Pedestrian Injury Severity Prediction Based on Logistic Regression Using Real-World Crash Data for AACN Systems

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Abstract Advanced Automatic Collision Notification (AACN) systems aim to estimate injury severity immediately after a crash to support rapid emergency response. This study developed a pedestrian injury severity prediction algorithm (Ped-ISP) using logistic regression based on real-world pedestrian crash data from Michigan, USA, and evaluated its performance using an independent, multi-site in-depth investigation dataset. Pedestrian crashes extracted from the Vulnerable Road User Injury Prevention Alliance (VIPA) database were analysed using vehicle-related factors and pedestrian characteristics. The analysis was restricted to crashes in which straight-moving or turning vehicles struck pedestrians, yielding 148 cases for model development. Injury severity was defined using the Injury Severity Score (ISS), and an optimal classification threshold for ISS ≥ 15 was determined via five-fold cross-validation. External validation was conducted using 54 cases from the Vulnerable Road User In-depth Crash Investigation Study (VICIS). Ped-ISP demonstrated good discriminative performance in the VIPA dataset and demonstrated a moderate level of performance in external validation. Impact speed and pedestrian age showed strong associations with injury severity, with impact speed identified as the primary predictor. However, misclassification analysis indicated that pedestrian injury risk cannot be explained by speed alone, highlighting limitations of current AACN applications and the need for further investigation.

Keywords Advanced Automatic Collision Notification, Pedestrian injury severity, Real-world crash data, Logistic regression, Vulnerable Road Users.

I. INTRODUCTION

While pedestrian traffic fatalities have shown a decreasing trend in Japan and Europe [1], they have increased and remain at an elevated level in the United States [2]. Over the past decade, pedestrians have accounted for approximately 17% of all traffic fatalities in the USA, underscoring the urgent need for integrated countermeasures addressing human, road, and vehicle factors. In response, the U.S. Department of Transportation identified traffic fatalities and serious injuries as a major public safety issue and released the National Roadway Safety Strategy (NRSS) in 2022 [3]. Prior to the NRSS, city- and state-level initiatives had already implemented systematic infrastructure improvements and traffic safety programs, with their effectiveness documented in studies [4–6]. These initiatives demonstrated reductions in crash frequency and injury severity and align closely with the Safe System Approach later formalized in the NRSS. In addition, the NRSS positions post-crash care as a key pillar for reducing traffic-related fatalities, highlighting the importance of timely and effective response following a crash.

Post-crash care refers to comprehensive efforts aimed at improving survival outcomes after traffic crashes by ensuring rapid access to emergency medical services and enabling first responders to operate safely and efficiently. Within this framework, advanced communication technologies, including Automatic Crash Notification (ACN) and Advanced Automatic Collision Notification (AACN), have attracted growing attention. ACN systems accelerate emergency response through automatic transmission of crash location information, while AACN systems further support emergency decision-making by transmitting vehicle-derived data, including crash severity and occupant characteristics, to call centres [7]. These technologies play an important role in improving the quality of post-crash medical response and reducing traffic-related mortality.

Although interest in telematics technologies supporting rapid post-crash medical intervention is increasing worldwide, the regulatory status of AACN varies by region. In the European Union, public eCall [8] has been mandated, with a transition toward next-generation eCall underway, whereas in the USA, AACN has been deployed primarily through market-driven telematics services without regulatory mandate [9]. References [10] and [11] provide concrete evidence that China and Japan have established institutional and evaluation frameworks for eCall/AACN systems, including technical requirements and formal schemes integrating accident

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emergency call systems into national vehicle safety policies. Although the regulatory status of AACN varies by region, the importance of post-crash injury severity estimation is widely recognised, emphasising the need for externally validated AACN algorithms based on real-world crash data.

Pedestrian injury characteristics differ fundamentally from those of vehicle occupants. While occupant injuries are mitigated by restraint systems and vehicle interior structures, pedestrian injuries are largely determined by direct impacts with the vehicle front, resulting in substantial variability in injured body regions. International comparative data from the University of Michigan Transportation Research Institute (UMTRI) [12] indicate that pedestrians frequently sustain injuries to the head and lower extremities, while thoracic injuries are a major contributor to fatal outcomes at AIS ≥ 3, following head injuries. These patterns reflect pedestrian-specific impact sequences in which the head contacts the hood or windshield and the thorax or pelvis impacts the hood leading edge, depending on vehicle geometry and pedestrian stature. Vehicle type also plays an important role: passenger cars are typically associated with head and lower extremity injuries, whereas sport utility vehicles (SUVs) and pickup trucks [13-15], which are characterised by higher front-end geometries, are associated with increased risk and severity of torso injuries, including the thorax and abdomen. Injury patterns vary further with age and body characteristics [12], with children more prone to head impacts and older pedestrians experiencing more severe lower extremity and thoracic injuries due to increased skeletal fragility [16]. Given the high fatality risk associated with head and torso injuries, understanding of pedestrian-specific injury mechanisms is essential.

Pedestrian injury risk has traditionally been estimated using logistic regression models [17-18], with impact speed serving as a primary predictor. Analyses by Lubbe *et al*. [14], using the German In-Depth Accident Study (GIDAS) [19], consistently demonstrated that impact speed is a dominant factor governing pedestrian injury severity. Similarly, studies by Monfort *et al*. [20] using the Vulnerable Road User Injury Prevention Alliance (VIPA) [21] and Vulnerable Road User In-depth Crash Investigation Study (VICIS) [22] datasets reported that, in addition to impact speed, vehicle front-end geometry – particularly hood leading edge height – substantially influences injury severity in the head and torso. Although machine-learning approaches [23] capable of modelling nonlinear interactions have been proposed, logistic regression remains a foundational method for injury severity estimation due to its interpretability and suitability for policy and real-world implementation.

Previous studies, such as that by Monfort et al. [20], have suggested that impact speed and vehicle geometry play important roles in determining pedestrian injury risk, and have developed injury risk curves incorporating detailed vehicle and crash-related parameters. In addition, efforts toward practical injury prediction have been made through AACN algorithms for pedestrians and cyclists, such as those proposed by Nishimoto et al. [24] However, these approaches differ in their underlying assumptions and scope of application. The study by Monfort primarily focuses on injury mechanism analysis, incorporating detailed vehicle geometry parameters such as front-end structure and hood shape. In contrast, existing AACN algorithms have been developed under specific traffic conditions, particularly reflecting those in Japan, and thus rely on environment-dependent assumptions and detailed variables. As a result, there remains a gap between high-fidelity injury risk modeling and practical implementation within AACN frameworks. The aims of this study are: (1) to develop a pedestrian injury severity prediction model based on real-world crash data, and (2) to evaluate its performance and applicability in AACN contexts using an independent external dataset. Specifically, a logistic regression-based pedestrian injury severity prediction algorithm was developed using Michigan pedestrian crash data from the VIPA database, and externally validated using the VICIS dataset to evaluate predictive performance and to examine threshold-dependent under- and over-triage characteristics relevant to AACN implementation.

