

Development of a pedestrian injury prediction model for potential use in an Advanced Automated Crash Notification (AACN) system

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Key findings

- Three pedestrian injury risk prediction models were developed in this study
- A mass crash data model was validated using in-depth crash data
- This model could theoretically be used in a pedestrian AACN system
- A refined model could potentially improve pedestrian collision injury outcomes
- Such a model would need to be widely deployed in an AACN system to be effective

Abstract

Advanced Automated Crash Notification (AACN) systems can inform emergency services of a serious road crash with minimal delay, giving the precise location of the crash and transmitting key information from the vehicle's event data recorder, including: the crashed vehicle's delta-V (vehicle change in velocity resulting from the crash), occupant seatbelt use, airbag deployment, and travelling speed. This information can be used to determine the likelihood of serious injury within the crashed vehicle using a suitable injury prediction algorithm. The purpose of this study was to examine two pedestrian crash data sets to develop pedestrian injury risk models using logistic regression analysis. Vehicle speed was used as the predictor variable and injury outcome was the response variable. The crash data used was from the in-depth crash database collected by the Centre for Automotive Safety Research (CASR) and from the South Australian Traffic Accident Reporting System (TARS) mass crash database. Three injury prediction models were developed and a discussion of the data and models are presented. Ultimately, the TARS data injury prediction model was selected as the most suitable injury prediction model, and this model was validated with the CASR in-depth data using receiver operator characteristic analysis. Suitability of the final model for use in a pedestrian AACN system was assessed using an injury threshold analysis. By accepting an injury underestimate rate of 10%, the minimum threshold for injury (for an AACN system activation) is 23%, which occurs at a vehicle speed 23 km/h; the corresponding injury over-estimation rate was 84%.

Keywords

Pedestrians, Injury Prediction, Advanced Automatic Crash Notification, Collision

Introduction

In the period 2000 to 2013, there were 1,788 people killed and 17,405 people seriously injured in road crashes in South Australia (Department of Planning, Transport and Infrastructure, 2017) from a population of approximately 1.7 million people (Australian Bureau of Statistics, 2017). Pedestrians accounted for 11.5% (n=205) of the fatalities and 8.7% (n=1507) of the serious injuries. Also over this period there has been a steady decline in pedestrian injuries.

Lowering of urban speed limits has resulted in reductions in pedestrian injuries in SA (Anderson, 2008) and improvements in vehicle design, have also led to improved

injury outcomes for pedestrians (Strandroth, Rizzi, Sternlund, Lie & Tingvall, 2011). Post-crash notification of collisions involving pedestrians is one area in road safety that is still overlooked. Currently, a physical phone call must be made to emergency services and details and location of any pedestrian collision must be verbally conveyed from a caller to a call taker, before an emergency medical response can be activated. This can cause delays with emergency response, particularly if there is a delay in an emergency call being made, or there are issues with conveying the precise location of the crash.

Advanced Automatic Collision Notification (AACN) systems have the potential to automatically notify emergency medical services of a crash and transmit the precise location of that crash, along with various data that might be captured by a vehicle's event data recorder (EDR). Data captured on EDRs may include delta-V, vehicle pre- and post-crash speed and potentially, other vehicle variables consistent with the specifications given by the National Highway Traffic Safety Administration¹ (National Highway Traffic Safety Administration, 2006). Generally, only crash events of a sufficient magnitude (for example, a crash that might involve the deployment of an airbag) would trigger an event to be recorded by an EDR.

Advanced Automated Crash Notification (AACN) systems already exist in certain vehicle models. After a crash is detected, vehicles with these systems can automatically transmit GPS location and delta-V to emergency services and this can be used to predict occupant injury levels (Champion et al., 2004; Kononen, Flannagan & Wang, 2011; Nishimoto et al., 2017). This theoretically may improve occupant injury outcome by way of improved emergency activation and response. Pedestrians and other vulnerable road users may also benefit from the development of an AACN injury prediction model and some initial research has already commenced in Japan (Nishimoto, Mukaigawa, Tominaga & Kiuchi, 2015).

