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Motor vehicle driver injury severity analysis utilizing a random parameter binary probit model considering different types of driving licenses in 4-legs roundabouts in South Australia

Hamsa Abbas Zubaidi [a,b], Ihsan Ali Obaid [a,b], Ali Alnedawi [c,*], Subasish Das [d]

[a] School of Civil and Construction Engineering, Oregon State University, Corvallis, OR 97331-3212, United States
[b] Roads and Transport Department, College of Engineering, University of Al-Qadisiyah, Iraq
[c] School of Engineering, Deakin University, Geelong, Victoria 3220, Australia
[d] Texas A&M Transportation Institute, 1111 RELLIS Parkway, Bryan, TX 77807, United States

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ABSTRACT

A roundabout may not provide an acceptable level of control and can be confusing to inexperienced drivers. Therefore, the purpose of this study is to identify the contributing factors that lead to specific driver injury severity by utilizing a random parameter binary probit model sustained by different experiences of motor drivers at 4-legs roundabouts in South Australia. Four models were estimated based on seven years of crash data (2012–2018), considering different types of motorist-driving license: learner, provisional, full, and for all datasets, including unknown licensures. The model estimates variables have been categorized into a driver, crash, temporal, spatial, vehicle, roadway characteristics, and vehicle movements. The results showed there are differences between resulting crash-injury severities when driver experience has been observed. Besides, several parameters were found to be random and normally distributed: safety equipment, crash type (rear-end crash), number of involved vehicles, weekdays indicator, stats area (crash occurred within metropolitan), vehicle type (passenger car), and posted speed limit (more than 50 km/hr.). In addition, the log-likelihood and the transferability test indicated that the data should be separated and analyzed according to the driver's license. Findings can help authorities to improve driver safety considering the influence of the driver experience.

1. Introduction

Properly designed roundabouts physically control the speeds of all entering and traveling vehicles (Zhao et al., 2018) and can be considered a safer choice than any other option of at-grade intersections (Steinmetz et al., 2017). However, roundabout may not provide an acceptable level of control, occupy more space per vehicle movement, can be confusing to inexperienced or unfamiliar drivers (Akçelik, 2008). Crashes still occurring at roundabouts, and low severity of crashes are on the rise (Zubaidi et al., 2020). The effects of property-damage-only (PDO) or no injury crashes at roundabouts are still unclear (Austroads, 2015).

Although there are several recent studies have been conducted considering the safety of the roundabout (Al-Marafi et al., 2019; AlKheder et al., 2020; Bahmankhah et al., 2019; Baker, 2020; Balado et al., 2019; Campisi et al., 2020; Chen et al., 2020; Ghanim et al., 2020; Patnaik et al., 2020; Pratelli et al., 2020; Shaaban and Hamad, 2020; Shen et al., 2020), studies investigating the contributing factors that impact motorist crashes-severity at roundabouts are scarce and sparse. Zubaidi et al. (2020) investigated the factors that may affect injury severity sustained by crash-involved motor vehicle drivers considering three different types of roundabout configurations in Oregon state. Results of each investigated configuration showed there is a major difference in both the combination and variables included in each model and the magnitude of impact of those variables. Mamlouk and Souliman (2019) investigated the effect of traffic roundabouts on accident rate and severity in Arizona State. It was found that the accident rate was less in single-lane roundabouts compared to double-lane roundabouts. Hu and Cicchino (2019) studied the long-term crash trends at single- and double-lane roundabouts in Washington State. It was concluded that safety can be improved over time at double-lane roundabouts as drivers gain experience. Claros et al. (2018) evaluated the safety performance analysis of roundabout interchanges in Missouri state. The outcomes

* Corresponding author at: Deakin University, Geelong Waurn Ponds Campus, Locked Bag 20000, Geelong, VIC 3220, Australia.
E-mail address: amaln@deakin.edu.au (A. Alnedawi).