II. METHODS

VIPA crash datasets

Pedestrian crash data from the VIPA database, maintained by the International Center for Automotive Medicine (ICAM) at the University of Michigan, were used to develop a pedestrian injury severity prediction algorithm. VIPA is an in-depth crash investigation database that has collected detailed vulnerable road user (VRU) cases since 2015 by identifying pedestrians, cyclists, and other VRUs from Michigan State Police crash reports (UD-10) [25]. For each case, comprehensive crash information is systematically recorded based on on-scene investigations by trained crash investigators, documentation of vehicle damage locations, and medical records, with multidisciplinary review involving trauma physicians, law enforcement, automotive engineers, and biomechanical experts.

The database includes roadway and environmental information (e.g. crash location, road conditions, and weather), as well as vehicle and crash variables, such as vehicle type (e.g. passenger car, SUV, pickup truck), impact speed, crash configuration, vehicle contact locations for the VRU (e.g. bumper, hood leading edge/surface, windshield, and A-pillar), and post-impact kinematics (e.g. wrap trajectory, lateral projection, fender vault, and roof vault). Impact speed is estimated based on available evidence, including the distance from the impact point to the final vehicle rest position, vehicle damage patterns, braking marks, and crash reconstruction simulations, incorporating expert judgement. Pedestrian injuries are coded for each body region using the Abbreviated Injury Scale (AIS) and confirmed using medical imaging, when available. Overall injury severity is assessed using the Injury Severity Score (ISS) derived from AIS codes.

Logistic regression was applied to the pedestrian crash cases. Crash scenarios were limited to cases in which a vehicle travelling straight or turning struck a pedestrian (Fig. 1), while other scenarios were excluded. These configurations represent common pedestrian crash scenarios and are relevant to AACN system applications. Vehicle-side predictors included impact speed and vehicle type. Impact speed was treated as a continuous variable after log transformation to account for skewed distributions, and vehicle type was modelled as a categorical variable with three levels (car, SUV, pickup). The original “van” category included both minivans and large vans; for consistency, minivans were grouped with passenger cars, while large vans were excluded due to their distinct structural characteristics and limited sample size. Pedestrian-side predictors included age, sex, and height. Height was treated as a continuous variable to preserve quantitative information, and sex was modelled as a binary categorical variable. Although prior studies [14][20] have shown that age affects injury risk, accurately obtaining pedestrian age immediately after a crash is difficult in real-world AACN operations; therefore, age was categorised into two groups using a threshold of 55 years. The list of variables used in the analysis is summarised in Table I.

Crossing at Mid-block | Crossing at Intersection | Crossing before/after Intersection | Vehicle Turning | Longitudinal same/opposite

Fig. 1. Type of crash categorised in VIPA (yellow arrow shows the VRU and blue arrow shows the vehicle direction). Reference from VIPA data [21].

TABLE I
PREDICTOR VARIABLES MEASURABLE FROM VEHICLE TELEMETRY OR CALL CENTRE

Variable	Description
Impact speed (kph)	Speed at which VRU was estimated to have been struck.
Type of accident	A characterization of the incident derived from the crash investigation, providing an overall summary of what occurred.
Vehicle type	Categories are the same as those used in NHTSA’s NASS data system.
Age (year)	Individual’s age recorded in years.
Sex	Reported gender of the individual.
Height (cm)	Individual's height measured in centimeters.
Injury Severity Score (ISS)	ISS assesses trauma severity and correlates with mortality, morbidity, and hospitalization duration. ISS greater than 15 is considered major trauma.

Pedestrian Injury Severity Prediction (Ped-ISP)

The field triage guidelines published by the U.S. Centers for Disease Control and Prevention (CDC) [26] propose a framework for identifying seriously injured patients based on telematics data transmitted from vehicles, in which an ISS of 15 or greater (ISS ≥ 15) is used as the criterion for severe injury. Consistent with this framework, Kononen *et al.* [27] adopted ISS ≥ 15 as the threshold for serious injury in occupant injury severity prediction studies. In contrast, other studies, such as those by Augenstein *et al.* [28], defined severe injury using a Maximum

Abbreviated Injury Scale (MAIS) score of 3 or greater (MAIS ≥ 3). Although these criteria were originally developed for occupant injury prediction, ISS ≥ 15 was selected in the present study to ensure consistency with prior research and to evaluate severe injury risk in pedestrian crashes. A logistic regression model was employed to estimate the probability of severe injury, defined as ISS ≥ 15, using the following equations:

$$P(ISS \geqq 15) = \frac{1}{\left(1 + exp(-z)\right)} \quad (1)$$

$$z = \beta_0 + \sum_{i=1}^{n} \beta_i x_i \quad (2)$$

where P (ISS ≥ 15) represents the probability of sustaining a severe injury, β_0 is the intercept, β_i denotes the regression coefficient corresponding to predictor variable x_i, and n is the number of predictors. Model coefficients were estimated using maximum likelihood estimation. Variable selection for the logistic regression model was conducted within the generalised linear model framework. Candidate models were evaluated using Akaike's Information Criterion (AIC), and the model with the minimum AIC value was selected as the final Ped-ISP model. Discriminative performance was assessed using receiver operating characteristic (ROC) curves and the area under the ROC curve (AUC). To evaluate the generalisation performance of the model, five-fold cross-validation was performed, and overall performance was summarised using the mean AUC across the five folds. All statistical analyses were conducted using MATLAB R2024a (MathWorks, Natick, MA, USA) [29].