Detection of pedestrian crashes however, is difficult, as it requires specialised contact sensors similar to those discussed in Fredriksson, Haland and Yang (2001) and Ito, Mizuno, Ueyama, Nakane and Wanami (2014) or non-contact pedestrian detection sensors such as those discussed in Oikawa, Matsui, Doi and Sakurai (2016). Some pedestrian impact sensors already exist in vehicles that deploy the vehicle's bonnet to mitigate pedestrian head injury in a pedestrian collision, for example, the 2015 Mazda MX-5 (Mazda, no date).

Significant efforts have already been undertaken by vehicle manufacturers to protect or mitigate the injuries sustained by pedestrians in collisions, these are in part, a result of EuroNCAP requirements (EuroNCAP, 2014). Further efforts will need to be undertaken by manufacturers to develop systems that can accurately detect pedestrian impacts. This is particularly important when a pedestrian's tolerance to injury is likely to be exceeded, which may occur when vehicle speeds in collisions exceed those specified by EuroNCAP (2014) for protection or injury mitigation.

Vehicle speed in a pedestrian collision influences pedestrian injury severity (Davis, 2001; Rosén & Sander, 2009). Knowing the vehicle speed can assist with injury prediction by emergency medical services if it can be transmitted easily from a vehicle event data recorder (EDR), post-crash, to emergency services (Champion et al., 2004; Kononen, et al., 2011; Nishimoto et al., 2017). An AACN system based on pedestrian crash data could potentially be a beneficial future vehicle technology.

The aim of the present study was to develop a proof-of-concept AACN pedestrian injury prediction model using two sources of road crash data from South Australia: mass police-reported crash from TARS and the CASR's at-scene in-depth crash data.

Data

Two sources of data were used in this study, mass crash data and in-depth data. The proceeding section briefly discusses each of these data sources.

Mass crash data

SA police must be notified of, and attend, any crash involving injury or significant property damage. Additionally, SA police are responsible for preparing a vehicle collision report (VCR) that includes various driver and vehicle details, the severity of injury sustained by people involved and an estimate of the speed of vehicles involved in the collision. Data from the VCRs are re-coded with additional crash information into the South Australian Traffic Accident Reporting system (TARS), maintained by the SA Government Department for Planning, Transport and Infrastructure.

Mass crash data from the TARS for the years 2000 to 2013 (for pedestrian crashes involving a single vehicle only) were used in this study as one data source. Cases were only included if a police reported vehicle speed was available (n=4,312). The speed data from TARS is the police estimated speed of a vehicle prior to the collision with a pedestrian, and can be made by police judgment or based on driver or witness statements. In some situations the speed in TARS may be the vehicle travel speed or the vehicle impact speed, depending on any evasive action taken or reported by a driver. There are four injury categories in TARS; fatal (death resulting from crash injuries within 30 day of a crash), admitted to hospital (treatment at an emergency hospital for 24 hours or more), treated at hospital (treatment at an emergency hospital for less than 24 hours and not admitted), private doctor (medical treatment or consultation at a non-emergency medical facility).

At-scene in-depth crash data

Independently of SA Police, The University of Adelaide's Centre for Automotive Safety Research (and the Road Accident Research Unit and Traffic Accident Unit before it) has been involved in at-scene in-depth crash investigation since the 1960's (McLean & Ryan, 1965, Baldock et al., 2009). The benefit of at-scene in-depth crash investigation is that very detailed information is collected and is used to reconstruct crashes, allowing for determination of vehicle speeds with greater precision (Kloeden, McLean, Moore & Ponte, 1997). The reconstruction methods used to determine the impact and travel speeds in the in-depth pedestrian crash data are documented in Kloeden et al., (1997). Hospital records pertaining to the pedestrians injured

¹ There are no specifications under any vehicle design rules that require vehicle manufacturers to make EDR data available in Australia. However, some vehicles in Australia do have data available for download, as a consequence of the NHTSA's specifications.

were also examined to code injury severity according to the Abbreviated Injury Scale (AIS; Association for the Advancement of Automotive Medicine, 2005).

