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Exploring the impacts of factors contributing to tram-involved serious injury crashes on Melbourne tram routes

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ABSTRACT

Previous research is limited regarding factors influencing tram-involved serious injury crashes. The aim of this study is to identify key vehicle, road, environment and driver related factors associated with tram-involved serious injury crashes. Using a binary logistic regression modelling approach, the following factors were identified to be significant in influencing tram-involved fatal crashes in Melbourne: tram floor height, tram age, season, traffic volume, tram lane priority and tram travel speed. Low floor trams, older trams, tram priority lanes and higher tram travelling speeds are more likely to increase tram-involved fatal crashes. Higher traffic volume decreases the likelihood of serious crashes. Fatal crashes are more likely to occur during spring and summer. Findings from this study may offer ideas for future research in the area of tram safety and help to develop countermeasures to prevent specific fatality types from occurring.

1. Introduction

Tram/streetcars are light rail transit vehicles operating on tracks positioned in the center lane of a road and sharing the road with general traffic (Korve et al., 1995; Currie and Shalaby, 2007; Korve and Siques, 2000; Naznin et al., 2015c). Tram systems have a number of attractive features including their high passenger capacity, good comfort, and very low emission of pollutants compared to other transit systems (Anna and Bruce, 2001; Cliche and Reid, 2007). Tram networks are found in many different parts of the world; especially in Australia, North America, many European cities and parts of Asia and Africa (Fouracre et al., 2003; Topp, 1999). In many countries tram networks have been extended in order to reduce traffic congestion and to improve the urban environment (Anna and Bruce, 2001; Cliche and Reid, 2007).

However, trams present a range of inherent safety issues as they possess unique characteristics compared to other transit modes regarding their design, mass and operational aspects (Grzebieta et al., 1999; Currie and Shalaby, 2007; Mitra et al., 2010; Candappa et al., 2013; Hedelin et al., 1996; Naznin et al., 2015b). Previous research has identified that arterial roads and intersections served by trams are relatively unsafe compared to buses (Cheung et al., 2008; Shahla et al., 2009; Sagberg and Saetermo, 1997). A recent study conducted by Vandenbulcke et al. (2014) identified that on-road tram track increases cyclist-involved crash risks in Brussels, as it increases the possibility of cyclists to get stuck in tram tracks and lose control. Several studies have identified safety concerns at tram stops under mixed traffic operation as trams, cars, and pedestrians share the same roadway (Korve et al., 1995; Currie and Shalaby, 2007; Korve and Siques, 2000; Wong et al., 2007). A study in Poland identified that trams approaching stops can significantly encourages pedestrians road crossings on a red signal, resulting in unsafe crossings and an increase crash risks (Kruszyna and Rychlewski, 2013).

Grzebieta et al. (1999) and Candappa et al. (2013) pointed out that the most common type of tram to vehicle collisions occur in Melbourne while vehicles make U-turns or right turns in front of trams. Grzebieta et al. (1999) also modelled the impacts of two different tram classes (Class ‘A’ and ‘Z3’) on cars and pedestrians using the computer simulation package MADYMO. The results found that ‘A’ class trams were more crash worthy compared to ‘Z3’ class trams due to the more vulnerable frontal design of the ‘A’ class trams. Some previous studies have investigated several route factors that influence tram-involved crash occurrence along tram routes; including general traffic volume, route section length, stop density, position of tram stops, transit priority measures in both

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Melbourne and North American cities (Shahla et al., 2009; Cheung et al., 2008; Richmond et al., 2014; Naznin et al., 2015a).

Melbourne, Australia has the largest tram/streetcar network (including light rail tracks) in the world by track length of 250 km (approx.) (Currie and Shalaby, 2007). Using trams to transport people has a long tradition in Melbourne (Mitra et al., 2010). However a considerable number of tram-involved crashes have been recorded in past years. Some 956 tram-involved collisions were recorded in 2007–2008 (Dowling and Duzelovski, 2008). While 4819 tram-involved collisions were recorded between 2009 and 2013 on the Melbourne tram network by Yarra Trams, the Melbourne tram operator (Yarra Trams, 2014). The most common types of tram related incidents are collisions between trams and road vehicles, tram-involved pedestrian collisions, collisions between trams, tram hits infrastructure and other obstructions (Transport Safety Victoria, 2016). Of the 4819 tram-involved collisions, 362 (7.5%) crashes were recorded as fatal or serious injury (FSI) crashes. Most of the FSI crashes (198 out of 362) involved pedestrians being hit by a tram. A previous tram-involved pedestrian fatality study conducted by Hedelin et al. (1996) in Gothenburg, Sweden found that fatal injury typically involved middle aged men, under the influence of alcohol, and during summer and night time. Pedestrians crossing tracks were considered to be vulnerable to fatality.

However, none of the previous research has considered modelling tram-involved crash severity in relation to basic safety dimensions. The goal of the 'Safe System' philosophy is to manage road users, roads and road sides, travel speed and vehicles in such a way as to minimize the probability of death and serious injury as a consequence of a road crash (Australian Transport Council, 2008; Langford, 2005). Therefore, the aim of this study is to investigate key vehicle, road, environment and driver related factors that influence the probability of a tram-involved serious injury crash on tram routes in Melbourne.

