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Variables Affecting the Risk of Vehicle Collisions in Australian Road Tunnels

Edwin Hidayat^{1a}, David Lange¹, Jurij Karlovsek¹, Jiwon Kim¹

¹ School of Civil Engineering, University of Queensland

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Abstract

The characteristics of road tunnels as part of the road network differ from those of general open roads, resulting in different vehicle collision characteristics. Understanding the characteristics of these collisions and the variables that contribute to them is critical for developing mitigation strategies. The purpose of this paper is to identify the characteristics of vehicle collisions in Australian road tunnels, as well as to investigate the variables that influence the number of casualties and the types of collisions. The study utilised data from seven road tunnels in Queensland and New South Wales. Data cleaning and transformation were carried out, yielding 12 variables for further analysis with statistical descriptive analysis, cross-tabulation, and logistic regression. The findings reveal that rear-end collisions are the most common type of collision in Australian road tunnels. Furthermore, only one variable had a significant impact on the number of casualties, while three variables had a significant impact on the types of collisions. These findings provide valuable insights for tunnel stakeholders in developing preventive measures to improve road tunnel safety.

Key findings

- Vehicle collisions in road tunnels mostly involved light passenger cars, whereas buses, trucks, and heavy vehicles were involved in a lower frequency of collisions.
- The type of collision is strongly related to variables such as speed limit, horizontal alignment, vehicle type, and number of vehicles involved.
- Rear-end collisions were more likely to involve multiple vehicles, particularly heavy vehicles and motorcycles, and occur when one or more of the vehicles involved is speeding.
- Speed limit is the major factor that affects vehicle crashes in tunnels, the likelihood of a crash is lower when the speed limit is restricted to 80 km/h or less and when the speed limit is strongly enforced in tunnels.

Introduction

Every year, approximately 1.35 million people are killed in vehicle collisions, resulting in an alarming rate of approximately 150 deaths per hour (WHO, 2018). Vehicle collisions are influenced by environmental conditions, traffic characteristics, vehicle factors, driver behaviour, and road characteristics. Among these factors, road characteristics are gaining attention because they influence traffic character-

istics and driver behaviour. Tunnel infrastructure is an essential part of the road network in areas where open roads cannot be built. In contrast to general road infrastructure, such as highways which typically have open spaces with natural lighting, road tunnels have relatively narrow spaces and artificial lighting, which creates a relatively dark environment. The contrasting characteristics of road tunnels and open roads result in distinct driver behaviour and collision characteristics (Bassan, 2016).

a Corresponding author: Edwin Hidayat, e.hidayat@uq.net.au

Existing studies on vehicle collisions in road tunnels have focussed mainly on particular aspects of the issue. For instance, rear-end collisions in road tunnels in Singapore (Meng & Qu, 2012), a crash model using data from tunnels in Italy (Caliendo et al., 2013), crash characteristics in urban river-crossing tunnels in China (Jiang et al., 2016) and statistics of vehicle collisions in road tunnels in Norway (Amundsen & Ranes, 2000). However, there has been little research attention into the variables that influence vehicle collisions in road tunnels, despite the importance in assisting tunnel designers and operators in developing effective crash prevention strategies. In addition, there is a scarcity of research from a country perspective, that is a lack of studies that used data from road tunnels in Australia. This is noteworthy given that Australia has approximately 28 years of experience in constructing and operating road tunnels, with cost and safety issues remaining points of controversy (Ridley, 2019). Therefore, investigating the variables influencing vehicle collisions in road tunnels in Australia can provide insight which may help to address any safety concerns.

As a result, the purpose of this study is to investigate the characteristics of vehicle collisions in road tunnels in Australia as well as investigate the variables that influence the risk of such collisions, particularly in terms of collision types and casualties. This research will provide valuable insights to aid in the improvement of safety measures in road tunnels in Australia.

Method

To achieve the purpose of this study, a three-step analysis approach is proposed, consisting of descriptive statistics, cross-tabulation, and logistic regression. An exemption from human research ethics approval was granted by the University of Queensland Research Ethics and Integrity committee.