VICIS dataset for validation

External validation of Ped-ISP model developed using Michigan pedestrian crash data was conducted using pedestrian crash cases from the VICIS, which is collected by the National Highway Traffic Safety Administration (NHTSA) as part of the Crash Investigation Sampling System (CISS) [30]. VICIS consists of detailed crash investigation data collected between 2020 and 2023 at four study sites in the U.S. (California, New Jersey, and two sites in Texas) and enables high-fidelity assessment of crash circumstances and injury outcomes based on police reports, medical records, on-scene measurements, photographs, and event data recorder (EDR) information. Among the pedestrian cases included in VICIS, a total of 54 cases with vehicle model year 2004 or newer and with complete information required for the analysis were selected for external validation. Predictor variables were defined consistently with the VIPA dataset and included impact speed, vehicle type, and pedestrian characteristics (age, sex, and height). Crash configurations were identified using *Vehicle Movement* variable, and to ensure consistency with the crash scenarios selected in the VIPA dataset, cases classified as *Going straight*, *Passing or overtaking another vehicle*, and *Turning left/right* were included in the analysis. Only complete cases were included in the analysis; as a result, 36 cases with missing data were excluded. The use of complete-case analysis may introduce potential selection bias if the excluded cases systematically differed from those included. Using this external dataset, the sensitivity, specificity, and receiver operating characteristic (ROC) of the developed Ped-ISP model were evaluated to assess its predictive performance.

III. RESULTS

VIPA and VICIS datasets

Table II summarises the baseline characteristics of the pedestrian crash cases analysed in this study. From the pedestrian crashes included in the VIPA dataset (2015–2025) and the VICIS dataset (2020–2023), cases with complete information on impact speed, crash configuration, vehicle type, age, sex, height, and ISS were selected for analysis. Impact speed was categorised into five speed ranges, from less than 20 kph to 80 kph or higher, and both datasets covered a wide range of crash severities from low to high-speed conditions.

Crash configurations were classified into three categories in the VIPA dataset: Crossing, Turning, and Longitudinal. In the VICIS dataset, crash configurations were defined based on the Vehicle Movement variable and mapped to the VIPA categories. Vehicle type was limited to three categories (car, SUV, pickup) and tabulated using the same definitions in both datasets. Pedestrian age was grouped into two categories (<55 years and ≥55 years), sex included both male and female pedestrians, and height was categorised into four ranges (<153 cm, 153–178 cm, 179–187 cm, and ≥188 cm).

As shown in Table II, differences in distributions between the VIPA and VICIS datasets were statistically assessed using p-values and effect sizes. Effect sizes were quantified using standardized mean differences (SMD), providing a measure of the magnitude of differences independent of sample size. A significant difference was observed in the type of accident (p = 0.015), primarily driven by a discrepancy in the frequency of longitudinal collisions (SMD = 0.77). In contrast, vehicle type distributions were highly comparable between the two datasets (p = 0.94). No statistically significant differences were found in impact speed or pedestrian height (p = 0.12 and p = 0.25, respectively), although moderate differences were observed in specific categories, particularly in the 60–79 kph impact speed range (SMD = 0.34) and in the ≥179 cm height categories. Similarly, no substantial differences were identified in age or injury severity (ISS ≥ 15), whereas a moderate difference was observed in sex distribution (SMD = 0.25). Overall, the two datasets exhibited broadly similar distributions, with some notable differences in specific variables.

To further illustrate these differences, the distributions of age and height for both datasets are shown in Appendix Fig. A1. Although both datasets spanned a wide range, the VIPA dataset showed a higher concentration of younger individuals, whereas the VICIS dataset exhibited a broader distribution among middle-aged individuals. Height distributions were largely comparable, with minor differences in peak density between the datasets.

TABLE II

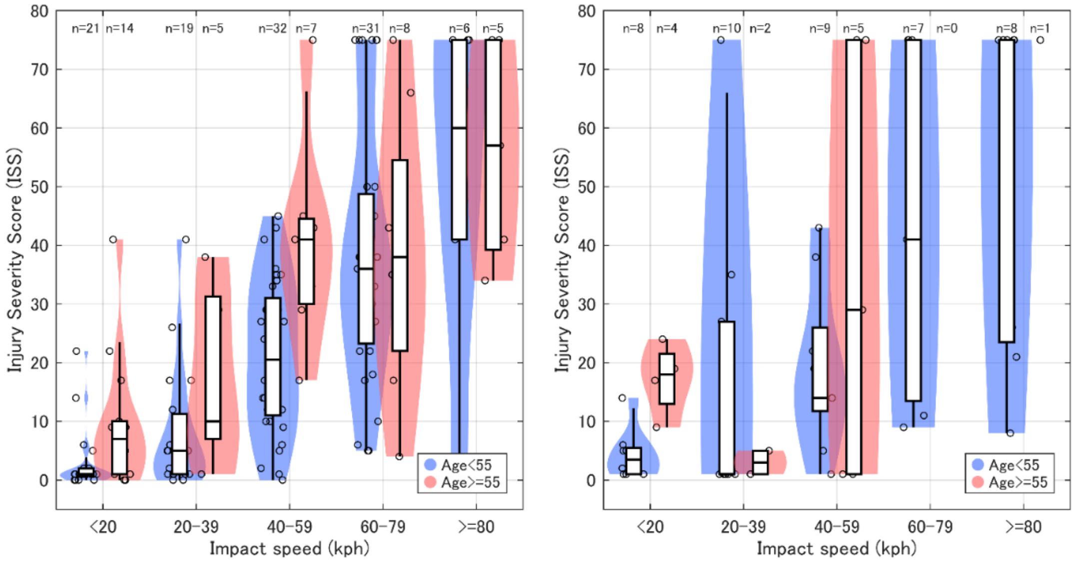
BASELINE CHARACTERISTICS OF PEDESTRIAN CRASH CASES IN THE VIPA AND VICIS DATASETS

Variable	Category	VIPA (n=148)		VICIS (n=54)		SMD	p-value
		Count	Percent (%)	Count	Percent (%)		
Impact speed (kph)							0.12
	Speed < 20	35	23.6	12	22.2	0.03	
	20–39	24	16.2	12	22.2	-0.15	
	40–59	39	26.4	14	25.9	0.01	
	60–79	39	26.4	7	13	0.34	
	>=80	11	7.4	9	16.7	-0.29	
Type of accident							0.01
	Crossing	97	65.5	42	77.8	-0.27	
	Turning	30	20.3	12	22.2	-0.05	
	Longitudinal	21	14.2	0	0	0.77	
Vehicle type							0.94
	Car	91	61.5	33	61.1	0.01	
	SUV	44	29.7	17	31.5	-0.04	
	Pickup truck	13	8.8	4	7.4	0.05	
Age (year)							0.59
	< 55	109	73.6	42	77.8	-0.10	
	>= 55	39	26.4	12	22.2	0.10	
Sex							0.15
	Male	81	54.7	36	66.7	-0.25	
	Female	67	45.3	18	33.3	0.25	
Height (cm)							0.25
	Height < 153	13	8.8	5	9.3	-0.02	
	153 <= Height < 179	102	68.9	37	68.5	0.01	
	179 <= Height < 188	24	16.2	12	22.2	-0.15	
	188 >= Height	9	6.1	0	0	0.50	
Injury Severity Score							0.64
	ISS >= 15	80	54.1	27	50	0.08	
	ISS < 15	68	45.9	27	50	-0.08	

Statistical significance was defined as p < 0.05.