As mentioned, the CASR in-depth reconstructed speed data includes vehicle travel speed and vehicle impact speed for each pedestrian collision. The speeds are based on all at-scene evidence available immediately after the crash such as skid marks, scuff marks and pedestrian throw distances or, in the absence of all other information, based on driver or witness estimates (21% of cases). In some crashes, in the absence of any evasive action by a driver, the travel and impact speeds are equivalent.

Pedestrian crashes investigated as part of CASR’s at-scene in-depth crash investigation program (1999-2005) were used as the second data source. Cases in which vehicle travel speed could be determined and a coded injury severity (AIS; AAAM, 2005) were used in the analysis. The AIS is used to code and rank individual body injuries sustained in traumatic events such as road crashes. Consistent with this, the CASR at-scene in-depth study database contains quantitative injury data coded using AIS, from which the highest valued or maximum AIS, (MAIS - indicating the highest threat to life body injury) can be derived.

Method

Initially, the injuries in each dataset were examined and then categorized into two levels of severity ‘serious injury’ and ‘minor injury’. As the in-depth crash data is also subset of the mass crash data, a comparison of coded injuries and vehicle speeds in each of the data sets was undertaken based on the individual crashes that were found in both datasets.

Utilizing the two sources of data, three pedestrian injury prediction models were developed using logistic regression analysis. This was done, in part, to explore and assess the effectiveness of the different datasets, and to see if they were somewhat consistent with their injury prediction. Three cut-off values for injury severity were used, as serious injury severity assessment can subjective and this allowed a further exploration of the data sets.

It is acknowledged that several factors influence risk of injury to a pedestrian in a collision (e.g. age, gender, vehicle year etc.), however, for this study, vehicle travel speed (a function of impact energy) was used as the single pedestrian injury risk predictor variable. The probability of injury (injury risk) for each model was $p(Y=1 | x)$, where travel speed was the predictor variable.

$$p = \frac{1}{1 + \exp[-(\beta_0 + \beta_1 x)]} \tag{1}$$

The response variables for the various injury prediction models were:

- Model 1: Y=1 for MAIS 2+ and Y=0 for MAIS 1
- Model 2; Y=1 for MAIS 3+ and Y=0 for MAIS 1 and 2
- Model 3: Y=1 for TARS serious injury and Y=0 for TARS minor injury.

Results

TARS crash data compared to in-depth crash data

The 4,312 pedestrian crashes from TARS were disaggregated into serious injuries (hospital admission; n=1,065 and fatal; n=119) and minor injuries (hospital treated; n=2,360 and private doctor treated; n=768). In comparison, the CASR in-depth speed/injury dataset consisted of a total of 84 pedestrian crashes with the following injury classification: MAIS 1 (n=35), MAIS 2 (n=23), MAIS 3 (n=8), MAIS 4 (n=7), MAIS 5 (n=7) and MAIS 6 (n=4).

While the in-depth crash database maintained by CASR contains a detailed sample of crashes in SA, the TARS mass crash database contains details of all crashes that have occurred in SA. Data from CASR can be matched with data in TARS to determine the correlation between MAIS and TARS recorded injury, as well as reconstructed CASR vehicle speeds and the estimates of vehicle speed in TARS.

TARS injury data compared to in-depth injury data

The relationship between MAIS from the CASR in-depth database and TARS injury categories is shown in Figure 1. A considerable proportion (80%) of the pedestrian MAIS 1 injuries in the CASR in-depth sample corresponded to minor injuries in TARS database (private doctor and treated at the hospital) with the remaining 20% of MAIS 1 injuries corresponding to TARS admitted to hospital category of injury.



Figure 1. In-depth injury severity vs TARS injury severity.