Data

The datasets used in this study were obtained from two sources: The Department of Transport and Main Roads (TMR) in Queensland and the Centre for Road Safety (CRS) in New South Wales. The TMR dataset covers the period from 1 January 2010 to 30 November 2019, the CRS dataset spans from 1 January 2015 to 31 December 2019. The difference in dataset timeframe is a result of differing policies between these two jurisdictions.

Although the TMR and CRS datasets share similarities, particular variables had to be modified to maintain the same format. For example, TMR classified crash types as single or multiple vehicle collisions, whereas CRS utilise the number of vehicles involved, which can be one, two, or more. During the data preparation process, inconsistencies in some variables and terminologies used by TMR and CRS were identified. As a result, only variables found in both datasets were included in the subsequent analysis.

Following the data cleaning process, the total number of vehicle collisions from both TMR and CRS datasets was 262.

These collisions were associated with 12 variables, which were classified into five different categories. Among these categories, the tunnel is the only category in which tunnel operators or designers can directly intervene in developing risk countermeasures, whereas the other categories, such as vehicle and driver, are mostly related to tunnel users. This information is important in identifying specific areas where interventions can be targeted by specific tunnel stakeholders. It is worth noting that the data apply to vehicle collisions occurring inside road tunnels and on the entry and exit ramps of these tunnels. [Table 1](#) presents a summary of the tunnels included in the study data.

After performing the data cleaning process, data transformation was performed to facilitate further analysis. The data were categorized into binary and nominal variables to simplify the analysis. For example, binary categories included time of collision (6am–6pm = 1; all other times = 0). The casualty variable included severity level (i.e., hospitalized, medically treated, serious, moderate, and minor injuries) that were allocated a binary category (injury and/or property damage = 1; no injury or property damage = 0). No data regarding fatalities were found in either the TMR or CRS datasets. [Table 2](#) presents the variables and descriptive statistics.

Data analysis

In the first step, a general statistical analysis was employed to identify and investigate the characteristics of vehicle collisions. This method was chosen for its straightforward implementation and as it provides valuable insights into the existing characteristics of vehicle collisions in Australian road tunnels, serving as the foundation for further analysis and the development of prevention strategies.

In the second step, a cross-tabulation analysis was performed to investigate the relationship between the dependent variables and the independent (explanatory) variables. Cross tabulation analysis facilitates the examination of joint frequencies and displays the relationship between two or more variables (Cakan et al., 2014). The Pearson chi-square analysis is used to determine statistical independence between variables. Independent variables with p-values greater than 0.05 are considered to have a weak relationship (Shariat-Mohaymany et al., 2011).

The third step aimed to extend and validate the findings from the previous step. The logistic regression model was utilised to identify the variables associated with the number of casualties and the types of vehicle collisions. Logistic regression offers several advantages for this analysis. Firstly, it enables the prediction of the probability of each dependent variable based on multiple independent variables. Unlike traditional regression analysis, logistic regression deals with binary or dichotomous response variables (Al-Ghamdi, 2002). Secondly, logistic regression is a versatile modelling tool that allows for the simultaneous comparison of multiple variables using logit analysis that allows for the simultaneous comparison of more than one variable (Ambo et al., 2020).

In this study, the dependent variables were the total number of casualties (binary level) and the types of vehicle

Table 1. Tunnels included in the study data

Tunnel	Location	Year Open	Length (km)
Clem 7	Queensland	2007	4.8
Airport link	Queensland	2012	6.7
Legacy way	Queensland	2015	4.6
Cross City	New South Wales	2005	2.1
Eastern Distributor	New South Wales	1999	1.7
Lane Cove	New South Wales	2007	3.6
South Western	New South Wales	2001	4.0

collisions (multiple levels) as presented in [Table 2](#). Binary logistic regression (BLR) was applied to the dependent variable with two dichotomous levels (1 or 0). The BLR equation was expressed as (Choi et al., 2014):

$$\text{Prob}(y_i = 1) = \frac{\exp[f(X_k, \beta_k)]}{1 + \exp[f(X_k, \beta_k)]}$$

Whereas $\text{Prob}(y_i = 1)$ is the probability of dependent variable y_i . X_k is a vector of independent variable representing factors affecting dependent variable, and β_k is a vector of estimated parameters.