SMD values of approximately 0.1, 0.3, and 0.5 indicate small, moderate, and large differences, respectively.

Figure 2 shows the distribution of ISS stratified by impact speed range and age group (<55 years vs ≥55 years). In both the VIPA and VICIS datasets, the spread of ISS values increased with higher impact speed ranges, accompanied by upward shifts in the median and upper percentiles. Within the same speed range, the ≥55-year age group consistently exhibited higher ISS distributions than the <55-year group, with the difference becoming more pronounced at moderate- to high-impact speeds (e.g. ≥40 kph). These findings are consistent with the impact speed and age distributions summarised in Table II and indicate that the analysed datasets encompass a wide range of crash conditions across both speed and age. Based on these observations, impact speed and age were suggested to influence the distribution of ISS, and the subsequent analysis quantified the contribution of each factor using a logistic regression model with ISS ≥ 15 as the outcome variable.



(a) VIPA (b) VICIS

Fig. 2. Distribution of Injury Severity Score (ISS) by impact speed range and age group in the (a) VIPA and (b) VICIS datasets.

Logistic regression model for pedestrian injury severity

Table III presents the results of the logistic regression analysis with severe injury (ISS ≥ 15) in pedestrian crashes as the outcome variable. Odds ratios (ORs) and corresponding 95% confidence intervals (CIs) are reported for each predictor in Table III, while the associated regression coefficients, standard errors, and confidence intervals are provided in the Appendix Table AI. Continuous variables were standardised and expressed as changes per one standard deviation (SD), and impact speed was log-transformed prior to analysis. For interpretability, one standard deviation corresponded to 22.9 kph for impact speed, calculated from the VIPA dataset used for model development. For vehicle type, car was used as the reference category.

As shown in Table III, log-transformed impact speed was significantly associated with severe injury, with an odds ratio of 9.12 per one SD increase (95% CI: 4.23–19.65, $p < 0.001$). Pedestrians aged 55 years or older had significantly higher odds of severe injury compared with those younger than 55 years (OR = 6.03, 95% CI: 1.59–22.82, $p = 0.008$). For height, the odds ratio per one SD increase was 0.47 (95% CI: 0.22–0.99, $p = 0.047$), indicating a decreasing likelihood of severe injury with increasing pedestrian height. In contrast, sex (female vs male) was not significantly associated with severe injury (OR = 0.54, 95% CI: 0.17–1.74). Although both SUV (vs car) and pickup (vs car) showed odds ratios greater than 1.0, their 95% confidence intervals included 1.0, and no statistically significant differences were observed. The direction and statistical significance of the regression coefficients reported in the Appendix were consistent with the odds ratio estimates presented in Table III.

TABLE III

LOGISTIC REGRESSION RESULTS FOR PEDESTRIAN INJURY SEVERITY (ISS ≥ 15)

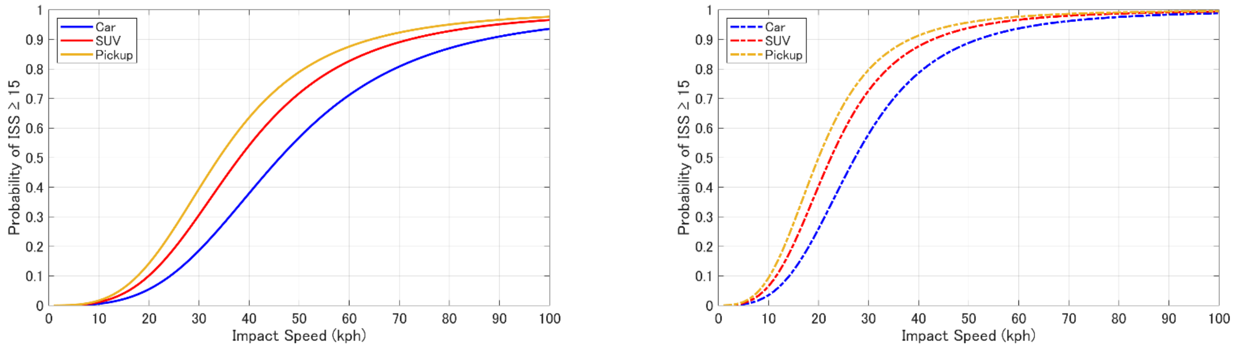
Variable	OR (95% CI)	p-value
Impact speed (log, per 1 SD)	9.12 (4.23–19.65)	< 0.001
Height (cm, per 1 SD)	0.47 (0.22–0.99)	0.047
Age (>=55 vs <55)	6.03 (1.59–22.82)	0.008
Sex (Female vs Male)	0.54 (0.17–1.74)	0.302
Vehicle type (SUV vs Car)	1.93 (0.67–5.54)	0.221
Vehicle type (Pickup vs Car)	2.85 (0.57–14.40)	0.204

Pedestrian injury risk curve for vehicle type

Figure 3 illustrates the relationship between impact speed and the predicted probability of severe injury (ISS ≥ 15) estimated by the Ped-ISP model, stratified by vehicle type. Results are shown separately for pedestrians younger than 55 years and those aged 55 years or older. Other covariates were fixed at representative values corresponding to a 50th percentile adult male dummy commonly used in crash testing (e.g., Hybrid III : 175 cm).

In both age groups, the predicted probability of severe injury increased monotonically with increasing impact speed, and the overall shape of the risk curves, representing the speed-dependent increase in injury risk, was broadly similar across vehicle types. In contrast, clear differences were observed in the absolute risk levels. Across the entire range of impact speeds, the lowest injury risk was observed for passenger cars, followed by SUVs, with pickup trucks exhibiting the highest predicted risk under the modelled conditions.

Additionally, for pedestrians aged 55 years or older, the injury risk curves were consistently shifted upward compared with those for pedestrians younger than 55 years. This indicates that, even under identical impact speed and vehicle type conditions, older pedestrians have a higher predicted probability of sustaining severe injury (ISS ≥ 15).