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showed that double lane roundabouts ramp terminals increases the total crashes. (Kathirgamalingam Somasundaraswaran and Megan Richardson, 2019) investigated the possibilities of specific crash types at roundabouts in Toowoomba, Australia. The analysis showed that angle crashes, hit-object crashes, and rear-end crashes are the prominent crashes at roundabouts. Burdett et al. (2017) evaluated roundabout-related single-vehicle crashes in Wisconsin state. It was found that both weather and impaired younger driving were main causes for more than half of all single-vehicle crashes. Al-Nabulsi and Jadaan (2019) developed safety performance functions for roundabouts in Amman, Jordan. The outcome revealed that the significant factors that influence the crash frequency are the AADT, entry angle-degrees, entry path radius, splitter radius, pedestrian crossing structure, inscribed diameter, central diameter, circulating width, entry width, number of circle legs. It can be seen from the available literature that the experience of motor vehicle drivers has not been under consideration in these studies.

It is generally accepted that driver experience can be related to the driver's age as the risk declines over time, assuming drivers gradually become more mature of the risky lifestyles (McCartt et al., 2009). Lin et al. (2020) analyzed crashes involved with teen drivers (no older than 20) on rural roads in West Texas; results showed that teen motorists were unsuccessful in yielding on the undivided roads with multi lanes, leading to severe injuries. Seacrist et al. (2020) investigated crashes for teen (16–19 yrs.), young (20–24 yrs.), adult (35–54 yrs.), and older (70 + yrs.) motorists. The results showed that total crash rates had been increased among young drivers compared with adult and older motorists. Duddu et al. (2019) identified crash-risk factors that are related to the injury severity of teen drivers, and they concluded that teen drivers tend to be severely injured on weekdays, particularly during peak hours. Adebisi et al. (2019) investigated the factors affecting injury severity of motor-vehicle crash for young (aged 16–25), middle-aged (aged 26–64), and older drivers (above 64) in the State of California. The finding demonstrated that old drivers have better risk perception among all age groups under the different roadway and environmental conditions. Ahmad et al. (2019) showed that elderly drivers become more experienced and tend to be more cautious as compared to younger drivers. Darban Khales et al. (2019) analyzed injury severity of teenage and older drivers; the weather condition was found to significant only in the adolescent driver model.

On the contrary, Ayuso et al. (2020) analyzed the driver age impact in crash severity, particularly drivers over 65 years old. The findings showed that crash severity and cost are significantly increased for drivers over 75 years of age. Chin and Zhou (2018) observed that older drivers are found to be the leading cause of fatal crashes compared to other drivers except for teen drivers. Loughran and Seabury (2018) estimated that passengers riding in a motor vehicle driven by an old driver are 6.73 times more likely to be killed than riding with a middle-aged driver. This could be explained that the physical and cognitive abilities decline with age and the elderly require longer perception-reaction times on the road (Amiri et al., 2020; Makizako et al., 2018)

Dunn et al. (2020) indicated that although both age and experience are crucial factors, the experience is more important than age when considering risk. Similarly, McCartt et al. (2009) showed that the length of licensure has a more powerful impact than the age of the driver. Das et al. (2019) also examined the association between licensure types of teens and their understanding of risk factors. The study found that driving experience is helpful for teens in understanding potential risk measures. In contrast, Curry et al. (2017) investigated two groups of drivers having the same three months post-licensure, the results showed that the crash rate of drivers (age 21 and older) is lower than drivers (age 17–20). However, they had the same licensure. Day et al. (2018) showed that drivers are at high risk of crashes when they begin independent driving; however, this decreases over the first three months. Clarke et al. (2006) found that cross-flow-turn accidents seem to decline the most with increased driver experience. Experienced drivers licensed for six years or more were found to exhibit less aggressive driving behavior (Sarwar et al., 2017). Learner driving experience was found to be associated with crash risk during independent driving (Ehsani et al., 2020; Steinbach et al., 2015). It can be seen that there is no agreement about the effect of the driver experience.

Although the literature showed limited studies considered the experience of drivers (i.e., length of licensure) in the crash injury severity analysis, these studies examined this experience as an explanatory variable in the modeling. That might lead to a heterogeneous concern. Heterogeneity has significant implications on safety countermeasure development as it might result in erroneous inferences and incorrect predictions (Mannering et al., 2016). It is not known yet whether driver experience, in terms of the license type, may be influenced by different factors which necessitate investigating the injury severity by the license type. Besides, and to our best knowledge, the contributing factors to the injury severity of motor vehicle crashes sustained by different experiences of drivers at 4-legs roundabouts have not been explored before.