For understanding the variables associated with casualties in vehicle collisions, the BLR analysis utilises the significance level (p-value or Sig.) and odds ratio (OR). The Sig. column displays the p-values for each variable, where values less than 0.05 indicate statistical significance. The OR indicates the probability of an event occurring based on a one-unit change in the independent variables while keeping all other variables constant. An OR greater than 1 (or positive coefficients) suggests that an increase in the independent variables leads to a higher likelihood of no injury. Conversely, an OR less than 1 (or negative coefficients) indicates a lower likelihood of no injury as the explanatory variables increase (Bham et al., 2012). The interpretation of OR for multinomial logistic regression (MLR) analysis follows the same principles as BLR.

The types of vehicle collisions is the dependent variable with multiple levels. MLR is applied for this dependent variable, as proposed by Chen et al (2016) and expressed as:

$$\log\left(\frac{\pi_i}{\pi_j}\right) = \alpha_i + x^T \beta_i$$

Whereas π_i represents the probability of the non-baseline category i of the dependent variable. $i = 1, \dots, p$ ($i \neq j$); p is the number of categories of the dependent variable. π_j is the probability of the baseline category j of the dependent variable. α_i is the intercept of the i -th equation. x^T is the transpose of the independent variable vector x . β_i is the coefficient vector for the i -th equation. The statistical analysis of variables affecting casualty and type of collision are performed using IBM SPSS statistics version 26 (SPSS, 2022).

Results

Collisions characteristics: Descriptive

A descriptive analysis was conducted using a dataset comprising 262 collision cases to explore the collisions charac-

teristics. The findings of the descriptive statistical analysis are summarised in [Table 2](#).

Collisions characteristics: Cross-tabulation

The association between the dependent variables (casualty and type of collision) and the ten identified independent variables was investigated using cross tabulation (crosstab) analysis. The association was measured based on the estimation of Pearson chi-square values, which indicate the level of association. Independent variables with Pearson chi-square (p-values) greater than 0.05 are considered to have a low association. [Table 3](#) shows the Pearson chi-square values for the ten independent variables.

Variables affecting collision casualties

The BLR analysis output in SPSS is divided into two blocks: Block 0 and Block 1. Block 0 represents the model without any independent variables. [Table 4](#) shows that the variables in Block 0 equation resulted in a p-value of 0.000 and an OR value of 2.69. This indicates that the model is significant even without the addition of independent variables, and the odds of no people being injured in a vehicle collision are 2.69 times greater than the odds of casualties in a vehicle collision.

[Table 4](#) presents the variables included in the equation for Block 0 of the BLR analysis, displaying the constant value, coefficient (B), standard error (S.E.), Wald statistic, significance (Sig.), and odds ratio (OR).

Moving on to Block 1, SPSS provides model coefficients to assess the performance of the model. [Table 5](#) shows the statistically significant independent variables in Block 1. Only the speed limit was statistically significant with a p-value of 0.002, the remaining variables were not statistically significant with p-values greater than 0.05. Six of the ten variables had odds ratios (OR) greater than one, but none had a p-value that was significant. This suggests that the only significant relationship in explaining the casualty is the speed limit. The OR value of speed limit is 0.096, indicating that a speed limit of 80 km/h is less likely to be associated with the occurrence of casualties.

Based on a single significant independent variable, the BLR model for predicting the number of casualties is as follows: 1.913 - 2.346 * speed limit.

