.001
Skull and facial bones	1.5 (1.0-2.3)	0.07	1.5 (0.9-2.5)	0.119	1.6 (0.9-2.8)	0.092	1.3 (0.6-2.8)	0.464
Cervical spine and other part of neck	0.9 (0.3-2.6)	0.826	0.7 (0.2-2.3)	0.557	-	-	-	-
Rib(s), sternum and thoracic spine	1.7 (0.9-3.5)	0.124	1.2 (0.6-2.7)	0.578	6.7 (1.6-27.7)	0.009	3.2 (0.7-14.2)	0.125
Pelvis and lumbar spine	0.5 (0.3-0.9)	0.023	0.7 (0.3-1.5)	0.347	0.1 (0.0-0.4)	0.003	0.1 (0.0-0.5)	0.006
Shoulder and upper arm	1.5 (0.9-2.5)	0.146	1.6 (0.9-3.1)	0.119	1.1 (0.6-1.8)	0.81	0.9 (0.4-1.9)	0.695
Forearm	1.4 (0.8-2.3)	0.215	2.0 (1.1-3.6)	0.028	0.6 (0.3-1.1)	0.088	0.8 (0.4-1.7)	0.544
Wrist and hand level	3.7 (1.7-8.2)	0.001	3.7 (1.6-8.9)	0.003	1.1 (0.5-2.1)	0.866	0.9 (0.4-2.1)	0.888
Femur	0.5 (0.3-0.7)	0.001	0.6 (0.4-1.0)	0.052	0.3 (0.2-0.7)	0.003	0.4 (0.1-0.9)	0.03
Lower leg, including ankle	0.5 (0.4-0.8)	0.001	0.6 (0.4-1.0)	0.077	0.8 (0.4-1.5)	0.497	0.8 (0.3-1.9)	0.62
Foot, except ankle	1.8 (0.9-3.4)	0.078	1.9 (0.9-4.1)	0.092	2.0 (0.7-5.5)	0.207	2.1 (0.6-7.3)	0.266

Abbreviation: CI; confidential interval

$$\text{Probability of being a Driver in a collision accident} = \frac{e^{(-0.96+2.13(\text{age15}-40)+2.99(\text{age}>40)+1.55(\text{male})-0.53(\text{pelvis\&lumber } Fx)+1.03(\text{wrist\&hand } fx)-0.79(\text{femur } fx)-0.70(\text{lower leg\&ankle } fx))}}{(1+e^{(-0.96+2.13(\text{age 15}-40)+2.99(\text{age }>40)+1.55(\text{male})-0.53(\text{pelvis\&lumber } Fx)+1.03(\text{wrist\&hand } fx)-0.79(\text{femur } fx)-0.70(\text{lower leg\&ankle } fx))}},$$

$$\text{Probability of being a Driver in a non-collision accident} = \frac{e^{-0.71+1.93(\text{age 15}-40)+2.86(\text{age}>40)+1.40(\text{male})-2.32(\text{pelvis\&lumber } Fx)-0.19(\text{wrist\&hand } fx)-1.16(\text{femur } fx)-0.33(\text{lower leg\&ankle } fx)}}{(1+e^{-0.71+1.93(\text{age15}-40)+2.86(\text{age}>40)+1.40(\text{male})-2.32(\text{pelvis\&lumber } Fx)-0.19(\text{wrist\&hand } fx)-1.16(\text{femur } fx)-0.33(\text{lower leg\&ankle } fx)}},$$

3.5 Model performance

Regarding discriminative ability, the AuROC yielded values of 0.79 and 0.77 for the predictive model in instances of both collision and non-collision accidents, as shown in Supplementary Figs. 1A-1B. A subgroup analysis for each collision subcategory demonstrated comparable performance in collisions with 2-wheeled motor vehicles and collisions with cars or pickup trucks. However, discriminative performance was notably insufficient in collisions with heavy transport vehicles (see Supplementary Table 1). The final model's calibration was visually represented through a calibration plot, highlighting a strong concurrence between the projected and observed probabilities, as depicted in Figs. 2A-2B. The efficacy of the two ultimate predictive models was evaluated for internal validity using a bootstrap resampling technique comprising 500 iterations. The calculated C-statistic optimism for the collision and non-collision predictive models were 0.003 and 0.002, respectively. Detailed sensitivity, specificity, positive likelihood ratio, and negative likelihood ratio values were tabulated across various probability thresholds for both models in Table 5. Each incremental change of 0.05 in the predicted probability resulted in a significant balance shift between sensitivity and speci-

Table 4. Estimated odds ratios of being driver, coefficients of final model in collision with another vehicle and non-collision accident.