Accordingly, the goal of this study is to examine crash-based investigations to get a better understanding of the features that may impact no injury to those of getting injured in 4-legs roundabouts in South Australia considering three different types of experiences in terms of driving licenses.

2. Methodology

2.1. Random parameter binary probit model

In this study, the main interest is to predict the driver injury severity, dependent variable, as a function of predictor variables. Obtaining detailed data for the crashes at the roundabouts that can capture the factors that contribute to crash severity is more complicated regarding the required sample size that accurately represents the population. For this research, random parameters binary probit models are used to model the probability of two possible crash severity outcomes. The response variable, driver injury severity, injury (aggregation of minor, severe and fatal crashes), or no injury, is a binary outcome. Subsequently, the twofold relapse models are appropriate procedures to utilize since they are created to anticipate a parallel subordinate variable as a work of indicator factors. Correctly, the binary probit model has utilized to analyze the data, assuming the disturbance term ε to be normally distributed, as is shown in Eq. (1).

$$P_n(1) = P(\beta_1 X_{1n} - \beta_2 X_{2n} \geq \varepsilon_{2n} - \varepsilon_{1n}) \tag{1}$$

The equation estimates the probability of outcome one occurring for observation n where ε_{1n} and ε_{2n} are normally distributed with mean equal to zero, variance σ_1^2 and σ_2^2 respectively and the covariance is σ_{22}.

With this data, a correlation between observables and unobservable may be expected, and simple variation among cases, which are not measured, can present a disparity into the model that impact the crash likelihood and injury severity outcome (Mannering et al., 2016). In an attempt to account for heterogeneous effects and any possible correlations among the unobserved factors, a random parameter binary probit model is used as shown in Eq. (2) (Greene, 2012)

$$\beta_i = \beta + u_i \tag{2}$$

where u_i is a randomly distributed term.

In a random parameter model, a few or all parameters are assumed to be random and will vary across observations. In this study, the random parameters are supposed to be normally distributed with a constant mean and variance. Since the normal distribution is symmetric and continuous, the coefficient for the same calculate may be positive for a few perceptions and negative for others. Moreover, in case the change or scale parameter is zero, at that point, the parameter is not random, and the calculate will have the same impact overall perceptions. Maximum likelihood estimation is performed through a simulation-based approach to estimate the random parameters and to address the computational complexity of computing the outcome probabilities. During analysis, normal, lognormal, triangular, and uniform distributions were considered for the random parameters' distribution; however, only the normal distribution was found to be statistically significant. Around 200 Halton Draws were utilized in this investigation to create a methodical, non-arbitrary arrangement of numbers. Halton sequences can give productive conveyance of the draws for numerical integration (Bhat, 2003; Pahukula et al., 2015). Finally, marginal effects are calculated to get the impact of a one-unit variation of instructive variable X on the injury result i as shown in Eq. (3) (Washington et al., 2011).

$$\frac{\partial Y}{\partial x_i} = \beta_i \phi(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n) \tag{3}$$

2.2. Significance of the model separation

Any information gathering without considering the sort of licensure may lead to incorrect deductions on the importance of specific revealing factors. Along these lines, a log-likelihood ratio test is estimated by using Eq. (4) to accurately test the overall significance of using a holistic model (all crashes regardless of the type of the driving license) over separate models (as mentioned above) (Washington et al., 2011):

$$\chi^2 = -2[LL(\beta_{ALL}) - LL(\beta_{LER}) - LL(\beta_{PROV}) - LL(\beta_{FULL}) \tag{4}$$

where $LL(\beta_{ALL})$ is the log-likelihood at the convergence of the all data model, $LL(\beta_{LER})$ is the log-likelihood at the convergence of the learner model, $LL(\beta_{PROV})$ is the log-likelihood at the convergence of the provisional model, and $LL(\beta_{FULL})$, is the log-likelihood at the convergence of the full model. The critical chi-square (χ^2) value associated with one-tailed probability level and degrees of freedom which equals to the summation of the number of the random estimated parameters in all separate models minus the number of the random estimated parameters in the all mode.