Table 2. Variables and descriptive statistics

Category	Variables (description)	Coding	Descriptive statistics	
			n	%
Dependent variables	CASUALTY_TOTAL (numbers of casualties)	0= no casualty 1= 1 or more casualties	71 191	27.1 72.9
	TYPES_OF_COLLISIONS (type of collision)	1= angle 2= hit object 3= other 4= overturned 5= rear end	79 38 3 7 135	30.2 14.5 1.1 2.7 51.5
Vehicle	NUMBER_VEHICLE_INVOLVE (number of vehicles involved in the incident)	0= multi veh 1= single veh	218 44	83.2 16.8
	VEHICLE_TYPE (type of vehicle involved in the incident)	0= Truck, bus, semi-trailer, heavy freight, Motorcycle 1= van, light passenger, station wagon, 4-wheel drive	91 171	34.7 65.3
Tunnel	HORIZ_ALIGN (horizontal alignment of the tunnel segment)	0= straight 1= curved	226 36	86.3 13.7
	SPEED_LIMIT (speed limit in the tunnel segment)	0= <80 km/h 1= ≥80 km/h	48 214	18.3 81.7
	ROAD_SURFACE (condition of the road surface)	0= sealed wet 1= sealed dry	21 241	8.0 92.0
Driver	FACTOR_SPEEDING (whether or not the driver of the vehicle was speeding)	0= no 1= yes	251 11	95.8 4.2
	FACTOR_FATIGUE (whether or not the driver of the vehicle was sleeping)	0= otherwise 1= fatigue	251 11	95.8 4.2
Environment	DAY_OF_COLLISIONS (day on which the incident occurred)	0= weekdays 1= weekends	185 77	70.6 29.4
	CRASH_HOUR (time of day at which the incident occurred)	0= otherwise 1= 6 am to 6 pm	47 215	17.9 82.1
	ATMOSPHERIC_COND (weather on the day of the incident)	0= raining 1= clear	28 234	10.7 89.3

Table 3. Crosstab results for ten independent variables

Variables	Pearson chi-square	
	Casualty	Type of Collision
Atmospheric Condition	0.125	0.070
Day of Collision	0.729	0.669
Hour of Collision	0.412	0.006
Vehicle Type	0.628	0.004
Vehicle Involved	0.067	0.000
Speed Limit	0.000	0.003
Horizontal Alignment	0.020	0.000
Road Surface	0.503	0.002
Speeding Factor	0.170	0.000
Driver Fatigue	0.170	0.000

Table 4. BLR-Block 0: Variables in the equation

		B	S.E.	Wald	Sig.	OR
Step 0	Constant	.990	.139	50.688	.000	2.690

Table 5. BLR-Block 1: Variables in the equation

Variables		B	S.E.	Wald	Sig.	OR
Step 1 ^a	ATMOSPHERIC_COND	.987	.687	2.066	.151	2.684
	CRASH_DAY_OF_WEEK	-.038	.329	.014	.907	.962
	CRASH_HOUR	.638	.404	2.501	.114	1.893
	VEHICLE_TYPE	-.344	.329	1.092	.296	.709
	VEHICLE_INVOLVED	.296	.498	.352	.553	1.344
	SPEED_LIMIT	-2.346	.776	9.154	.002	.096
	ROAD_HORIZ_ALIGN	.190	.642	.087	.768	1.209
	SURFACE_CONDITION	-.114	.828	.019	.890	.892
	FACTOR_SPEEDING	1.320	1.099	1.441	.230	3.742
	FACTOR_FATIGUE	1.068	1.204	.786	.375	2.910
	Constant	1.913	.957	3.993	.046	6.775

Table 6. MLR: Likelihood Ratio Tests

Effect	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	90.534 ^a	.000	0	.
ATMOSPHERIC_COND	91.830 ^b	1.296	4	.862
CRASH_DAY_OF_WEEK	96.533 ^b	5.998	4	.199
CRASH_HOUR	94.408 ^b	3.874	4	.423
VEHICLE_TYPE	103.429 ^b	12.895	4	.012
VEHICLE_INVOLVED	278.896	188.362	4	.000
SPEED_LIMIT	96.571 ^b	6.036	4	.196
ROAD_HORIZ_ALIGN	95.128 ^b	4.593	4	.332
SURFACE_CONDITION	97.767 ^b	7.232	4	.124
FACTOR_SPEEDING	124.619 ^b	34.084	4	.000
FACTOR_FATIGUE	91.469 ^b	.935	4	.920

Variables affecting types of collisions

The MLR analysis performed in SPSS, using the likelihood ratio test, produced slightly better results than the casualty model in the BLR analysis. Based on their p-values, three variables were determined to be statistically significant. The variable VEHICLE_TYPE had a p-value of 0.012, VEHICLE_INVOLVED had a p-value of 0.000, and FACTOR_SPEEDING had a p-value of 0.000. [Table 6](#) shows the likelihood ratio test results for the type of collision.