(a) Age < 55 yr. (b) Age ≧ 55 yr.

Fig. 3. Pedestrian injury risk curves by vehicle type estimated using the Ped-ISP model.

Model performance and threshold-dependent behaviour on the ROC curve

ROC analysis demonstrated good discriminative performance, with an apparent AUC of 0.899 and a cross-validated mean AUC of 0.873, indicating stable internal performance across validation folds. Figure 4 shows the ROC curve constructed using the predicted probabilities of severe injury (ISS ≥ 15) for all cases. To examine the effect of threshold selection under practical implementation scenarios, multiple predicted-probability thresholds, ranging from 0.1 to 0.9, were plotted along the ROC curve. Table IV summarises the corresponding sensitivity (true positive rate) and specificity (1 − false positive rate) for each threshold, illustrating the trade-off between these performance metrics. As the threshold decreased, sensitivity increased at the expense of a higher false positive rate, whereas increasing the threshold reduced the false positive rate (i.e. increased specificity).

The generalisation performance of the model was further assessed using five-fold cross-validation. For each fold, a ROC curve was constructed using the training data, and the predicted probability that maximised the Youden index [31] was selected as the optimal threshold. Because the optimal threshold varied slightly across folds, the average of the fold-specific optimal thresholds (0.545) was defined as the mean optimal threshold. This threshold was then fixed and applied to the corresponding test data in each fold. As a result, cross-validated performance metrics yielded a mean sensitivity of 0.825, a mean specificity of 0.793, and a mean AUC of 0.873. In Fig. 4, the mean optimal threshold is overlaid as a red marker on the ROC curve derived from the full dataset.

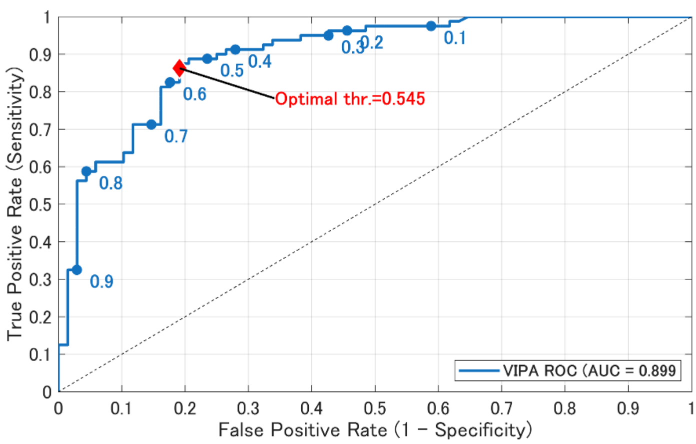


Fig. 4. Receiver operating characteristic (ROC) curve and cross-validated optimal threshold for the Ped-ISP model.

TABLE IV
THRESHOLD-DEPENDENT SENSITIVITY AND SPECIFICITY OF THE PED-ISP MODEL

Threshold	Sensitivity	Specificity
0.1	0.975	0.412
0.2	0.963	0.544
0.3	0.950	0.574
0.4	0.913	0.721
0.5	0.888	0.765
0.6	0.825	0.824
0.7	0.713	0.853
0.8	0.588	0.956
0.9	0.325	0.971

External validation using the VICIS dataset

External validation of the Ped-ISP model developed using the VIPA dataset was performed using pedestrian crash cases from the VICIS dataset. Only cases with crash configurations classified as *Going straight*, *Turning left/right*, and *Passing or overtaking another vehicle* were included to ensure consistency with the crash definitions applied in the VIPA dataset. For external validation, impact speed in the VICIS dataset was log-transformed in the same manner as in the VIPA analysis. Using the regression coefficients estimated from the VIPA dataset, the predicted severity index P (ISS ≥ 15), representing the probability of severe injury, was calculated for each VICIS case based on impact speed, age, height, sex, and vehicle type. The mean optimal threshold derived from the five-fold cross-validation in the VIPA dataset was applied to classify cases as severe injury (ISS ≥ 15) or non-severe injury. Under this fixed threshold, classification performance on the VICIS dataset yielded a sensitivity of 0.741 and a specificity of 0.701. In addition, a ROC curve was constructed using the predicted probabilities P (ISS ≥ 15) for the VICIS dataset. As shown in Fig. 5, the resulting AUC was 0.756, indicating a reduction in discriminative performance compared with the ROC curve obtained from the VIPA dataset (AUC ≈ 0.899). Multiple predicted probability thresholds ranging from 0.1 to 0.9 were also overlaid on the VICIS ROC curve, confirming a trade-off between sensitivity and specificity depending on the selected threshold.

Calibration performance was further evaluated using the calibration intercept, slope, and Brier score. The calibration intercept was −0.053, indicating minimal systematic bias in the overall predicted risk. In contrast, the calibration slope was 0.41, suggesting potential overfitting, with predicted probabilities being overly extreme. Brier score was 0.213, indicating moderate overall predictive accuracy. A calibration plot illustrating these results is provided in Appendix Fig. 2A.

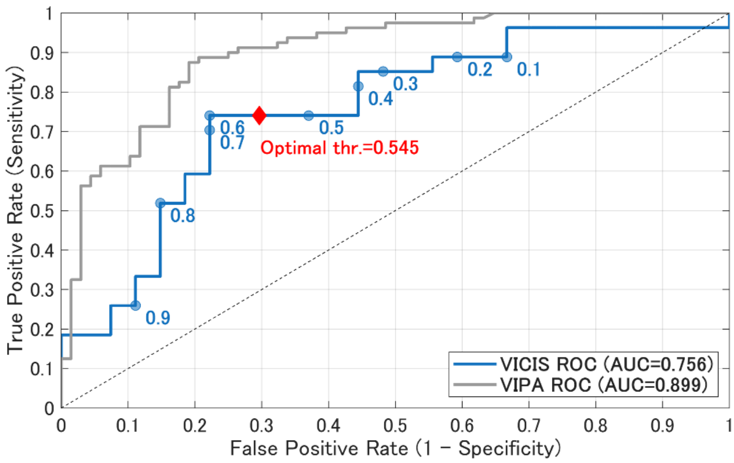


Fig. 5. Classification performance of the Ped-ISP model on the VICIS dataset.

