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# A pedestrian serious injury risk prediction method based on posted speed limit

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ABSTRACT

The purpose of this study was to develop a serious injury risk prediction algorithm for pedestrians, using data from the South Australian Traffic Accident Reporting System. Two algorithms were developed to estimate serious injury risk, using a logistic regression analysis of 6,868 vehicle-pedestrian crashes extracted from TARS data. In this study, an optimal model based on the best combination of risk factors according to the Akaike information criterion (AIC) was developed. Additionally, a secondary GPS model using only crash site characteristics that can be derived from GPS coordinates from the crash scene was also developed. The optimal model is based on site and environmental conditions that could be derived from GPS data (posted speed limit, distance from crash site, natural lighting conditions, road geometry, road horizontal alignment and road vertical alignment) as well as pedestrian age/gender, driver age/gender and vehicle model year. The second model only included features that could be derived from GPS data. The optimal model was reasonable in accuracy and gave an under-triage rate of 10% when the injury threshold was set to 15%, with a corresponding over-triage rate of around 60%. The GPS model, despite not being as accurate as the optimal model may be adequate in the absence of all the risk factors required for the optimal model, requiring an injury threshold of 20% to give an under-triage rate of 10%, with the corresponding over-triage rate being around 70%. Both models can potentially be used for serious injury risk prediction (SIRP) for pedestrians involved in a collision with a vehicle.

## 1. Introduction

In South Australia (SA), the number of pedestrian deaths due to traffic accidents has decreased from 40 in 1995 to 9 pedestrian deaths in 2016. The 2016 fatality rate for pedestrians was 0.5 deaths per 100,000 population compared to 3.9 vehicle occupant deaths per 100,000 population in SA (Australian Bureau of Statistics, 2016; Department of Planning, Transport and Infrastructure, 2017). However, in 2016, the proportion of pedestrian injuries from road crashes resulting in a fatality was 2.8% (9 fatalities out of 320 total injured pedestrians), more than double the occupant fatality/injury rate of 1.2% (64 fatalities out of 5,224 total injured occupants; Department of Planning, Transport and Infrastructure, 2017).

There are many factors that influence the injury risk for pedestrians involved in vehicle collisions. Foremost, there is research that demonstrates an increase in pedestrian injury risk with increased speed of the colliding vehicles (e.g. Davis, 2001; Anderson et al., 2004; Rosén and Sander, 2009; Kong and Yang, 2010). Lowering the urban default speed limit in 2003 (from 60 km/h hour to 50 km/h) in response to the speed-injury risk relationship is partly responsible for a reduction in pedestrian casualties in SA (Kloeden et al., 2007).

A number of studies have also shown that pedestrian age and vehicle characteristics also influence pedestrian injury risk. Elderly pedestrians have an increased risk of injury in pedestrian vehicle collisions compared to other age groups (e.g. Henary et al., 2006; Loo and Tsui, 2009; Tefft, 2013; Niebuhr et al., 2016) and improvements in vehicle design have also led to improved injury outcomes for pedestrians (Strandroth et al., 2011). However, particular vehicle types seem to present a higher injury risk to pedestrians (D'elia and Newstead (2015)). The present study examined a number of risk factors that influence pedestrian serious injury, to develop a serious injury risk prediction (SIRP) algorithm for pedestrians.

For car occupants, there are several injury risk prediction algorithms that have been developed (Nishimoto et al., 2017; Malliaris et al., 1997; Augenstein et al., 2006; Bahouth et al., 2012; Kononen et al., 2011) and these have been used in Advanced Automatic Collision Notification (AACN) systems. The aim of AACN systems is to reduce road crash fatalities and improve injury outcome, by facilitating earlier

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crash notification to emergency medical services (EMS) with additional information that allows a rapid and informed EMS response (e.g. Rauscher et al., 2009; Emergency Medical Network of Helicopter and Hospital (HEM-net) et al., 2015). Stitzel et al. (2017) estimated that if their AACN algorithm was deployed across all vehicles in the United States, it would have assisted in predicting appropriate treatment for 2,747 serious injured occupants and would have potentially reduced the unnecessary use of a trauma centre for 162,302 minor injured occupants in a year. For pedestrians however, there is currently no serious injury risk prediction algorithm despite their higher fatality per injury rate compared with car occupants.

The purpose of this study was to develop a serious injury risk prediction algorithm for pedestrians using the South Australian Traffic Accident Reporting System (TARS) mass crash database. The unique focus of this study, is that serious injury risk prediction algorithms are proposed, such that pedestrians may benefit from an AACN system based predominantly on crash site characteristics. The fundamental requirement of this proposed AACN system is the reporting of the global positioning system (GPS) coordinates (latitude and longitude) of the crash location, so that crash site information may be derived from a relevant geographical information system (GIS). The use of an AACN system for pedestrians using the SIRP algorithms proposed in this study, demonstrates potential in reducing pedestrian traffic fatalities in countries and regions such as Australia where event data recorder (EDR) telemetry systems are not widespread. Even in the absence of EDR telemetry, information required for use in the proposed SIRP algorithms can be relayed by telephone to emergency services, by first responders. Two SIRP algorithms were constructed. An optimal model requiring several crash parameters, and a secondary model requiring only GPS data. The two unique algorithms were evaluated using a 10-fold cross-validation method, and serious injury risk prediction thresholds were examined using pedestrian crashes from the serious injury database held by Centre for Automotive Safety Research (CASR). This final step was undertaken to determine acceptable over and under-triage rates.

## 2. Materials and methods

### 2.1. TARS pedestrian accident data

A number of studies have employed the use of in-depth crash data in order to estimate injury risk (e.g. Rosén et al., 2009; Davis, 2001; Rosén et al., 2011). However, these studies weight the in-depth injury data using national crash injury statistical data, which is necessary to ensure there is no sample-outcome bias (Rosén et al., 2011). An alternative method is to use mass crash statistical data to develop an injury prediction algorithm and in-depth crash data to validate the algorithm (Nishimoto et al., 2017). In the present study, mass crash statistical data is used to develop a serious injury risk prediction algorithm and this is assessed using a 10-fold cross-validation method to evaluate the accuracy of the SIRP model.