2. Variables and site selection

Tram-involved crash data deployed for this study was obtained from Yarra Trams crash reporting database, called the "Tram Incident Database" (Yarra Trams, 2014). The database records all tram-involved incidents on Melbourne tram network. The detailed crash data includes time and date of incident, location of incident, tram route number, direction of travel, and several tram driver and tram vehicle related features. The incidents are divided into two categories i.e. 'A' and 'B' type incidents in the database. An 'A' type incident represents fatal or serious injury, and is always investigated by Victoria Police and Yarra Trams. Category 'B' incidents are the minor incidents or non-fatal incidents reported by tram drivers. All tram drivers in Melbourne are responsible to report any incident that they notice during their journey. 'A' type and 'B' type injury have been defined as 'fatal' and 'non-fatal' injury respectively for this study.

A total of 4482 tram-involved collisions were recorded along 25 tram routes on the Melbourne tram network (tram routes number 1, 3, 5, 6, 8, 16, 19, 24, 30, 48, 55, 57, 59, 64, 67, 70, 72, 75, 78, 79, 82, 86, 96, 109 and 112) for a five year period between 2009 and 2013. All the selected tram routes operate as regular tram routes, and cover both inner and middle suburban Melbourne. Due to missing data in terms of driver age and experience for 186 crash counts (5 fatal and 181 non-fatal crashes), the number of crash counts was reduced to 4296 for this analysis. Among this reduced pool, 336 (7.8%) were reported as fatal and 3960 (92.2%) were reported as non-fatal crashes.

12 crash risk factors were considered for this study under four categories. (1) Tram drivers characteristics: age and experience; (2) Vehicle characteristics: floor type, length of tram and age of tram; (3) Environmental factors: lighting condition, day of week and season of year; (4) Road characteristics: traffic condition, land use, lane type and average tram travel speed;

The age of drivers was categorized into six groups (20–30, 30–40, 40–50, 50–60, 60–70 and 70–80 years) depending upon a normal distribution of entire tram drivers' age with a mean of 52.2 years and a standard deviation of 10.6 years (Yarra Trams, 2015b). Tram driver experience was categorized into five groups (<3, 3–15, 15–30, 30–40 and >40 years) assuming a normal distribution of all tram drivers' working experience with a mean of 14.6 years and standard deviation of 11.4 years.

Trams were fitted into two length categories, one category was from 14 to 16.64 m (Tram class A, W and Z) and another category was more than 16.64 m (Tram class B–E) (Vicsig, 2015). Tram age was divided into two groups, pre- and post-2001, based on the year when Yarra Trams introduced the first low floor trams (Vicsig, 2015). Travel speeds were categorized based on the average tram travelling speed on Melbourne tram network, i.e. 16 km/h (Yarra Trams, 2015c). The average tram travelling speed along different tram routes was obtained from Yarra Trams network development information system (Yarra Trams, 2011), which is the average speed from terminus to terminus for a particular route. This study has used the average speed of tram route for analysis, not the exact speed at the time of incident. The above-mentioned five variables were treated as continuous variables in the regression model for more precise outcomes, while the remaining seven variables were considered as categorical data. The list of variables is summarized in Table 1.

3. Methodology

A wide range of crash severity models have been developed by the safety researchers to understand the factors that exacerbate the degree of crash severity (Savolainen et al., 2011; Mannering and Bhat, 2014). Crash injury severity data is represented by discrete categories such as fatal, serious injury, minor injury and property damage only (Austroads, 2002). Crash severity models are developed either considering binary response (fatal and non-fatal) or multiple response variables (fatal, serious injury, minor injury and no injury).

For the present study, the injury severity data is categorized as the binary response variables, 'fatal injury' and 'non-fatal injury'. A binary logistic regression (i.e. Binary logit) model has been adopted to estimate the likelihood of serious injury crashes involving trams. This is a 'generalized linear model' with a logistic distribution function. The binary logit model allows the prediction of a binary outcome from a number of covariates that can be continuous and/or categorical (Al-Ghamdi, 2002; Washington et al., 2010).

As the dependent variable is dichotomous, it is assumed to follow a Bernoulli distribution, taking the value of 1 with a probability of p for an event occurring and a value of 0 with probability *1-p* for an event not occurring. The relationship $p/(1-p)$ represents the odds ratio and the natural logarithm of the odds ratio represents a logit transformation. The logit is a function of covariates and the model form for this study is presented in Eq. (1) (Washington et al., 2010; Kononen et al., 2011):

$$y_i = \ln\left(\frac{p_i}{1-p_i}\right) = \beta_0 + \sum_{i=1}^{n} \beta_i x_i \qquad (1)$$

where p_i is the probability of a serious crash occurring, β_0 is the model constant, x_i is the set of explanatory variables and β_i are the coefficients of estimated parameters corresponding to the explanatory variables x_i. The coefficients are estimated using the maximum likelihood estimation (MLE) method. The likelihood-