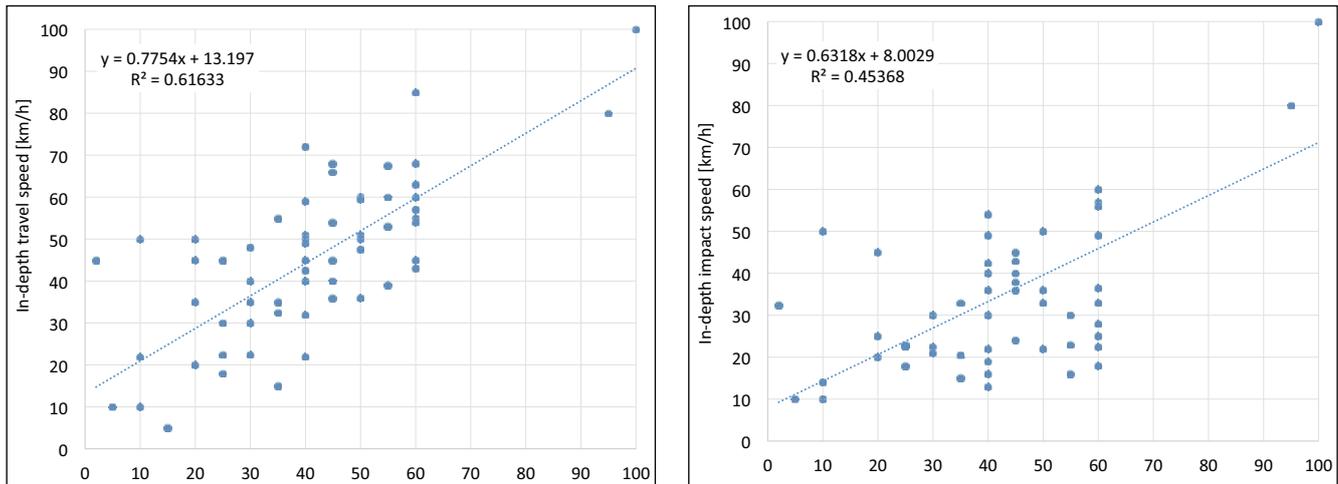


Figure 2. (a) In-depth travel speed vs TARS speed (n=84); (b) In-depth impact speed vs TARS speed (n=62).

A majority of number MAIS 2 injuries (87.5%) were associated with TARS admitted to hospital injuries. Generally, MAIS 2 – 5 injuries were associated with TARS admitted to hospital category and the remaining MAIS 4 + injuries ultimately resulted in a fatality.

In-Depth Speed Compared To TARS Recorded Vehicle Speed

It was not clear whether the speed data in TARS was more aligned with vehicle travel speed or impact speed, so a comparison was made with cross-matched CASR travel and impact speeds. Figure 2 (a) shows the CASR in-depth travel speed compared to TARS speed while Figure 2 (b) shows the CASR in-depth impact speed compared to TARS speed. While not showing exceptional correlation, TARS speed does correlate better with the CASR in-depth travel speed

values ($R^2 = 0.6163$ for travel speed compared with $R^2 = 0.4537$ for impact speed). It was assumed then that travel speed was the reported variable in TARS.

Logistic regression results

The coefficients, standard errors and p-values resulting from the logistic regression are shown in Tables 1, 2 and 3. Each of the three regression models had low p-values ($p < 0.005$), indicating a statistically significant relationship between speed and pedestrian injury severity.

Injury risk curves for pedestrian crashes

Each of the logistic regression models can be used to plot injury risk curves. These risk curves show the relationship between vehicle travel speed and the probability of a pedestrian collision resulting in a specific injury level. The

Table 1. Logistic regression model 1, Y=1 for MAIS2+ (n=49) and Y=0 for MAIS 1 (n=35)

Risk factors	Coefficients	Standard Error	p-value
Intercept (β_0)	-2.419	0.809	0.003
Travel speed (β_1)	0.062	0.018	<0.001

Table 2. Logistic regression model 2, MAIS3+ (n=26) and Y=0 for MAIS 1 & 2 (n=58)

Risk factors	Coefficients	Standard Error	p-value
Intercept (β_0)	-3.455	0.916	<0.001
Travel speed (β_1)	0.054	0.017	0.002