Mass crash statistical data is available from the SA Traffic Accident Reporting System (TARS), a database derived from vehicle collision reports (VCRs) prepared by police, in response to traffic accidents that have occurred in South Australia. CASR's serious injury database has been developed by examining all injury records for road crash casualties that presented to SA's major trauma centre, the Royal Adelaide Hospital, for the period July 2014 to December 2016. There were 96 pedestrians involved in a collision with another vehicle in this data-set. The hospital records for each pedestrian were examined in detail and matched to SA Traffic Accident Reporting System (TARS) data. The injuries for these pedestrians were coded using the Abbreviated Injury Scale (AIS; Association for the Advancement of Automotive Medicine, 2005).

All pedestrian crashes involving cars and car derivatives (sedans, wagons, hatchback, SUVs etc.) were extracted from TARS for the twenty-seven years from 1990–2016. In total, there were 11,087 car or car derivative-pedestrian injury crashes. 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 h or more), treated at hospital (treatment at an emergency hospital for less than 24 h and not admitted), private doctor (medical treatment or consultation at a non-emergency medical facility).

In this study, in order to predict a serious injury requiring early treatment, a binomial algorithm was constructed by classifying pedestrians with fatal or admitted to hospital injuries as being *seriously injured* and pedestrians who were treated at hospital or treated by a private doctor as having a *minor injury*.

### 2.2. Pedestrian injury risk factors

Several studies have shown that the risk of pedestrian injury increases as the collision speed increases (e.g. Davis, 2001; Anderson et al., 2004; Rosén and Sander, 2009; Kong and Yang, 2010). There is also research showing that pedestrian injury risk and pedestrian fatality rates increase with increasing posted speed limit; posted speed limit being strongly correlated with vehicle traveling speed (Sze and Wong, 2007; Senserrick et al., 2014; Olszewski et al., 2015; Doecke et al., 2018). Buendia et al. (2015) and Candefjord et al. (2015) found that posted speed limit was a good indicator of occupant injury, particularly in the absence of known vehicle speed. In the current research, accurate vehicle crash speed could not be derived from the mass crash data, although posted speed limit was available. Hence, for the present study, posted speed limit was selected for use in the model as the most significant injury risk factor. Speed limit, while being a categorical variable is treated as a continuous variable in the analysis, with the details and reasoning described in Section 5.

The second most significant injury risk factor considered in the prediction algorithm of this study was the distance from the centre of Adelaide in SA (the General Post Office [GPO], as an indicator of the distance to SA's major trauma centre[1]) to the accident location. Pedestrian mortality risk is higher in rural areas compared to urban areas (Senserrick et al., 2014) and this injury risk factor has been found to be important even for occupant injury risk prediction, particularly in the absence of telemetry data (Buendia et al., 2015; Candefjord et al., 2015). Distance from GPO to crash location in the present study is a strong injury risk indicator as it also encapsulates the degree to which an area is rural or urban by distance (rather than statistical boundary), and is also an indicator of emergency transport retrieval time. Actual time-to-treatment is likely to be a better indicator of risk and a better algorithm could potentially be developed if this data were available. As mentioned previously, age and vehicle characteristics also influence injury risk and hence were also considered as injury risk factors.

The full list of the 13 injury risk factors identified in TARS and considered initially in the models are shown in Table 1, along with the variables within each of those risk factors. The common risk factors used in both the optimal model and the GPS model, were the characterisitics that could be derived from the crash location, which include speed limit, the distance from GPO, road geometry, road alignment horizontal, road alignment vertical, traffic control and natural lighting conditions. Additionally, vehicle model year, vehicle type, weather, age and gender of pedestrian and driver were also initially selected for the optimal model.

Crashes missing any of the injury risk factors or variables were

[1] A majority (40%) of pedestrian casualties in the sample were transported to SA's major trauma centre, the Royal Adelaide Hospital and the second highest proportion of pedestrian casualties (around 17%) were delivered to SA's second major trauma centre, the Flinders Medical Centre. Around 87% of pedestrian casualties in the sample were transported to one of SA's seven metropolitan "Accident and Emergency Hospitals".

**Table 1**
Definition of risk factors.

| Risk factors | Category | Comments |
|---|---|---|
| GPS | | |
| Speed limit [km/h] | 10 km/h (69 cases, 1.0%)<br>20 km/h (14 cases, 0.2%)<br>25 km/h (89 cases, 1.3%)<br>30 km/h (5 cases, 0.1%)<br>40 km/h (83 cases, 1.2%)<br>50 km/h (1,391 cases, 20.3%)<br>60 km/h (4,865 cases, 70.8%)<br>70 km/h (82 cases, 1.2%)<br>80 km/h (157 cases, 2.3%)<br>90 km/h (12 cases, 0.2%)<br>100 km/h (51 cases, 0.7%)<br>110 km/h (50 cases, 0.7%) | Posted speed limit is treated as a continuous variable in the injury severity prediction regression models. |
| Distance from GPO | Under 9.9 km (3,820 cases, 55.6%)<br>10.0 - 49.9 km (2,189 cases, 31.9%)<br>50.0 - 99.9 km (201 cases, 2.9%)<br>Over 100 km (658 cases, 9.6%) | Distance between Adelaide's General Post Office (GPO) and crash location. GPO is located within the centre of the capital city of SA. This distance is related to whether a crash occurred in an urban or rural area. |
| Road geometry | Undivided road (2,240 cases, 32.6%)<br>Divided road (1,654 cases, 24.1%)<br>Cross intersection (1,097 cases, 16.0%)<br>Other (1,877 cases, 27.3%) | Other includes T-junction (N = 1,308), Pedestrian crossing (N = 210), multiple geometry (N = 50), one way (N = 21), Miscellaneous other (N = 288). |
| Road horizontal alignment | Straight road (6,547 cases, 95.3%)<br>Curved road (321 cases, 4.7%) | |
| Road vertical alignment | Level (5,491 cases, 80.0%)<br>Not level (1,377 cases, 20.0%) | |
| Traffic control* | No control (5,286 cases, 77.0%)<br>Traffic signals (1,168 cases, 17.0%)<br>Yield signs (389 cases, 5.7%)<br>Other (25 cases, 0.4%) | Yield sign includes give way signs (N = 154), stop signs (N = 146) and roundabouts (N = 89). Other includes railway crossings (N = 4) and undefined other control (N = 21). |
| Natural lighting conditions | Daylight (4,843 cases, 70.5%)<br>Night (2,025 cases, 29.5%) | Dawn and dusk was excluded from analysis (N = 65). |
| Vehicle | | |
| Model year | Before 1995 (4,457 cases, 64.9%)<br>1996-2004 (1,611 cases, 23.5%)<br>After 2005 (800 cases, 11.6%) | The Australasian New Car Assessment Program crash testing requirements may have influenced vehicle pedestrian safety after 2005. |
| Vehicle type* | Car (4,841 cases, 70.5%)<br>Station wagon (1,120 cases, 16.3%)<br>Other (907 cases, 13.2%) | Other include utility vehicles (N = 375), panel vans (N = 304), taxi cabs (N = 191), forward control passenger vans (N = 1). |
| Environment | | |
| Weather* | Not raining (6,302 cases, 91.8%)<br>Raining (566 cases, 8.2%) | |
| Pedestrian | | |
| Pedestrian age | 0 - 4 years (255 cases, 3.7%)<br>5 - 15 years (1,339 cases, 19.5%)<br>16 - 29 years (1,758 cases, 25.6%)<br>30 - 54 years (1,677 cases, 24.4%)<br>55 - 64 years (504 cases, 7.3%)<br>Over 65 years (1,335 cases, 19.4%) | |
| Pedestrian gender | Male (3,796 cases, 55.3%)<br>Female (3,072 cases, 44.7%) | |
| Driver | | |
| Driver gender | Male (4,402 cases, 64.1%)<br>Female (2,466 cases, 35.9%) | |
| Driver age | 16 - 29 years (2,760 cases, 40.2%)<br>30 - 59 years (3,266 cases, 47.6%)<br>Over 60 years (842 cases, 12.3%) | Persons aged under 15 years cannot legally obtain a driver's license and were excluded from analysis (N = 7). |