The MLR model was then built using the three statistically significant variables based on the likelihood ratio test results. [Table 7](#) shows the MLR model with three explanatory variables, predicting the type of collisions as the dependent variable. The types of collisions included angular collisions, hit object collisions, other collisions, overturned collisions, and rear-end collisions. The 'Other' collision was used as the reference category in the dependent variable in this MLR analysis. As a result, the MLR model only provides estimates for four categories. To assess the impact of these collision types, the three explanatory variables, namely ve-

hicle type, vehicle involved, and speeding factor, are compared in the discussion section.

Discussion

Collision characteristics

This section focuses on the discussion of casualties and types of collisions observed in road tunnels within the greater Brisbane and greater Sydney areas, utilising the data presented in [Table 2](#) for descriptive analysis. This analysis divided the characteristics of vehicle collisions into four categories: vehicle, tunnel, driver, and environment. In addition, collision characteristics are also discussed using cross tabulation analysis, providing a broader perspective on collision characteristics in Australian tunnels.

The vehicle category identified the different types of vehicles involved in collisions. The majority of road tunnel collisions (65.3%) involved light passenger cars, while buses, trucks, and other heavy vehicles have a lower frequency of collision events. This finding supports the overall traffic characteristics observed in Australian road tunnels

Table 7. Estimation results of MLR model

CRASH_NATURE		B	Std. Error	Wald	OR interpretation
Angular	Intercept	-30.070	359.679	.007	
	[VEHICLE_TYPE=0]	8.650	51.651	.028	More likely
	[VEHICLE_INVOLVED=0]	34.205	309.284	.012	More likely
	[FACTOR_SPEEDING=0]	9.512	229.023	.002	More likely
Hit Object	Intercept	18.147	43.470	.174	
	[VEHICLE_TYPE=0]	-1.335	1.286	1.078	Less likely
	[VEHICLE_INVOLVED=0]	-.648	143.628	.000	Less likely
	[FACTOR_SPEEDING=0]	-15.203	43.457	.122	Less likely
Overturned	Intercept	.255	1066.533	.000	
	[VEHICLE_TYPE=0]	1.099	1.633	.453	More likely
	[VEHICLE_INVOLVED=0]	1.228	155.677	.000	More likely
	[FACTOR_SPEEDING=0]	-.255	1066.532	.000	Less likely
Rear-end	Intercept	-17.483	201.976	.007	
	[VEHICLE_TYPE=0]	7.939	51.650	.024	More likely
	[VEHICLE_INVOLVED=0]	33.596	243.997	.019	More likely
	[FACTOR_SPEEDING=0]	-1.698	.000	.	Less likely

a. The reference category is: Other

(Ridley, 2019). It has been reported that in two-lane tunnels, heavy vehicles tend to dominate lane-1 and travel at a slower speed than passenger vehicles in lane-2. Drivers in lane-1 adjust their vehicle speed to maintain a safe following distance, whereas in lane-2, higher speeds are observed. Multi-vehicle collisions are more common in Australian tunnels, single-vehicle collisions (16.8%) occur primarily as a result of contact with specific objects. Single-vehicle collisions are most common near tunnel entrance or exit portals (Austroads, 2018).

The tunnel category focused on horizontal alignment, speed limits, and road surface conditions. The majority of vehicle collisions occurred in tunnels with speed limits exceeding 80 km/h (81.7%). Speed limits regulate driving speeds by balancing travel time and risk, and the geometric design of tunnels plays a crucial role in this setting (Wilson et al., 2010). Another important geometric design parameter that influences driving speed is horizontal alignment. Drivers have difficulty estimating the curvature in road tunnels because of the obstruction caused by tunnel walls (Caliendo et al., 2013). As a result, drivers are more cautious, resulting in a lower collision frequency in curved tunnel sections (13.7%). Vehicle collisions have been found to be most common in tunnel sections with straight horizontal alignment. In terms of road surface conditions, the majority of collisions (92.0%) occurred on sealed dry roads. This is to be expected, as road tunnels are enclosed infrastructures where rainfall has little impact on surface conditions, unless there is a leak in the water supply or drainage system.