For further validation, a more extensive transferability test was conducted to test if modeling injury severity at the roundabouts according to driver license need to be modeled separately. This log-likelihood ratio test for transferability is as follows (Washington et al., 2011).

$$\chi^2 = -2[LL(\beta_{M1_{M2}}) - LL(\beta_{M1})] \tag{5}$$

where $LL(\beta_{M1_{M2}})$is the log-likelihood at the convergence of a model using the converged parameters from the M_2 model with M_1 data, and $LL(\beta_{M1})$ is the log-likelihood at convergence for model M_1. χ^2 is the chi-square statistics that will be utilized with degrees of freedom that equal to the number of the estimated parameters in ($\beta_{M1_{M2}}$) model.

3. Data description

Driver experience might be assessed in several approaches; by driven distance (McCartt et al., 2003), the net period of driving (Kaneko and Jovanis, 1992), time working (Blom et al., 1987), length of licensure (Cornwall, 1962), rate of exposure (Clarke et al., 2006) or combinations of these (Dorn and Af Wåhlberg, 2008). However, the number of years spent driving since licensure is the most widely measured of the driving experience (Af Wåhlberg and Dorn, 2019).

Generally, the driver licensing system was developed to ensure that drivers are competent enough to commence driving and acknowledge the obligations (Bates et al., 2018). In this study, the type of driving license is considered to describe the driver experience. Table 1 explains the types of driving licenses of motor vehicles in South Australia, which was summarized from DPTI (2020). This includes license type, minimum driver age, the minimum length of licensure, restrictions, and penalties.

In the present study, the road crashes data in the South of Australia were used (Data.Sa, 2018). Individually, seven years of crash data from 2012 to 2018 were analyzed to focus on road crashes for motor vehicle drivers in 4-legs roundabouts. Fig. 1 shows the dataset contained a total of 8702 crash records in roundabouts, with 6623 of the crashes occurred in 4-legs roundabouts, which is used in this study.

The number of crashes is 6623, 4017, 662,184, and 1760 for all data, full, provisional, learner, and unknown, respectively, as shown in Fig. 2. Fig. 3 shows the number of crashes according to the injury severity and license type. For example, in the full model, the number of injuries and no injury is 1181 and 2836, respectively. Fig. 4 provides a general idea of how the types of driving licenses are distributed among different groups of age.

Table 1
Types of driving license of motor vehicles in South Australia.

Details	**Driving license types**			
	Learner license (L)	Provisional 1 license (P1)	Provisional 2 license (P2)	Full license (F)
Minimum Age	16 years	17 years	18 years	20 years
Minimum length of licensure	One year (Not holding license before) Six months (already hold a license or over 25 years of age)	One year	Two years	Unlimited
Restrictions				
Drive independently	No	Yes	Yes	Yes
Blood alcohol level	Zero	Zero	Zero	0.05
Display permit plates on front and rear of the vehicle	Yes	Yes	Yes	No
Ride over 100 kph	No	No	No	Yes
Drive high-powered vehicle if under the age of 25	No	No	No	Yes
The ride between midnight and 5 am vehicle if under the age of 25	No	No	No	Yes
Breaking the rules (maybe applied)				
Fined, incur demerit points,	Yes	Yes	Yes	Yes
Change to licensure (if disqualified from driving, permit canceled)	Hold a learner's permit for a more extended period	Re-apply for the provisional license	Re-apply for the provisional license	Re-apply for the provisional license
	–	Hold P1 again for one year	Hold P2 again for two years	If return to P1 stage must hold P1 again for one year and P2 for two years
	–	–	–	If return to the P2 stage must hold P2 for two years