* Risk factors subsequently excluded as a result of the AIC/logistic regression model ranking process.

excluded from the sample, as were crashes with drivers under the age of 15 who are legally unable to obtain drive a vehicle. Senserrick et al. (2014) report that crashes occurring at dusk or dawn are associated with a higher risk of severe injury to pedestrians; however, in the present sample, few crashes (N = 65) were coded as having occurred under those natural lighting conditions and were thus excluded from analysis. Hence, after removing crashes from TARS sample with insufficient data, there were a total of 6,868 injured pedestrians in the sample (from the period 1990–2016) to develop the serious injury risk prediction algorithm. The 27-year crash period was deliberately chosen to maximise the sample size and to examine the effect of vehicle age on pedestrian injury risk. Limiting the sample size to a 10-year period would have reduced the crash sample size to only 2,141 pedestrian crashes and would have given less statistical strength to the SIRP algorithms. In the injured pedestrian sample, 34% were serious (360 fatally injured and 1,971 admitted to hospital injured pedestrians) while the remainder had a minor injury (3,705 treated at hospital and 832 private doctor).

### 2.3. Logistic regression analysis

The pedestrian SIRP algorithm was constructed using a logistic regression analysis on the TARS data sample. In the logistic model shown in Eq. (1), the logarithmic odds of the occurrence probability $p$ are linearly regressed. The value $p$ gives serious injury risk, which is the probability of a serious injury (given the occurrence of a pedestrian crash) by defining $p = 1$ for seriously injured (fatal or admitted to hospital) and $p = 0$ as minor injury (treated at hospital or private doctor). The variable $x_i$ corresponds to the partial regression coefficient $\beta i$ defining each risk factor.

$$\log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_i x_i + \cdots \beta_n x_n \tag{1}$$

For the logistic regression analysis, the partial regression coefficients were determined using maximum likelihood estimation, that maximizes the likelihood L defined in Eq. (2).

$$L = \prod_{i=1}^{n} (p(i))^{y_i}(1 - p(i))^{1-y_i} \tag{2}$$

For each $i$ ($i$ = 1, 2,…, $n$) in the data set, the probability of serious injury is calculated using the model $p(i)$, $y_i = 1$ for seriously injured and $y_i = 0$ for minor injury, and the value L is obtained. The value of the likelihood L increases as predicted injury using the model is closer to $p = 1$ for the seriously injured data and $p = 0$ for minor injury data. Therefore, the likelihood becomes larger as the goodness of fit for the data set is higher. R version 3.4.3 was used for the analysis in this study.

### 2.4. Optimal model selection based on Akaike information criterion (AIC) and secondary GPS model

In this study, the Akaike Information Criterion (AIC) was used for selection of the logistic regression model with optimal combinations of risk factors (e.g. Kuniyuki, 2012; Zhang, et al., 2013; Parenteau et al., 2014). AIC can be calculated from Eq. (3), using a model's maximum likelihood value $L$ and the number of variables in the model $k$.

$$\mathrm{AIC} = -2\log L + 2k \tag{3}$$

AIC is an index for selecting a regression model in consideration of the trade-off between the goodness of fit and the number of variables or model complexity. AIC estimates the quality of a particular regression model and variables relative to other regression models and their variables. The value of AIC can be used for ranking models, with a smaller value of AIC giving a model a higher rank. However, the value of AIC is influenced by both $L$ and $k$, so while a fit might improve by adding variables and the first term in Eq. (3) decreases, the second term increases with an increased number of variables. AIC also allows comparisons between different regression models. Once the highest ranked model is determined, differences in AIC between the highest ranked model and other models can indicate levels of empirical support. Smaller differences in AIC values between the highest ranked model and any comparison models indicate that the level of empirical support for the model is better; differences between 0–2 indicating a substantial level of empirical support, 4–7 considerably less, while values greater than 10 indicate essentially no empirical support between a comparison model and the highest ranking model (Burnham and Anderson, 2002; International Organization for Standardization, 2014).

### 2.5. Validation methods

A 10-fold cross-validation was applied to both the optimal and the GPS model. In the 10-fold cross-validation, the sample of 6,868 injured pedestrians from TARS data were randomly assigned, but evenly distributed across 10 sub-samples. Ten SIRP models were then developed using unique combinations of nine sub-samples, with the remaining sub-sample not used in a particular model, being withheld as test data for that model.