The driver category investigated variables such as speeding and driver fatigue. The percentage of collisions that involved speeding was relatively low (4.2%). Notably, driver fatigue had the same frequency of occurrence (4.2%). How-

ever, there is a contradiction in the existing literature. For example, Chen et al (2016b) found a significant association between fatigue and speeding for truck drivers, whereas other studies have not found a statistically significant relationship between fatigue and speeding (Høye, 2020). This relationship warrants further investigation.

The environment category included atmospheric conditions and collision occurrence times. Vehicle collisions predominantly occur under clear weather conditions. However, atmospheric conditions have no direct impact on collisions inside road tunnels, as tunnels are enclosed environments with artificial lighting. On the other hand, the change in lighting from the open road with natural lighting to the tunnel with a relatively dark environment causes a disruption in visibility. Drivers must be extremely cautious to avoid colliding with the tunnel walls, as the tunnel environment can cause misperception of road conditions and a lack of spatial orientation (Vashitz et al., 2008). In terms of collision occurrence time, weekdays account for 70.6 percent of all collisions. However, considering weekdays comprised five days and weekends comprised two days, the average collision frequency per single day is roughly comparable. Collisions are most common between the hours of 6 am and 6 pm. This finding is not surprising given that people typically conduct their activities during this time period.

In addition, the cross tabulation analysis for casualties revealed that only two out of ten variables had a strong association with the number of casualties. Speed limit and horizontal alignment had significant associations with values of 0.000 and 0.020, respectively. The remaining variables, on the other hand, showed low associations and did not adequately explain casualties. The finding about the effect of speed limits on casualties is consistent with previous research on the severity of truck-involved collisions in tun-

nels in China (S. Chen et al., 2020). However, the finding on horizontal alignment is contradictory. The difference may lie in the type of vehicle involved and the specific tunnel configurations.

Meanwhile, the cross tabulation analysis for the types of collisions revealed eight out of ten variables had a strong association with the type of collision, as indicated by p-values less than 0.05 in Table 3. Notably, the time or hour of the collision has a strong relationship with the type of collision. This finding supports previous research on the relationship between nighttime periods and rear-end collisions (Abe et al., 2010), as well as the impact of peak or non-peak hour on the frequency of lane-changing collisions (Wang et al., 2016).

The association between vehicle types and types of collision is strong, which supports previous research using a multivariate Poisson-lognormal model (Hosseinpour et al., 2018). Moreover, the finding regarding the variable of vehicle involvement aligns with previous research using negative binomial distributions (Venkataraman et al., 2013), which demonstrates an association between the number of vehicles involved and the type of collisions. As a result, single-vehicle collisions are expected to have characteristics which are distinct from multi-vehicle collisions.

According to Table 3, the type of collision had a strong association with the speed limit. This finding supports a previous study on lane-changing behaviour in a tunnel with a high speed limit, which can lead to a rear-end collision (Linjun et al., 2014). Rear-end collisions account for more than half of all incident types in the data set. Because of the strong association between speed limits and casualties and types of collision, speed limit reduction may become the most commonly used countermeasure to reduce the occurrence of crashes on roads in Australia (Doecke et al., 2020). Furthermore, the horizontal alignment and road surface variables were strongly related to the type of collision. This finding supports previous research on single-vehicle crashes (Bham et al., 2012). Speeding and fatigue are variables with low frequency in the occurrence of collision even though these variables have a strong association with the type of collisions. An in-depth analysis of single-vehicle crashes and rollover collision in tunnels mostly involved speeding and driver fatigue (Pervez et al., 2020).

From the discussion, a pattern emerges where rear-end and side-impact collisions are associated with the multi-vehicle collisions, particularly when involved drivers were speeding.