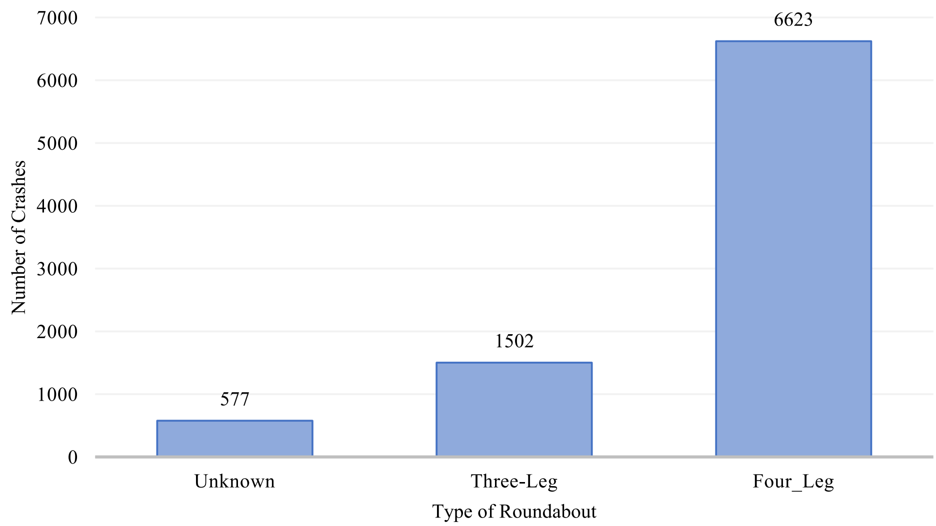

Fig. 1. Number of crashes according to the type of roundabouts.

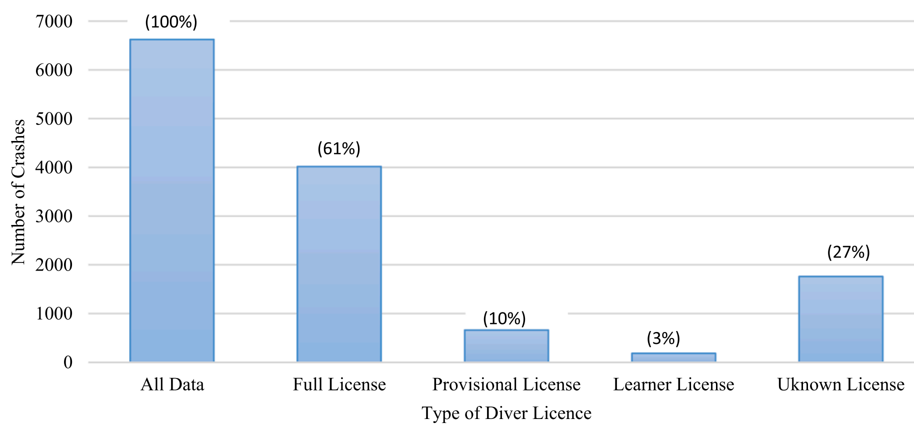

Fig. 2. Number of crashes according to the license's type.

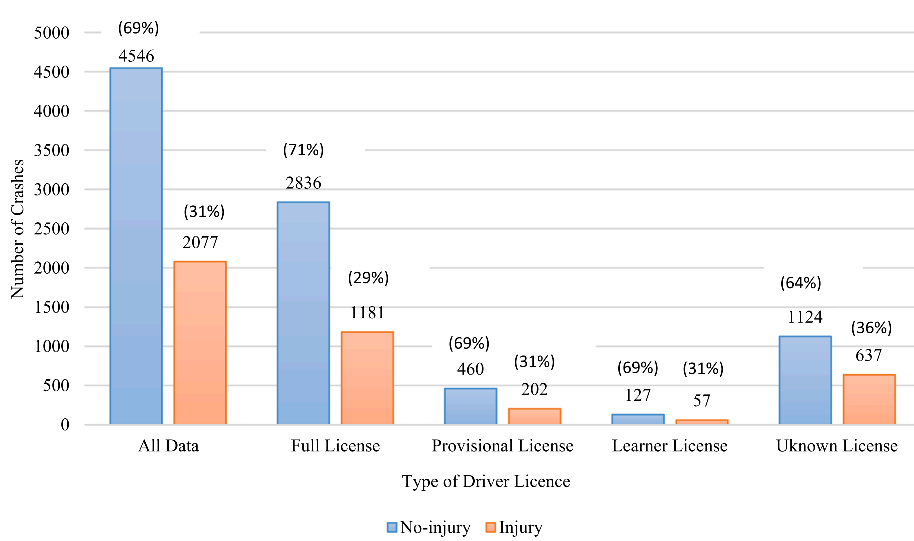

Fig. 3. Number of crashes according to the injury severity and license's type.