A Receiver Operating Characteristic (ROC) analysis was carried out ten-fold, for each SIRP model, and tested with the appropriate withheld sub-sample test data, and the mean value of the area under the curve (AUC) was determined for each fold. In the ROC analyses, sensitivity and specificity (the proportion of actual serious injury and actual minor injury cases that are correctly predicted by the models), when the threshold value for determining serious injury is varied from 0 to 100%, was calculated. The ROC curve is constructed by plotting sensitivity on the vertical axis and 1 - specificity on the horizontal axis and the area under the curve (AUC) can then be calculated. Larger values of AUC correspond to better goodness of fit for the data used for the verification (Fischer et al., 2003; Akobeng, 2007).

## 3. Results

### 3.1. Risk factor selection result

The common variables that the gave the lowest AIC values for the optimal model (AIC = 8,260) and the GPS model (AIC = 8,394), in addition to speed limit, included the distance from the crash to the Adelaide GPO, road geometry, road alignment (vertical and horizontal) and natural lighting conditions. Additionally, the optimal model also included model year as well as age and gender of pedestrians and drivers.

Traffic control type was the only risk factor that did not contribute to the reduction of AIC from all data that can be obtained from GPS data. This result suggests that traffic regulation has less influence on pedestrian injury risk in comparison to other road infrastructure features. The results of the AIC analysis also indicates that the influence of vehicle body type on pedestrian injury risk is small compared with speed limit or vehicle age (although Li et al., 2017, found a relationship between the forward shape of the car body and pedestrian injury risk). Weather conditions at the time of crash (presence of rain or not) did not contribute to lowering of AIC and this is consistent with findings from Tay et al. (2011) and Kim et al. (2017).

### 3.2. Serious injury risk prediction logistic regression results

The SIRP algorithm predicts serious injury risk for each combination of risk factors. Table 2 shows the partial regression coefficient, the standard error, the significance probability of the Wald test and the odds ratio (OR) resulting from the logistic regression analysis for the optimal model, using the final 10 injury risk factors in addition to speed limit. A majority of the variables used as injury risk factors in the optimal model were statistically significant, ($p < 0.05$) as seen in Table 2. Fig. 1 (a) shows the risk curve for distance from crash to the Adelaide GPO, and (b) speed limit and the serious injury risk by pedestrian age.

Serious pedestrian injury risk increases with speed limit and there is an additional increase in risk based on crash distance from Adelaide GPO (Fig. 1 (a)). There is a distinct increase in pedestrian injury risk for crashes occurring greater than 50 km away from the Adelaide GPO compared to those occurring within 50 km.

The elderly (aged 65 years and older) and children aged (0–4 years) are significantly more vulnerable to serious injury compared to other age groups ($p < 0.001$, OR = 1.9 for 65 years and older age group; $p < 0.001$, OR = 1.8 for 0–4 year age group) as shown in Fig. 1(b)). The increase in the risk of serious injury in the elderly is consistent with Davis (2001), Tefft (2013) and Niebuhr et al. (2016). Serious injury risk decreases for those aged 5–15 years of age, 55–64 years of age, 30–54 years of age and 16–29 years of age, respectively.

Pedestrian crashes occurring on divided roads result in a higher serious injury risk compared to those on undivided roads ($p < 0.001$, OR = 1.3). Pedestrian serious injury risk at cross road intersections was found to be low ($p < 0.001$, OR = 0.7) and this is somewhat consistent with Roudsari et al. (2006), who found changes in traveling speed resulting from vehicles turning left and right at intersections corresponded to lower pedestrian serious injury risks. Other notable variables that increased pedestrian serious injury risk include road

**Table 2**
Logistic regression results for the optimal model.

| Risk factors | Variables | Coefficients | S.E. | *p*-value | Odds ratio |
|---|---|---|---|---|---|
| Intercept | – | −2.781 | 0.196 | < 0.001 | – |
| Speed limit | [km/h] | 0.027 | 0.003 | < 0.001 | 1.0 |
| Distance from GPO | Under 9.9km | 0.000 | – | – | – |
| | 10.0–49.9km | 0.099 | 0.062 | 0.114 | 1.1 |
| | 50.0–99.9km | 0.319 | 0.159 | 0.045 | 1.4 |
| | Over 100km | 0.383 | 0.094 | | 1.5 |
| Road geometry | Undivided | 0.000 | – | – | – |
| | Divided road | 0.274 | 0.074 | < 0.001 | 1.3 |
| | Cross intersection | −0.313 | 0.088 | < 0.001 | 0.7 |
| | Other | −0.004 | 0.071 | 0.956 | 1.0 |
| Road horizontal alignment | Straight road | 0.000 | – | – | – |
| | Curved road | 0.196 | 0.124 | 0.114 | 1.2 |
| Road vertical alignment | Level | 0.000 | – | – | – |
| | Not level | 0.252 | 0.067 | < 0.001 | 1.3 |
| Natural lighting conditions | Daylight | 0.000 | – | – | – |
| | Night | 0.788 | 0.063 | < 0.001 | 2.2 |
| Model year | Under 1995 | 0.188 | 0.067 | 0.005 | 1.2 |
| | 1996–2004 | 0.000 | – | – | – |
| | Over 2005 | −0.276 | 0.103 | 0.008 | 0.8 |
| Pedestrian age | 0–4 years | 0.592 | 0.146 | < 0.001 | 1.8 |
| | 5–15 years | 0.149 | 0.086 | 0.082 | 1.2 |
| | 16–29 years | −0.133 | 0.077 | 0.084 | 0.9 |
| | 30–54 years | 0.000 | – | – | – |
| | 55–64 years | 0.070 | 0.116 | 0.547 | 1.1 |
| | Over 65 years | 0.633 | 0.083 | < 0.001 | 1.9 |
| Pedestrian gender | Male | 0.000 | – | – | – |
| | Female | −0.186 | 0.055 | < 0.001 | 0.8 |
| Driver age | 16–29 years | 0.090 | 0.058 | 0.119 | 1.1 |
| | 30–60 years | 0.000 | – | – | – |
| | Over 61 years | −0.171 | 0.089 | 0.056 | 0.8 |
| Driver gender | Male | 0.000 | – | – | – |
| | Female | −0.150 | 0.057 | 0.009 | 0.9 |