Affecting variables

The OR interpretation column (Table 7) indicates that values greater than one indicate a higher likelihood (more likely), values less than one indicate a lower likelihood (less likely). In the case of angular collisions, the OR interpretation identified that vehicle type, vehicle involvement, and speeding were more likely. This means that angular collisions are more likely to involve trucks, buses, semi-trailers, heavy freight vehicles, or motorcycles. Heavy vehicles are most likely to be involved due to the driver's restricted view by vehicle blind spots, whereas motorcycle riders are more

prone to being in blind spots due to their smaller vehicle size. Multiple vehicles are frequently involved in angular collisions, and speeding is not a contributing factor. On the open road, angular collisions typically occur at road intersection or T-Junctions (Razi-Ardakani et al., 2018), road tunnels have limited or no intersections, which affects the occurrence patterns of angular collisions. Furthermore, angular collisions in roadway tunnels are approximately ten times more likely to result in injured people than other types of collisions (Jung & Qin, 2021).

In contrast to angular collisions, the hit object collision has OR interpretations as less likely for all explanatory variables, indicating that the hit object collisions are less likely to occur on heavy/large vehicles or motorcycles, multiple vehicles involvement, and no speeding. In other words, a hit object collision involving vans, light passenger vehicle, station wagons, or 4-wheel drives are more likely to occur. This finding is consistent with the previous reports indicating that the majority of hit object collisions in tunnels in Australia involve single-vehicle collisions (Austroads, 2018).

Overtaken or rollover collisions are more likely to occur when multiple vehicles are involved, in which the types of vehicles involved are truck, bus, semi-trailer, heavy freight, and motorcycle, with speeding. This conclusion is based on an OR with a value greater than one for vehicle type and vehicle involved, but the OR value for speeding factor is less than one. The finding regarding speeding aligns with previous research that speeding and improper lane change increase the risk of rollovers at tunnel exit (Pervez et al., 2020). Furthermore, trucks and buses are more prone to rollover collisions due to adverse conditions such as crosswinds and sudden acceleration or braking (Malviya & Mishra, 2014).

Similar to the findings for overturned or rollover collisions, rear-end collisions are more likely to involve multiple vehicles, such as trucks, buses, semi-trailers, heavy freight vehicles, and motorcycles, and more likely to occur with speeding. The OR value for both vehicle type and vehicle involved are greater than one, the OR value for speeding factor is less than one. This finding is consistent with previous research indicating that speeding significantly contributes to rear-end collisions, with a 40 percent higher occurrence rate compared to non-speeding scenarios (Xi et al., 2019).

Pattern on affecting variables

The BLR analysis reveals that the speed limit is a significant variable associated with the number of casualties. Collisions resulting in casualties are less likely to occur when the speed limit is below 80 km/h. Higher speed limits increase the risk of casualties in the event of a vehicle collision.

On the other hand, MLR analysis reveals that angular collisions tend to occur without speeding. However, speeding has a significant association on hit-object, rollovers, and rear-end collisions. Speeding reduces driver visibility and judgement, making it difficult to detect traffic signs and respond effectively in an emergency. Furthermore, the

relatively dark and monotonous environment of road tunnels may increase the likelihood of becoming visually tired (Qin et al., 2020). As a result, a sudden deceleration by the leading vehicle in an emergency can trigger a chain reaction of multi-vehicle rear-end collisions.

Certain types of vehicles, such as trucks, buses, semi-trailers, heavy freight vehicles, and motorcycles are statistically more associated with angular, rollover, and rear-end collisions. The types of vehicles statistically more associated in hit-object collisions were sedans, vans, light passenger cars, station wagons, or 4-wheel drives. The vehicle types influence the ability of vehicles to manoeuvre. Vans have relatively easy handling, manoeuvring and higher likelihood of stability control due to their small size compared to trucks or buses. In contrast, trucks are large and have higher pressures from sudden acceleration or braking which create difficulties when performing a manoeuvre. Motorcycles are generally easier to manoeuvre due to their small size. It is important to note that motorcycle crashes occur more frequently on open roads with curved alignment (Thompson et al., 2020), but it is unclear whether motorcycle manoeuvring has a strong association with the curved alignment in road tunnels. Thus, the type of vehicle plays a crucial role in the type of collision.