Predictors	Collision group			Non-collision group		
	Coefficient	Odds ratios (95%CI)	p-value	Coefficient	Odds ratios (95%CI)	p-value
Constant	-0.96			-0.71		
Age						
<15	Reference	1		Reference	1	
15-40 years	2.13	8.61 (4.65-15.96)	<0.001	1.93	6.90 (3.26-14.60)	<0.001
>40 years	2.99	20.32 (10.20-40.48)	<0.001	2.86	17.53 (7.62-40.34)	<0.001
Male	1.55	4.64 (3.09-6.99)	<0.001	1.4	4.05 (2.41-6.81)	<0.001
Skull and facial bones	Not included			Not included		
Cervical spine and other part of neck	Not included			Not included		
Rib(s), sternum and thoracic spine	Not included			Not included		
Pelvis and lumbar spine	-0.53	0.59 (0.29-1.18)	0.135	-2.32	0.10 (0.02-0.48)	0.006
Shoulder and upper arm	Not included			Not included		
Forearm	Not included			Not included		
Wrist and hand level	1.03	2.73 (1.21-6.18)	0.001	-0.19	0.82 (0.40-1.69)	0.6
Femur	-0.79	0.48 (0.29-0.79)	0.001	-1.16	0.32 (0.15-0.71)	0.005
Lower leg, including ankle	-0.7	0.49 (0.32-0.74)	0.002	-0.33	0.72 (0.36-1.44)	0.352
Foot, except ankle	Not included			Not included		

Abbreviation: CI; confidential interval.

ficity. The study refrained from defining an official cutoff point. As such, an official model cutoff point wasn't defined. We suggested favoring high specificity as a reasonable approach to guide further investigations, including full autopsies and x-rays for concealed fractures.

3.6 Post Hoc sensitivity analysis

We have acknowledged the major limitation regarding our outcomes, that the data was self-report data from patients. To demonstrate the robustness of our model, we conducted a sensitivity analysis by randomly substituting passengers for drivers to simulate fault determination scenarios. We estimated the AuROC for each scenario, including situations where all passengers were assigned fault determination (100% incorrect) and 50%, 25%, and 10% fault determinations. Each scenario underwent 200 sampling replicates. Both models maintained acceptable discriminative ability when fault determination did not exceed 25% (see Supplementary Table 2).

3.7 Demonstration of individual predictions from the final prediction models

To illustrate the practical implications, four patients originating from two actual cases were selected for presentation, as depicted in Fig. 2. The first case involved a collision involving a husband (the driver) and his wife (the passenger). Following the husband's death due to multiple injuries, the wife modified her statement to the insurance company, aiming to secure higher compensation. However, considering the fracture distribution and clinical attributes outlined in Supplementary Table 3, the computed probabilities of being the driver were 99.0% for the husband and 88.4% for the wife. The second scenario entailed a motorcycle collision involving two teenagers (Patients A and B), both 16-year-old males. The estimated probabilities of being the driver were 97.7% for Patient A and 77.4% for Patient B, as revealed in Supplementary Table 3. Notably, Patient B was discovered deceased at the scene, while Patient A survived. Initially, security footage indicated Patient A as the driver, yet he later

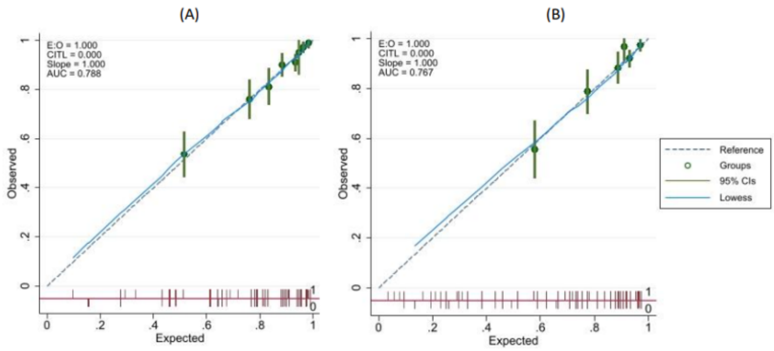

Fig. 2. Calibration plot of final prediction model for collision accident (A) and non-collision accident (B).

asserted that he had transitioned to being a passenger midway through the incident. The predicted probability at each specific condition is illustrated in Fig. 3.