gradient; there was an increased risk of pedestrian serious injury on a sloped road compared to a level road ($p < 0.001$, OR = 1.3). Regarding natural lighting conditions, the serious injury rate at night was significantly higher ($p < 0.001$, OR = 2.2) compared to the day. With respect to the year of vehicle manufacture, vehicles built before 1995 resulted in a higher risk of serious injury ($p < 0.005$, OR = 1.2) compared to vehicles built between 1996–2004, and vehicles manufactured after 2005 resulted in a lower serious injury risk ($p = 0.008$, OR = 0.8). For driver age, the risk of serious injury to pedestrians was found to be low ($p < 0.01$, OR = 0.8) for drivers aged 60 years old and over, compared to 30 to 59 year old drivers. This result is consistent with a Pour-Rouholamin and Zhou (2016), who found that elderly drivers were not associated with an increased risk of serious injury to pedestrians compared to younger drivers. Finally, female pedestrians were at a lower risk of sustaining serious injury ($p < 0.001$, OR = 0.8) in a pedestrian crash compared to males, and female drivers were less likely to increase injury risk to pedestrians (p = 0.009, OR = 0.9) compared to male drivers.

Table 3 shows the partial regression coefficient, the standard error, the significance probability of the Wald test and the odds ratio (OR) as a result of the logistic regression analysis for the GPS model, using the final 5 injury risk factors in addition to speed limit. For the GPS model there is also a distinct increase in pedestrian injury risk for crashes occurring greater than 50 km away from the Adelaide GPO compared to those occurring within 50 km.

Pedestrian crashes occurring on a divided roads result in a higher serious injury risk compared to those on undivided roads ($p < 0.001$, OR = 1.3). Pedestrian serious injury risk at cross road intersections was found to be low ($p < 0.001$, OR = 0.7). Risk of pedestrian serious injury on a sloped road was higher compared to a level road ($p < 0.001$, OR = 1.4), the serious injury rate at night was significantly higher ($p < 0.001$, OR = 1.9) compared to the day.

### 3.3. ROC analysis

The results of applying a 10-fold cross-validation to the serious injury risk prediction model based on TARS data (N = 6,868) are shown in Table 4. The optimal model gave an average AUC of 0.67, and the GPS model gave an average AUC of 0.64. Fischer et al. (2003) suggested that a model giving an ROC with an AUC 0.5 - 0.7 has low precision, 0.7 - 0.9 has medium precision, and 0.9 or more as high precision. The optimal model was found to have borderline medium precision using the 10-fold cross-validation method and hence may potentially be acceptable for use by EMS to assist with injury management planning.

## 4. Threshold setting based on the under-triage rate

Before proposing a serious injury risk prediction algorithm in an AACN system, it is necessary to determine a threshold for serious injury risk to guide an appropriate emergency medical activation response. The threshold setting criteria based on the expert panel of the Centre for Disease Control and Prevention (CDS) in the United States recommends a 20% positive predictive value (PPV) for prediction of severe injury (injury severity scale > 15, Sasser. et al., 2012). In under-triage cases, the model will erroneously predict a minor injury, when the actual injury is serious. This results in an increased risk of pedestrian serious injury/death due to a potential delay in life-saving treatment. In over-triage scenarios, the model erroneously predicts a serious injury for a minor injury crash and emergency medical resources might be unnecessarily dispatched to a low injury severity pedestrian crash, resulting in inefficient use of medical resources. Unfortunately, as there is a trade-off between the under-triage rate and the over-triage rate with respect to a set injury threshold values, it is difficult to prevent all occurrences of under- and over-triages. An under-triage level of 10% or less and an over-triage level of 50%, is recommended by Josten et al. (2012). Injury risk prediction algorithms which have controlled under-