TABLE V
SENSITIVITY AND SPECIFICITY OF THE PED-ISP MODEL ON THE VICIS DATASET

Threshold	Sensitivity	Specificity
0.100	0.889	0.333
0.200	0.889	0.407
0.300	0.852	0.519
0.400	0.815	0.556
0.500	0.741	0.630
0.600	0.741	0.778
0.700	0.704	0.778
0.800	0.519	0.852
0.900	0.259	0.889

Table VI presents the confusion matrix obtained by applying the Ped-ISP model, developed using the VIPA dataset, to the VICIS dataset with the mean optimal threshold derived from cross-validation. Severe injury (ISS ≥ 15) was defined as the positive class. Among the 27 non-severe injury cases (ISS < 15), 19 cases were correctly classified as non-severe injuries (true negatives), while 8 cases were classified as severe injuries, corresponding to over-triage (false positives). Among the 27 severe injury cases (ISS ≥ 15), 20 cases were correctly classified as severe injuries (true positives), whereas 7 cases were classified as non-severe injuries, corresponding to under-triage (false negatives). These results indicate that, although a reasonable level of classification performance was achieved on the VICIS dataset, both under-triage and over-triage cases were observed.

Figure 6 shows the relationship between impact speed and the predicted probability of severe injury P (ISS ≥ 15) for under-triage and over-triage cases only. Under-triage cases are indicated by gray squares, and over-triage cases by orange triangles. The horizontal axis represents impact speed, and the vertical axis represents the predicted probability. The dashed line indicates the mean optimal threshold determined from the VIPA dataset. Under-triage cases were primarily distributed in the low-to-moderate impact speed range and were located below the optimal threshold, whereas over-triage cases were more frequently observed in the moderate-to-high-speed range and were located above the optimal threshold. These results demonstrate distinct distribution patterns of under-triage and over-triage cases as a function of impact speed and predicted probability.

Figure 7 further summarises the distribution of injury severity by body region for under-triage and over-triage cases in the VICIS dataset. For under-triage (false negative, n=7) and over-triage (false positive, n=8) cases, the maximum AIS by body region (MAIS body region) is shown. Each case is annotated along the vertical axis with impact speed, age, and vehicle type, while the horizontal axis represents body regions defined by the AIS coding system (Head, Face, Neck, Thorax, Abdomen, Spine, Upper Extremity (UEX), and Lower Extremity (LEX)). Bubble size and colour indicate AIS severity.

Under-triage cases were characterised by severe injuries distributed across multiple body regions, particularly the thorax, abdomen, and lower extremities, in addition to head injuries. Notably, several cases involved AIS ≥ 3 thoracic and abdominal injuries occurring at moderate impact speeds (30–50 kph), as well as run-over events at relatively low impact speeds (5–10 kph). These patterns suggest that injury severity in such cases is influenced by complex impact sequences and post-impact kinematics, which are not fully captured by impact speed alone. As a result, the model tended to underestimate injury severity in scenarios involving distributed or non-head-dominant injury mechanisms.

In contrast, over-triage cases were more frequently associated with high impact speeds and relatively localised injury patterns. Although some cases involved MAIS 3 thoracic injuries, many exhibited only mild head and facial injuries (AIS1–2), with comparatively limited injury severity in other body regions. In these cases, the model overestimated injury severity based primarily on impact speed, without accounting for mitigating factors such as pedestrian orientation and impact configuration, which may reduce injury severity.

Overall, these findings indicate that under-triage and over-triage cases are associated with distinct injury distributions and underlying mechanisms. This highlights the limitations of relying primarily on impact speed and supports the need for incorporating additional biomechanical and contextual variables, such as pedestrian posture and detailed impact dynamics, to improve prediction accuracy. Importantly, these case-based analyses provide complementary insights beyond conventional statistical metrics, revealing the mechanisms underlying model misclassification in real-world scenarios.

TABLE VI
CONFUSION MATRIX FOR EXTERNAL VALIDATION USING THE VICIS DATASET

VICIS (54 Cases)		Predicted probability (ISS >= 15) >= 0.545	
		Minor	Severe
ISS	<15	**19**	**8**
	>=15	**7**	**20**
Sensitivity		**0.741**	
Specificity		**0.704**	

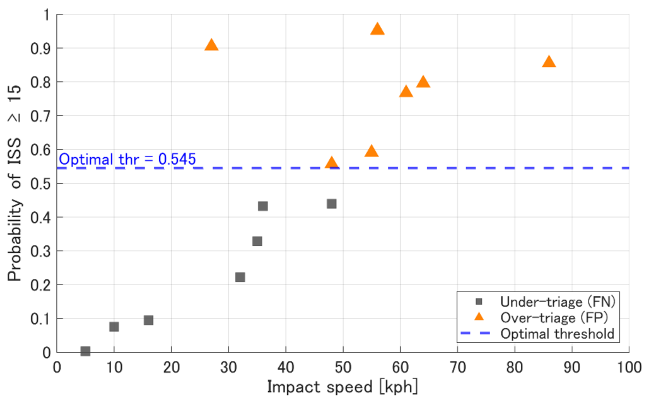
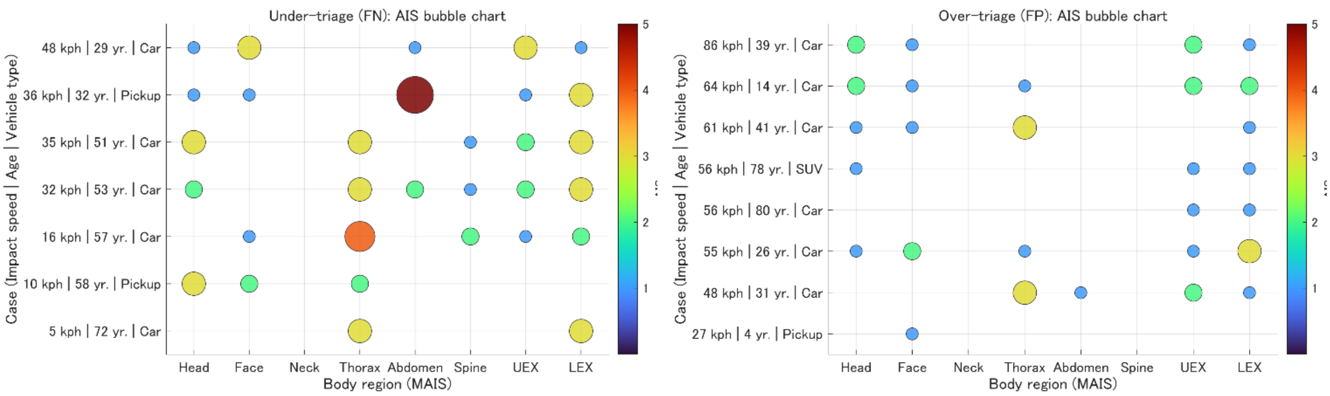


Fig. 6. Relationship between impact speed and predicted probability for under-triage and over-triage cases.