4. Discussion

In pursuit of delineating the driver from passengers in motorcycle accidents, our research endeavored to construct a predictive model. This model prognosticated the likelihood of being the driver in both collision and non-collision incidents. Utilized predictors comprised age, gender, and fractures at specific anatomical sites: femur, wrist/hand, leg/ankle, and pelvis/lumbar spine. These were imperative for deducing associated probabilities. Model evaluations demonstrated acceptable discrimination (0.79 for collision-related scenarios, 0.77 for non-collision scenarios) and calibration.

Fracture distribution patterns revealed inconsistencies between collision and non-collision accidents. Forearm fractures in collision scenarios were associated with an odds ratio of 1.4 in driver identification, diverging from non-collision cases. Collision-involved drivers exhibited a higher frequency of wrist and hand fractures compared to their non-collision counterparts, likely due to the positioning of limbs during impact. Conversely, femur and lower leg fractures, inclusive of ankle fractures, were predominantly observed in passengers, contradicting previous studies suggesting minimal differences between drivers and passengers [8, 15]. Factors such as the drivers' foot placement and the protective barrier of the motorcycle's front frame influenced fracture distributions [16]. Additionally, the angle of impact altered risk profiles, with an increased angle intensifying femur fracture risks for passengers [17].

The study embraced a method analogous to an autopsy guide prediction score utilized for discerning drivers from passengers in fatal automobile collisions, acknowledging the caveat of model overfitting [18]. A stepwise backward elimination methodology was employed, and the model distilled all the factors down to six salient predictors, balancing predictor sufficiency and sample size adequacy.

Fig. 3. Predicted probability chart at each specific condition.

Table 5. Sensitivity, Specificity, Positive, and Negative likelihood ratio for each predicted probability of being driver in both models.

Predicted probability	Sensitivity (95% CI)	Specificity (95% CI)	LR+ (95% CI)	LR- (95% CI)
Prediction mode for collision with another vehicle				
0.95	27.4(24.6-30.4)	95.9 (91.3-98.5)	6.7 (3.1-14.8)	0.8 (0.7-0.8)
0.9	58.5 (55.3-61.6)	80.3 (72.9-86.4)	3.0 (2.1-4.1)	0.5 (0.5-0.6)
0.85	79.3 (76.6-81.8)	65.3 (57.0-73.0)	2.3 (1.8-2.9)	0.3 (0.3-0.4)
0.8	81.5 (78.9-83.9)	61.2 (52.8-69.1)	2.1 (1.7-2.6)	0.3 (0.3-0.4)
0.75	93.3 (91.5-94.8)	38.8 (30.9-47.2)	1.5 (1.3-1.7)	0.2 (0.1-0.2)
Prediction mode for non-collision				
0.95	30.2 (26.7-34.0)	94.2 (87.0-98.1)	5.2 (2.2-12.3)	0.7 (0.7-0.8)
0.9	68.5 (64.7-72.1)	72.1 (64.4-81.2)	2.5 (1.7-3.5)	0.4 (0.4-0.5)
0.85	83.1 (79.9-85.9)	58.1 (47.0-68.7)	2.0 (1.5-2.6)	0.3 (0.2-0.4)
0.8	85.0 (81.9-87.7)	53.5 (42.4-64.3)	1.8 (1.5-2.3)	0.3 (0.2-0.4)
0.75	92.4 (90.1-94.3)	41.9 (31.2-53.0)	1.6 (1.3-1.9)	0.2 (0.1-0.3)

Abbreviation: CI; confidential interval, LR+; positive likelihood ratio, LR-; negative likelihood ratio

The fracture distribution as predictors was underscored, devising distinct models for collision and non-collision incidents to refine diagnostic specificity. Limitations included retrospective data analysis, incomplete documentation on helmet usage, protective gear, and bioengineering data. Outcome data, based on self-reporting, held a potential bias due to the absence of extensive evidence such as CCTV footage. Sensitivity analyses accounted for the variability in fault determination, maintaining model robustness within a 25% error margin. The study predominantly included participants capable of self-reporting seat positions, hence possibly not capturing the full spectrum of high-energy trauma cases. External validation is recommended to affirm the model's efficacy and applicability.

The development and internal validation of these models aim to support healthcare and forensic professionals in accurately identifying the driver in motorcycle accidents. Despite promising results, further external validation is essential prior to widespread application.

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