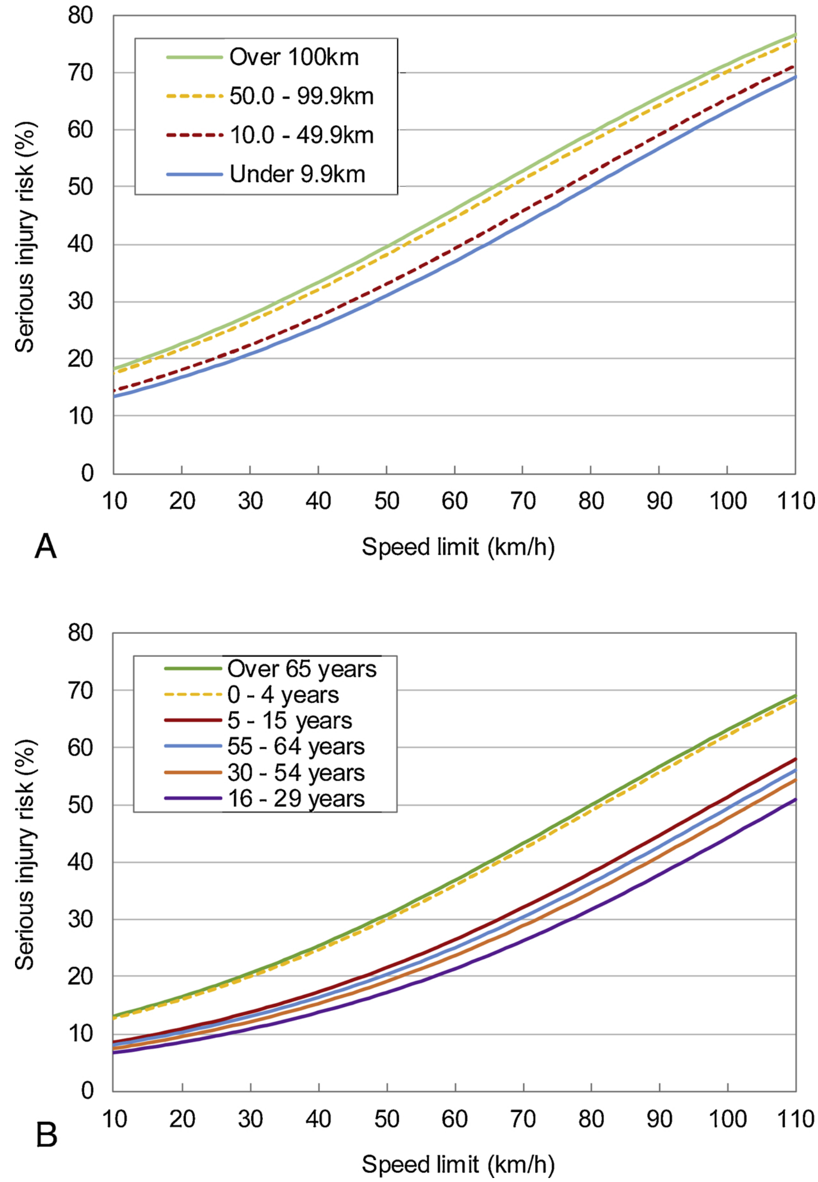


**Fig. 1.** (a) Distance from crash location to Adelaide GPO. Risk curve based on optimal model under the following baseline conditions: Male pedestrian aged over 65 years, male driver of 30–59 years, daylight, vehicle model year over 2005, undivided, straight and level road. Fig. 1 (b) Pedestrian age groups. Risk curve based on optimal model under the following baseline conditions: Crash to Adelaide GPO distance less than 9.9 km, male pedestrian, male driver aged 30–59 years, daylight, vehicle model year over 2005, undivided straight and level road.

triage and over-triage rates have been reported in studies by Nishimoto, et al. (2017) and Stitzel et al. (2016) for crashed vehicle occupants. In the present study, a similar triage-control method is employed using the CASR serious injury database, for each of the two pedestrian SIRP models.

For this triage-control method, 96 pedestrian crashes from CASR's serious injury database for the period July 2014 – December 2016 were used. The cases in CASR's serious injury database were matched with TARS data for crashes where detailed analyses for both data samples were available. For threshold setting of the models, serious injury in the CASR data was defined using maximum AIS (MAIS) and was used as the indicator to test against SIRP calculated by the models. The serious injury category (admitted to hospital or fatal) defined in this study has previously been found to correlate with MAIS 2 + injury (Ponte and Nishimoto, 2018), despite MAIS 3 + generally being considered the threshold for serious injury. Hence for defining level of injury, injured pedestrians with MAIS 2 + were defined as having a serious injury (N = 79) while injured pedestrians with MAIS 1 and lower (N = 17) were considered having a minor injury for testing against the SIRP algorithms. Fig. 2 shows the relationship between the under-triage rate and the over-triage rate with respect to the injury threshold for the optimal model. An under-triage level of 10% can be achieved in the optimal model by setting the injury threshold value to 15%, this results in an over-triage level of 58.8% as shown in Fig. 2.

For the GPS model, the under-triage rate and the over-triage rate curves are shown in Fig. 3. A 10% under-triage rate is achieved when the injury threshold value is set to 20%, resulting in an over-triage level of 70.6%.

## 5. Discussion

Automatic crash notification (ACN) systems and advanced automatic crash notification (AACN) systems are still an emerging safety technology, even for automobile occupants. Minimizing delays in medical treatment after a serious road crash can improve occupant injury outcome and ACN systems can assist with minimizing any

**Table 3**
Logistic regression results for the GPS model.

| Risk factors | Variables | Coefficients | S.E. | *p*-value | Odds ratio |
|---|---|---|---|---|---|
| Intercept | – | −2.724 | 0.178 | < 0.001 | – |
| Speed limit | [km/h] | 0.029 | 0.003 | < 0.001 | 1.0 |
| Distance from GPO | Under 9.9km | 0.000 | – | – | – |
| | 10.0 - 49.9km | 0.082 | 0.061 | 0.178 | 1.1 |
| | 50.0 - 99.9km | 0.358 | 0.157 | 0.023 | 1.4 |
| | Over 100km | 0.441 | 0.093 | < 0.001 | 1.6 |
| Road geometry | Undivided | 0.000 | – | – | – |
| | Divided road | 0.260 | 0.072 | < 0.001 | 1.3 |
| | Cross intersection | −0.349 | 0.087 | < 0.001 | 0.7 |
| | Other | 0.016 | 0.070 | 0.823 | 1.0 |
| Road horizontal alignment | Straight road | 0.000 | – | – | – |
| | Curve road | 0.180 | 0.123 | 0.144 | 1.2 |
| Road vertical alignment | Level | 0.000 | – | – | – |
| | Not level | 0.301 | 0.065 | < 0.001 | 1.4 |
| Natural lighting conditions | Daylight | 0.000 | – | – | – |
| | Night | 0.662 | 0.056 | < 0.001 | 1.9 |

potential delay. There is a movement toward mandatory legislation and regulations in various international jurisdictions. For European Union member countries, ACN systems (eCall) have been mandatory for all new models of cars since March 31, 2018 (European Parliament, 2015). AACN is expected to further improve injury outcomes by estimating the severity of injury for an automobile occupant, based on transmitted EDR data and by using a suitable injury risk prediction algorithm. In the United States, various algorithms are already used, including the URGENCY algorithm (Malliaris et al., 1997; Augenstein et al., 2006; Bahouth et al., 2012) and the OnStar algorithm (Kononen et al., 2011). In Japan, an AACN system referred to as D-Call Net is currently being trialled (HEM-Net et al., 2015) and is based on an algorithm developed by Nishimoto et al. (2017). In the present, unique study, two SIRP algorithms for pedestrians, using mass crash data have been developed.

In an ideal situation, the optimal algorithm would be utilized for any pedestrian collision that has been reported to emergency medical services, with the emergency caller or a first responder conveying all the pertinent information required for the SIRP algorithm to give an estimate of serious injury risk. Unfortunately in many situations this may simply not be possible, and only basic information about the crash location can be conveyed. For any pedestrian crash requiring emergency response, an accurate location must be conveyed to emergency services and this can be done quite easily by giving GPS coordinates from the crash scene (latitude and longitude) using a GPS enabled smart phone or vehicle navigation system. From the GPS data and using integrated GIS data, the speed limit, distance from GPO, road geometry (including vertical alignment and horizontal alignment) as well as natural lighting conditions, can be determined, and then used in the SIRP algorithm. As a result, the secondary model can be used for SIRP for pedestrians by using only the GPS coordinates from the crash scene (latitude and longitude) conveyed by a first responder by telephone or transmitted by an ACN system via telemetry, as part of the minimum data requirements of an ACN system.