Table 3. Logistic regression model 3, Y=1 for TARS Serious Injury+ (n=1,184) and Y=0 for TARS minor injury (n=3,128)

Risk factors	Coefficients	Standard Error	p-value
Intercept (β_0)	-1.934	0.066	<0.001
Travel speed (β_1)	0.031	0.002	<0.001

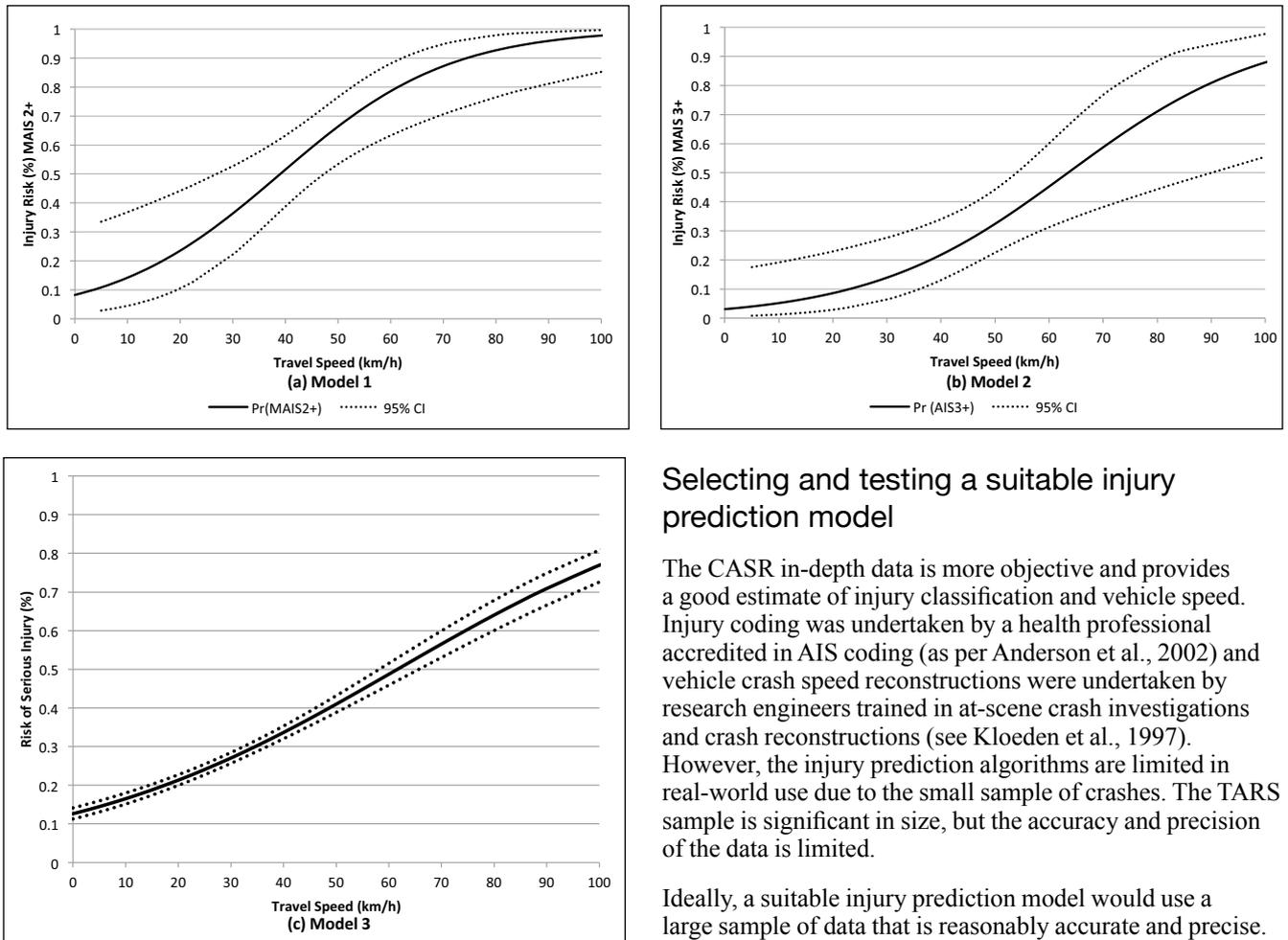


Figure 3. Pedestrian injury risk curves with 95% Confidence Intervals (Pezzullo, 2015) according to travel speed in-depth data for MAIS2+ (a), MAIS3+ (b) and TARS data (c).