(a) Under-triage (b) Over-triage

Fig. 7. Distribution of maximum AIS by body region in under-triage and over-triage cases (VICIS dataset).

IV. DISCUSSION

In this study, a Ped-ISP model, based on logistic regression, was developed using detailed pedestrian crash data collected in Michigan (VIPA), and its performance was further evaluated using the VICIS database. Given the limited size of the external validation sample (n = 54), this study should be interpreted as a pilot evaluation of external performance rather than a definitive assessment of generalizability. The model was constructed using variables that are potentially estimable immediately after a crash, including impact speed, vehicle type, age, height, and sex, with severe injury defined as ISS ≥ 15. In the VIPA dataset, the model demonstrated high discriminative performance (AUC ≈ 0.90), and stable sensitivity and specificity were observed through five-fold cross-validation. In addition, vehicle type-specific risk curves showed a monotonic increase in injury risk with increasing impact speed, along with consistent differences in absolute risk levels among passenger cars, SUVs, and pickup trucks. These findings are consistent with prior studies by Lubbe *et al*. [14] and Monfort *et al.* [20], which identified impact speed as the dominant determinant of pedestrian injury severity and reported vehicle type-related differences in injury risk. The agreement with previous research suggests that the Ped-ISP model captures important trends in pedestrian injury mechanisms. External validation using the VICIS dataset demonstrated moderate discriminative performance (AUC = 0.76), indicating that the Ped-ISP provides a reasonable initial estimate of pedestrian injury severity in AACN contexts. In addition, calibration analysis indicated that the model predictions were overly extreme, as reflected by a calibration slope substantially below 1.0, suggesting potential overfitting when applied to the external dataset and a tendency to overestimate risk at higher predicted probabilities and underestimate risk at lower probabilities. Overall, these results suggest that the proposed Ped-ISP shows some discriminative ability for predicting pedestrian injury within AACN systems, although calibration remains suboptimal, particularly in the external dataset.

Notably, pedestrian height showed an inverse association with severe injury in the current model. This finding may appear unexpected and should be interpreted cautiously, as it may reflect residual confounding related to post- impact kinematics. Taller pedestrians may be more likely to experience different trajectory patterns (e.g., wrap or vault), which can alter impact sequences and injury outcomes, yet trajectory type was not modeled in the present study due to practical AACN constraints. Moreover, severe injuries can also occur in mechanisms such as forward projection or run-over, indicating that the relationship between height, kinematics, and injury severity is complex. Future analyses with larger datasets and explicit kinematic information will be needed to clarify the role of height and trajectory in pedestrian injury severity.

The datasets used in this study – VIPA (148 cases) and VICIS (54 cases) – are relatively small compared with large-scale datasets commonly employed in machine-learning applications. This limited sample size represents one of the main constraints of the present study. However, both datasets consist of high-quality, in-depth crash investigations based on detailed scene examinations, medical records, and multidisciplinary expert review, resulting in high information density despite the limited number of cases. In addition, the present analysis was conducted using unweighted data. Survey weights assigned to datasets such as CISS [30] are designed to estimate national-level crash populations by correcting for sampling designs that over-represent severe injury cases, thereby enabling statistical inference for the general crash population dominated by minor injuries [32]. In contrast, AACN systems are triggered by events such as airbag deployment or crashes exceeding a certain energy threshold and therefore target a crash population that differs fundamentally from the general crash population. Applying survey weights in this context may distort the injury severity distribution relevant to AACN operations and potentially degrade injury prediction performance. Indeed, previous work by Owen *et al* [33] has reported improved model stability and discrimination when logistic regression models were developed without weighting. Based on these considerations, the present study adopted an unweighted approach to prioritise applicability to the AACN operational population.

Vehicle type-specific injury risk curves were derived using logistic regression, and classification thresholds for ISS ≥ 15 were explored based on ROC analysis and Youden index. The resulting risk curves were broadly consistent with those reported in previous studies using GIDAS and VIPA, reproducing the nonlinear increase in injury risk once impact speed exceeds a certain level, confirming a tradeoff between sensitivity and specificity. However, there may be heterogeneity within each vehicle category, particularly for SUVs and pickup trucks, which further limits the interpretation of vehicle type effects. With respect to vehicle type effects, although differences in injury risk across vehicle types were observed, these differences were not statistically significant and should be interpreted with caution. Vehicle type is likely acting as a proxy for underlying factors such as front-end geometry and vehicle mass, and therefore does not necessarily represent a direct causal factor. Further analyses incorporating more detailed vehicle characteristics would be necessary to better understand these relationships.

Although ISS was used as the injury severity metric in this study, alternative approaches based on MAIS have also been proposed in the literature [34]. In real-world emergency response, injury metrics for triage are not universally standardised and depend on EMS protocols, coordination with medical facilities, and clinical judgement. Consequently, threshold selection for AACN-based injury prediction should not be determined solely by statistical optimality but should be adjusted to account for clinical and operational requirements. In particular, from a triage perspective, established guidelines recommend prioritizing sensitivity to minimize under-triage (<5%), even at the expense of higher over-triage (<35%). In this context, lower probability thresholds may be more appropriate for AACN applications, as they reduce the risk of missing severe injuries. The proposed model allows flexible adjustment of decision thresholds to accommodate such operational requirements. In addition, although precision-recall curves are recommended for evaluating rare event prediction, their dependence on event prevalence limits their comparability across datasets; accordingly, ROC-based metrics were prioritized in this study.

In the external validation using the VICIS dataset, both under-triage and over-triage cases were observed. Under-triage cases often involved severe thoracic and abdominal injuries contributing to ISS ≥ 15 at relatively low- to moderate-impact speeds, suggesting that injury mechanisms not fully captured by impact speed may play a role. In particular, run-over scenarios demonstrated that severe injuries could occur even at low speeds. In contrast, over-triage cases included situations in which high-impact speeds did not result in severe injuries, likely due to differences in pedestrian orientation at impact [23] or post-impact kinematics that mitigated injury severity. These findings highlight inherent limitations of single-threshold classification and suggest that AACN systems may therefore benefit from conservative threshold settings prioritising sensitivity or from multi-stage triage strategies tailored to different operational objectives.