Fig. 4 shows the application of the optimal SIRP algorithm. After a pedestrian collision has occurred, it is anticipated that in an ACN enabled car, an automatic crash notification would be transmitted from the crash vehicle, to an EMS provider or similar, with GPS data provided within the notification. The GPS data would be decoded using a GIS and appropriate software, to derive the site and environmental characteristics for initial input into the optimal SIRP algorithm. Standard procedure with automatic notification systems is that a communication channel between EMS providers and the crashed vehicle is attempted after a notification is received. Once a communication channel is established, supplementary details such as pedestrian age/gender, drive age/gender and vehicle model year can be provided by the vehicle occupants or first responders/bystanders, to input into the algorithm to calculate a serious injury prediction. If the optimal model SIRP is 15% or greater, the pedestrian injury is classified as 'serious' and the EMS can prepare appropriately for the emergency response. An appropriate response may include selection of the emergency response team and the transport mode, as well as pre-selection of the destination hospital. This would facilitate the process of early transport to a trauma center to improve pedestrian survival rate and ultimately potentially reduce the number of fatalities.

In situations where some or all of the supplementary data cannot be obtained, the algorithm would be used under a 'worst case scenario'. In this scenario, the higher valued supplementary injury risk variables (and corresponding coefficient values) are input into the optimal SIRP algorithm, to give the highest serious injury risk prediction.

With the GPS SIRP model (also depicted in Fig. 4), the injury prediction is based only on the algorithm input variables that can be derived from GPS data. This GPS data can be conveyed from a bystander or witness directly to the EMS provider using a GPS enabled smart phone. This can subsequently be decoded using GIS and input into the GPS SIRP model to give a serious injury prediction value. If GPS model SIRP is 20% or greater, then the pedestrian injury is classified as serious and the EMS can prepare appropriately for the response.

In the United States, only under-triage is considered and a rate of 5% is recommended (American College of Surgeons Committee on Trauma, 2014), whereas Japan and Germany have recommended an

**Table 4**
10-fold cross-validation AUCs based using TARS data.

| | Round | | | | | | | | | | Average |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | |
| Optimal model | 0.71 | 0.67 | 0.67 | 0.68 | 0.65 | 0.67 | 0.64 | 0.65 | 0.67 | 0.67 | 0.67 |
| GPS model | 0.68 | 0.64 | 0.63 | 0.66 | 0.62 | 0.64 | 0.62 | 0.65 | 0.63 | 0.64 | 0.64 |

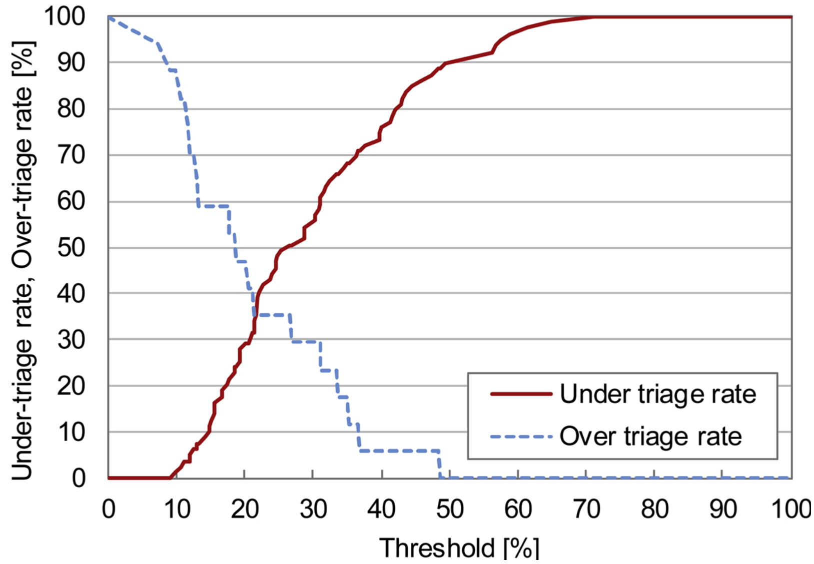


**Fig. 2.** Threshold for the optimal SIRP algorithm with respect to under-triage and over-triage rates, based on CASR's serious injury database.

under-triage rate of 10% and an over-triage rate of 50%. When the over-triage rates of both models are set to 10%, the optimal model gives an over-triage rate of 58.8% while the GPS model's under-triage rate is significantly higher at 70.6%. Despite this high over-triage rate, it is more important to prevent under-triage, to ensure inadequate medical responses to serious pedestrian crashes are minimized. The under-triage rate for the GPS model can be suppressed to 10% by accepting the higher over-triage rate as a consequence. It must be noted that the over-triage curves are quite sensitive, and this is a limitation of the small validation data set. In the future, the reliability of the over-triage rate may improve with a larger crash sample and larger validation data set.

In this study, despite posted speed limit being a categorical variable, a regression analysis was undertaken with speed limit as a continuous variable. This was done because the speed limit in this study is essentially a proxy for vehicle travel speed/impact speed. In the future, vehicle EDRs will be able to provide travel speed/impact speed and hence a continuous variable speed limit injury risk curve would be suitable in the interim. Additionally, most of the pedestrian crashes in the sample occurred in 60 km/h zones (71% of crashes) and 50 km/h zones (20% of crashes) with much smaller crash numbers at other speed limits (especially 30 km/h). Table 1 (shown previously) shows the speed distribution in the sample.

Fig. 5 shows a comparison of the predicted injury risk for the optimal model comparing speed as a categorical variable and a continuous variable. Generally, using speed limit as a categorical or continuous variable gave similar serious injury risk predictions, however the serious injury risk was paradoxically high at 10 km/h and 30 km/h. This is because there were considerably fewer crashes at those speed limits and hence the serious injury prediction at those speeds are likely to be heavily influenced by random variation. Therefore, in this study, this issue was overcome by regression of the speed limit as a continuous variable, and using speed limit as a continuous variable allows smoothing of the data to counteract the effect of low numbers of crashes at some speed limits. For these reasons using speed limit as a continuous variable was the better option in this study.