injury-risk curves for each of the three models (and the corresponding 95% confidence intervals for the data) are shown in Figures 3 (a), (b) and (c). In a pedestrian collision where a vehicle involved had been travelling at 60 km/h, the likelihood of MAIS 2+ injury (model 1) would be around 79% [95% confidence interval: 63% to 88%] and the likelihood of MAIS 3+ injury (model 2) would be around 45% [95% confidence interval: 31% to 60%]. For model 3 a 60 km/h travel speed corresponds to a 48% risk of a serious injury [95% confidence interval: 46% to 52%].

Selecting and testing a suitable injury prediction model

The CASR in-depth data is more objective and provides a good estimate of injury classification and vehicle speed. Injury coding was undertaken by a health professional accredited in AIS coding (as per Anderson et al., 2002) and vehicle crash speed reconstructions were undertaken by research engineers trained in at-scene crash investigations and crash reconstructions (see Kloeden et al., 1997). However, the injury prediction algorithms are limited in real-world use due to the small sample of crashes. The TARS sample is significant in size, but the accuracy and precision of the data is limited.

Ideally, a suitable injury prediction model would use a large sample of data that is reasonably accurate and precise. Mass road crash data is routinely available, so the TARS injury prediction model (model 3) was selected as the suitable injury prediction model, and was evaluated against the CASR in-depth crash data, using receiver operator characteristic (ROC) analysis.

The test data consisted of the 84 pedestrian crashes in the CASR in-depth crash database that could be matched with the TARS sample of pedestrian crashes (as described previously). MAIS 2+ was used as the serious injury threshold (N=49) for the in-depth data while MAIS 1 (N=35) was considered as the minor injury threshold. This seemed most appropriate given the association between MAIS2+ injuries and hospital admission. Since model 3 was developed to predict the probability of a serious injury

Table 4. Classification matrix for ROC analysis

		Model 3 Injury Prediction	
		Predicted Positive	Predicted Negative
Actual Injury Severity	Actual Positive MAIS2+	True Positive (TP) <i>Pedestrian serious injury correctly predicted to be a MAIS2+</i>	False Negative (FN) <i>Pedestrian serious injury incorrectly predicted to be a MAISI (under triage)</i>
	Actual Negative MAISI	False Positive (FP) <i>Pedestrian minor injury incorrectly predicted to be a MAIS2+ (over triage)</i>	True Negative (TN) <i>Pedestrian minor injury correctly predicted to be a MAISI</i>

resulting from a pedestrian collision, the sensitivity and specificity can be calculated based on how effective model 3 is at classifying injury. Table 4 shows the classification matrix for the ROC analysis for the four categories of prediction that can be made by model 3.

The sensitivity (true positive rate) of the algorithm (equation 2) is the rate of the true positives compared to true positive and false negatives, that is, how often the model correctly predicts actual serious injuries. The specificity (true negative rate) of the model (equation 3) is the rate of the true negatives compared to true negatives and false positives, that is, how often the algorithm correctly predicts minor, rather than serious, injuries. The false positive rate, can be determined using equation 4.

$$\text{Sensitivity} = \frac{TP}{TP+FN} \quad (2)$$

$$\text{Specificity} = \frac{TN}{TN+FP} \quad (3)$$

$$1 - \text{Specificity} = 1 - \frac{TN}{TN+FP} = \frac{FP}{TN+FP} \quad (4)$$

The ROC curve of sensitivity (vertical axis) against 1- Specificity (horizontal axis), or the true positive rate against the false positive rate, is shown in Figure 4. The injury prediction model has a sensitivity value of 1.0 only when 1-Specificity also has a value of 1.0 in Figure 4. This represents a scenario in which all genuine pedestrian serious injuries in the CASR in-depth sample were correctly predicted by the TARS model to be serious injuries, however, this also resulted in all genuine pedestrian minor injuries incorrectly predicted by model 3 as serious injuries. In this situation there would be a high level of over-triage, or lack of triage, as all injuries are predicted to be urgent.