From an implementation perspective, variables such as pedestrian age and height are difficult to obtain accurately immediately after a crash, representing a practical gap between research models and real-world deployment. In addition, AACN systems are typically triggered by high-severity events such as airbag deployment, and therefore the observable pedestrian crash population may be biased toward high-energy impacts. This inherent selection effect may limit the generalizability of the model to lower-severity pedestrian crashes. Nevertheless, the present results indicate that impact speed remains the most influential predictor, while age and height function primarily as risk modifiers. Therefore, in practical AACN implementations, it may be reasonable to rely primarily on vehicle-derived parameters, such as impact speed and vehicle type, while applying conservative assumptions for pedestrian characteristics (e.g. assuming older age) to reduce the risk of under-triage. Looking ahead, advances in onboard sensing technologies, including camera- [35] and radar-based [36] pedestrian detection systems, may enable indirect estimation of pedestrian height and impact location, thereby enhancing injury prediction accuracy. The proposed Ped-ISP provides a foundation for stepwise refinement, enabling implementation with currently available vehicle data and allowing future extensions aligned with the evolution of AACN systems.

Limitations

This study is subject to several limitations. First, the number of cases available for external validation was limited (n = 54), which constrains the robustness of performance evaluation and limits definitive conclusions regarding generalizability.

In addition to this limitation, pedestrian kinematic trajectory types are known to be biomechanically important from the perspective of injury mechanisms. However, under current AACN operational constraints, such information is difficult to obtain reliably in practice, and as a result, trajectory variables were excluded from the present analysis. This omission may contribute to residual confounding. In pedestrian crashes, injury severity tends to differ across trajectory types, while substantial variability in injury severity can also be observed within the same trajectory category. As the number of available crash cases is limited, the effects of trajectory types could not be quantitatively evaluated. With the accumulation of larger crash datasets in the future, it may become feasible to assess trajectory-specific effects more explicitly.

Another limitation relates to the use of a binary age classification, as grouping children and younger adults into a single category may not fully capture differences in injury mechanisms. This simplification reflects practical AACN constraints, where age information may not be readily available immediately after a crash. The threshold of 55 years was selected as an approximate boundary for increased injury vulnerability; however, its appropriateness across the full lifespan requires further validation. Future studies with larger datasets will be needed to refine age classification.

V. CONCLUSION

In this study, a Ped-ISP based on logistic regression was developed using detailed pedestrian crash data collected in Michigan (VIPA), and its predictive performance was externally validated using a multi-site in-depth investigation dataset (VICIS). Despite the use of a limited set of explanatory variables – impact speed, vehicle type, age, sex, and height – the model demonstrated high discriminative performance in the VIPA dataset (AUC ≈ 0.90) and maintained a reasonable level of predictive performance in external validation using the VICIS dataset. However, differences in sampling frameworks between the VIPA and VICIS datasets may influence the observed validation results and should be considered when interpreting model performance. Analysis of vehicle type-specific risk curves revealed a nonlinear increase in severe injury risk with increasing impact speed, along with consistent differences in absolute risk levels among passenger cars, SUVs, and pickup trucks. Furthermore, examination of under-triage and over-triage cases in the external validation dataset suggested the presence of pedestrian-specific injury mechanisms that cannot be fully captured by impact speed alone. Nevertheless, this study is subject to limitations related to sample size and the inherent constraints of binary classification based on a single decision threshold. Future work should incorporate larger and more diverse crash datasets and consider additional information related to crash circumstances and pedestrian characteristics to further reduce under-triage and over-triage. Given the limited size of the external validation sample, these findings represent preliminary evidence rather than conclusive validation. Overall, the proposed Ped-ISP provides preliminary external evidence supporting the feasibility of pedestrian injury severity prediction for AACN systems and serves as a foundation for future refinement of AACN operational strategies and algorithm development.

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VIII. APPENDIX

TABLE AI

LOGISTIC REGRESSION RESULTS FOR PEDESTRIAN CRASH INJURY RISK FOR ISS >=15

Variable	Estimate	SE	Lower95CI	Upper95CI	p-value
(Intercept)	-5.355	4.855	0.000	64.153	0.270
Impact speed (log)	3.515	0.623	9.916	114.037	0.000
Vehicle type (SUV)	0.658	0.538	0.673	5.540	0.221
Vehicle type (Pickup)	1.048	0.826	0.565	14.404	0.204
Age (55 yr)	1.797	0.679	1.594	22.815	0.008
Height (cm)	-0.047	0.024	0.911	0.999	0.047
Sex (F)	-0.613	0.594	0.169	1.735	0.302

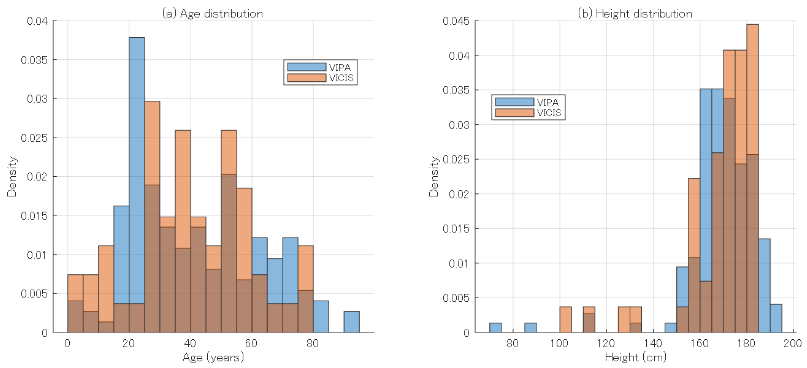

Fig. A1. Density-normalized histograms of (a) pedestrian age and (b) pedestrian height in the VIPA and VICIS datasets. Density normalization enables comparison of distribution shapes independent of sample size.

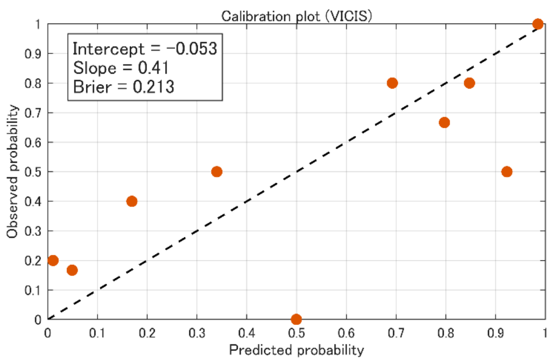

Fig. A2 Calibration plot for the VICIS dataset. Predicted probabilities are compared with observed event rates across deciles.