While the accuracy is likely to be improved by integrating EDR data within a telemetry system in the future, the optimal model and the GPS model in this study could be beneficial in the absence of such a system. By using the SIRP algorithms (the optimal model or the secondary GPS model) developed in this study, it is possible to gain the benefits of an

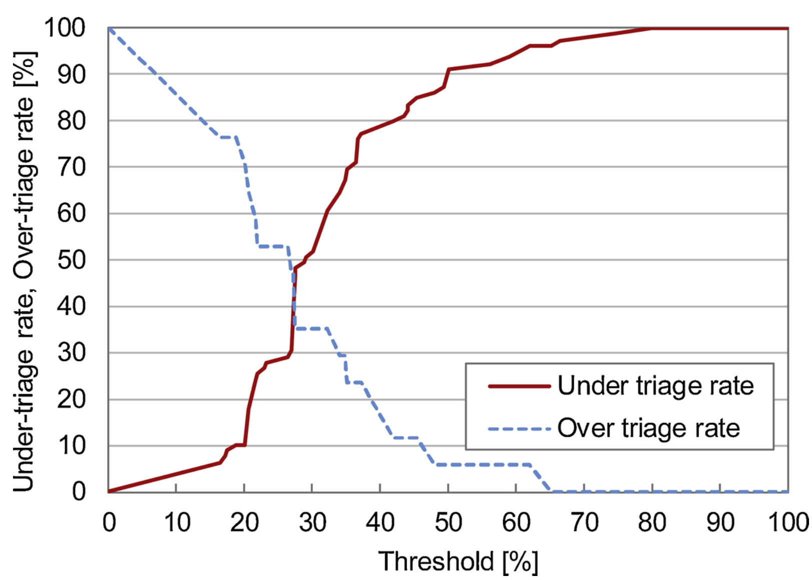


**Fig. 3.** Threshold for the GPS SIRP algorithm with respect to under-triage and over-triage rates, based on CASR's serious injury database.

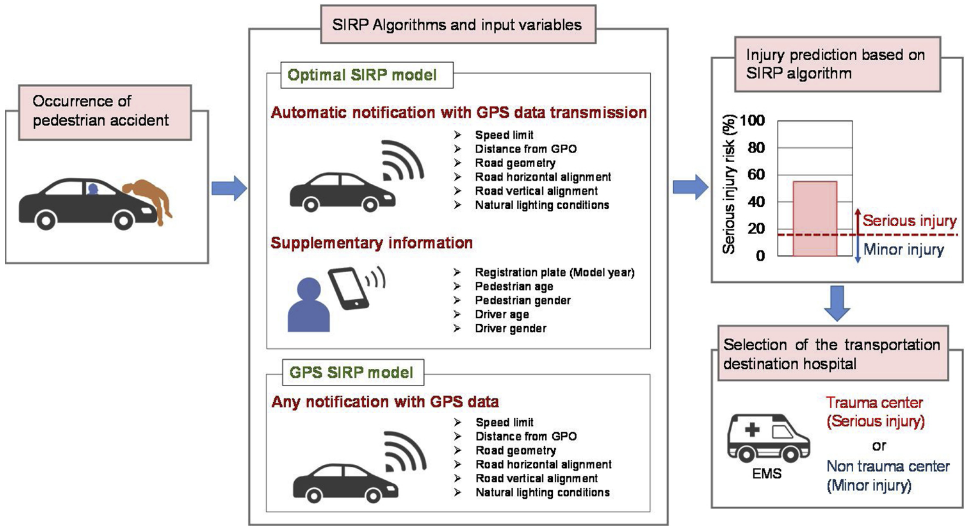


**Fig. 4.** Application of the SIRP algorithm to the emergency services for pedestrian crash.

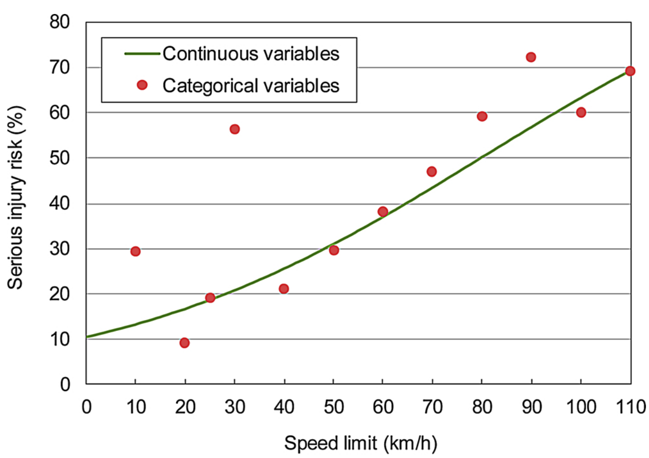


**Fig. 5.** A comparison between using speed limit as a continuous variable compared to using it as a categorical variable in the optimal model, under the baseline conditions: Crash to Adelaide GPO distance under 9.9 km, male pedestrian aged over 65 years, male driver aged 30–59 years, daylight, vehicle build date after 2005, undivided, straight and level road.

AACN system even in areas where EDR/telemetry systems are not widespread (for example in Australia), and this may potentially contribute to the reduction of pedestrian serious injuries and fatalities.

## 6. Conclusion

1) In this study, two SIRP algorithms for pedestrians, based on the South Australia traffic accident reporting system (TARS) mass crash data were developed. The algorithms are based on a regression analysis of pedestrian crash data (N = 6,868) for pedestrian crashes that occurred in South Australia between 1990 and 2016 using speed limit as a continuous variable. The algorithms were evaluated using a 10-fold cross-validation method and the serious injury thresholds were determined using CASR's in-depth serious injury crash data.
2) An under-triage level of 10% in the optimal model could be achieved by setting the serious injury threshold value to 15%, and this results in an over-triage level of around 60%. In contrast, an under-triage level of 10% in the GPS model was achieved by setting the serious injury threshold value to 20%, but this results in an over-triage level of around 70%.
3) The SIRP algorithms developed in this study could potentially be used in an ACN system. GPS data transmitted to EMS after a vehicle-pedestrian collision has occurred can be supplemented with other key injury risk factors required in the optimal model or the GPS model can be used when other data is not available. The SIRP algorithms may assist EMS with deciding on the most appropriate post-crash response, including selection of the emergency response team and transport mode, as well as pre-selection of the destination hospital. This may facilitate the process of early transport to a trauma center to improve pedestrian survival rate and ultimately reducing the number of fatalities.

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