A decrease in the sensitivity of the model from a value of one introduces a level of under-triage while concurrently decreasing over-triage. Under-triage occurs when the level of emergency medical care is under-estimated and a seriously injured pedestrian is given a lower level of medical treatment, which may potentially result in an adverse injury outcome. Conversely, over-triage occurs when the level of

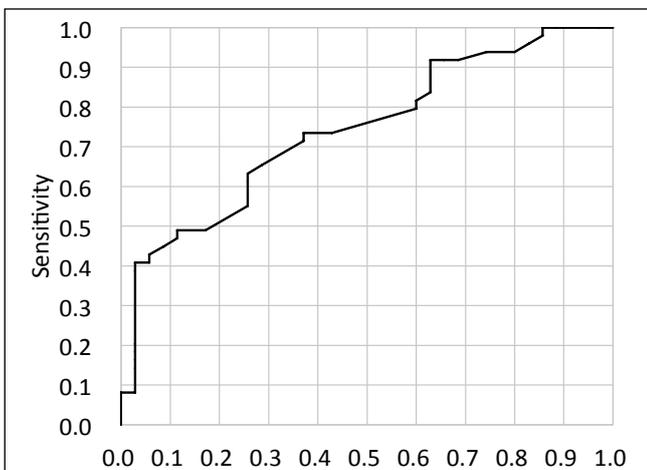


Figure 4. ROC curve for model 3, tested using matched in-depth cases

emergency medical care is over-estimated and a pedestrian with minor injuries is given a higher level of medical treatment than might be needed, resulting in inefficient use of medical resources.

Hence, depending on what levels of under- and over-triage can be tolerated, the ROC curve indicates various levels of triage threshold. The accuracy of the model can be determined by analysing the ROC curves, or more specifically the area under the curve (referred to as AUC). The AUC can vary from 0.5 (values occurring by chance alone) 0.7-0.9 (moderately accurate), greater than 0.9 (high accuracy) and up to 1 (perfect test) (Fischer, Bachman & Jaeschke, 2003).

The ROC curve in Figure 4 is not a smooth curve due to the limited number of CASR in-depth cases ($n=84$) available for verification of model 3. Nevertheless, the AUC was determined to be 0.743 for model 3, hence it can be considered moderately accurate.

Injury thresholds for model 3 for use in AACN systems

Before the predictive model can be used in an AACN system, the optimal injury thresholds for notifications need to be determined so that occurrences of under-triage and over-triage rates are minimised. The under-triage rate and over-triage rates can be calculated using equations (5) and (6) respectively where the denominators and numerators are previously defined in Table 4.

$$\text{Under - triage rate} = \frac{FN}{TP+FN} \quad (5)$$

$$\text{Over - triage rate} = \frac{FP}{TN+FP} \quad (6)$$

Further, the 'fitting rate', (equation 7) is the ratio of the algorithm's prediction of genuine serious injuries (TP) and minor injuries (TN) to all predictions including those resulting in over- and under-triage.

$$\text{Fitting rate} = \frac{TP+TN}{TP+TN+FN+FP} \quad (7)$$

Determining the notification thresholds on the basis of an under-triage rate and over-triage rate is important. In this study, the notification threshold is determined on the basis of an acceptable under-triage of pedestrian serious injuries of 10% or less in the prediction model. In this situation, fewer than 1 in 10 pedestrian injuries might be classified erroneously as a minor injury when they might genuinely be a serious injury.

The under-triage and over-triage rate curves for model 3 are shown in Figure 5. The two rate curves in the figure are approximately inversely proportional to each other. Also shown in the figure is the fitting rate curve. For the injury prediction model, an under-triage rate of 10% corresponds to a notification threshold of 23% for prediction of a serious injury. The over-triage rate is subsequently around 84% and the hit rate around 63%. In an AACN system using model



Figure 5. Relationship between threshold and triage rates for model 3.