In terms of the number of vehicles involved, hit object collisions are more likely to occur in single-vehicle collisions, which are caused by loss of vehicle control or driver unfamiliarity with the road conditions on a particular route, resulting in collisions with objects. Angular, rollover, and rear-end collisions were most commonly associated with multiple vehicles.

Study strengths and limitations

The study's strength is that it examines variables related to road tunnel collisions using a comprehensive approach that includes descriptive, cross tabulation, and logistic regression analyses. This study identifies significant associations between variables and casualties, as well as collision types, providing valuable insights into the variables that contribute to different collisions.

In contrast, this study has limitations in using data from road tunnels in specific geographical areas, so the results may differ in different geographical areas. Furthermore, this study heavily relied on data from transportation agencies without detailed information about the methods used to collect the data, which may include biases in the data reported and not reported. This study describes descriptive statistics and the relationship between variables, but it does not consider the significance of causal interrelationships between variables. Other critical variables, such as traffic volume and driver behaviour, are not explicitly addressed, however are important elements to consider in future studies.

Conclusions

The purpose of this study was to look into the characteristics of road tunnel collisions in the greater Brisbane and

greater Sydney areas, and to identify key variables associated with the types of collisions and casualties. The findings shed light on four categories: vehicles, tunnels, drivers, and the environment.

Light passenger cars were the most common vehicles involved in road tunnel collisions, while buses, trucks, and heavy vehicles were less common. Multi-vehicle collisions were more common than single-vehicle collisions. Collisions occurred most frequently in tunnels exceeding the speed limits 80 km/h and with straight horizontal alignment. Speeding and driver fatigue had relatively low collision occurrence rates, but the relationship with collision types required further investigation. Collisions were most common during clear weather conditions, and weekdays between 6 am and 6 pm were the peak periods for collisions.

The number of casualties was strongly associated with speed limits and horizontal alignment. Vehicle type, vehicle involvement, and speeding were all significant variables influencing collision types, with angular collisions more likely to involve trucks, buses, and motorcycles. The hit object collisions were more likely to involve vans and light passenger cars. Rollover and rear-end collisions were associated with multi-vehicle collisions and were more likely to occur in the presence of speeding.

The speed limit was a significant variable affecting the number of casualties, with collisions resulting in casualties less likely to occur at speed limits less than 80 km/h. Speeding was associated with a significant increase in hit-object, rollover, and rear-end collisions, highlighting the negative impact of speeding on collision risk and severity. Implementing speed cameras as a strong enforcement measure to prevent drivers from exceeding the speed limit (speeding) may be one way to address this issue.

Future research is needed and should consider data from additional geographic areas to validate and generalise the findings. Investigating the causal interrelationships between variables and including variables such as traffic volume and driver behaviour into account would provide a more comprehensive understanding of road tunnel collisions. To capture complex interrelationships among these variables, probabilistic methods such as Bayesian networks could be a viable alternative to traditional statistical analysis. Furthermore, investigating strategies to reduce the occurrence and severity of specific collision types, such as rear-end collisions or rollovers, could help to improve tunnel safety outcomes.

This study provides valuable insights into the characteristics and influencing variables of road tunnel collisions. The findings have implications for tunnel design, speed limit regulations, driver awareness, and other measures aimed at improving tunnel safety and reducing the occurrence and severity of collisions.

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Author contributions

Edwin Hidayat: the lead author of this article, study conception, study design, data analysis, result interpretation, and initial manuscript draft. David Lange: study design, interpretation of results, and manuscript revision. Jiwon Kim and Jurij Karlovsek: conception and manuscript review. All authors have read and agreed to the published version of the manuscript.

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Human Research Ethics Review

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Data availability statement

Data is available on application from the Department of Transport and Main Roads (Queensland) and the Centre for Road Safety (New South Wales).

Conflicts of interest

The authors declares that there are no conflicts of interest.

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