3 to predict the likelihood of a serious pedestrian injury, the 23% threshold for the serious injury rate (for a 10% under-triage rate), corresponds to a vehicle speed of 23 km/h.

Discussion

Automatic Collision Notification and Advanced Automatic Collision Notification systems are still emerging vehicle technologies. Several types of systems have been developed and deployed to various degrees, throughout different countries, to better assist vehicle occupants in post-crash emergency response scenarios. Arguably, road user groups such as pedestrians, cyclists and motorcyclists are in greater need of immediate post-crash emergency response, particularly as they are more vulnerable to injury and are not given the same protection as a vehicle occupant in a carefully designed vehicle with a full suite of primary and secondary safety systems. As a consequence, vulnerable road users such as pedestrians are generally over-triaged by post-crash emergency responders, as there is no way of knowing the severity of a pedestrian collision with a vehicle.

An AACN system that can determine that a pedestrian collision has occurred, immediately notify emergency services of that collision and the precise location will certainly aid in quicker response. In addition, if adopted by emergency services, this basic crash information theoretically could be supplemented by one of three models proposed in this research, to predict the likely probability of an MAIS 2+ (model 1) or MAIS 3+ (model 2) or likelihood of a serious injury according to model 3. This information can be useful for emergency triaging, particularly when there might be competing demands for emergency service attendance for multiple incidents at different locations. An AACN system for pedestrians (and indeed all vulnerable road users) may also assist those injured by drivers involved in hit and run incidences with the crash, location and speed of the vehicle being transmitted even in the absence of the vehicle and driver.

The critical part in the future development of an AACN system for pedestrians is pedestrian detection. As mentioned earlier, pedestrian impacts are generally not severe enough to deploy a vehicle safety system that might trigger an event

data recording, so specific pedestrian impact detection devices (such as those mentioned previously) are required. Potentially, if integrated with vehicle EDRs, camera based autonomous emergency braking systems (where a time to collision might be such that the collision cannot be avoided) or forward collision warning systems (where the system detects a pedestrian, but the driver may not be able to stop in time and the collision still occurs) may also be useful as pedestrian detection systems for the activation of an AACN system.

The injury prediction models presented here are certainly not without limitations. The authors acknowledge that the data from the CASR in-depth crash investigations, while high in quality, are few in number. The mass crash data is limited in accuracy although being reasonably large in sample size. Additionally, the authors acknowledge that not all AIS2+ or 'hospital admitted' injuries are necessarily time-critical or require a rapid emergency response. Despite these limitations, an attempt was made at validating model 3 (the TARS model) with the CASR in-depth data, and the AUC of the ROC curve was determined to be 0.743 for the TARS model, which is moderately accurate according to Fischer et al., (2003).

Internationally, accepted levels of under-triage rates are between 5% and 10% and the desired level of over-triage is 50%. (American College of Surgeons, 2014; Josten et al., 2012). For model 3, an under-triage rate of 10% resulted in an over triage rate exceeding 70%. This is greater than the recommended 50% over-triage rate. The risk with such a high over-triage rate is that emergency medical resources will potentially be tasked to attend considerably more pedestrian serious injuries than might occur in reality. This is not too problematic, as pedestrian crashes in the absence of any AACN are generally over-triaged due to a pedestrian's inherent vulnerability to injury.

Conclusions

This research indicates that the development of proof-of-concept pedestrian injury risk prediction model is feasible using South Australian crash data and provides a starting point for further development for use in a pedestrian AACN system. A validated and refined model, when combined with an AACN system, could be used to provide an initial guide to assist with medical triage and could theoretically reduce the time to initial post-crash medical treatment for those with serious injuries and subsequent emergency transport to medical facilities. For those with predicted minor injuries, time to treatment could increase. Such a system, if widely implemented, would potentially reduce pedestrian collision serious injuries and fatalities.

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