Table 2 provides a summary of all the detailed data information about the significant variables, including their definitions, descriptions, mean, and standard deviation in the parenthesis. The correlation matrix between the significant variables have been tested to be ensure that there are no interactions among them. Explanatory variables are classified into seven categories: driver characteristics, vehicle movement,

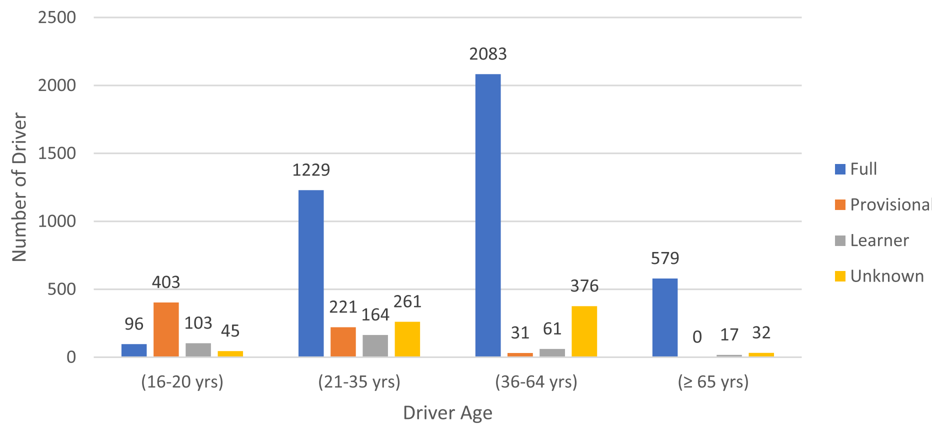

Fig. 4. Distribution of the driver license according to driver age.

crash characteristics, temporal characteristics, spatial characteristics, vehicle characteristics, and roadway characteristics. As shown in Table 2, dummy variables (0–1) are also created for each classification variable. Furthermore, crash falls into four levels outcome: fatal, serious, minor, and no injury. With the minimal number of observations of the severe and fatal, the findings have been grouped into two outcomes: injury (minor, sever, and fatal together) and no injury. After the data cleaning process, all observations are selected and used in developing the random parameter binary probit model.

4. Results and discussion

The provisional model log-likelihood, with a chi-square statistic of 9.82 and 2 degrees of freedom, is also performed better with over 98% confidence. A chi-square statistic of 17.32 and 4 degrees of freedom indicates that with 99% confidence, the random parameter log-likelihood of the full model has a higher statistical significance than the fixed one. As for the results regarding model separation, applying Eq. (4) comes about in a chi-square measurement of 2280.16 with six degrees of freedom being the total number of estimated parameters in the three driving license models minus the number of the random estimated parameters in the all data model. Therefore, Eq. (4) suggests that crashes at the 4-legs roundabouts need be modeled separately according to the driving license type with well over 99% confidence, so just the separated models will discuss in this study (learner, provisional, and full models).

The transferability test results were conducted by applying Eq. (5) are shown in Table 3. The results indicated that according to the estimated chi-squares with the specific degrees of freedom values (in the parenthesis) with 99.99% confident level of using separated models according to driver license of the roundabout.

Table 4 summarized the results for 6623 crashes for four random parameters binary probit models depended on the driver experience in terms of the type of licensure. All variables that were significant at a 90% confidence level and more were retained for the subsequent analyses. A parameter with a positive sign indicates that the injury severity level for this variable has increased, while a negative sign indicates that the injury severity level has decreased.

4.1. Driver characteristics

The study of marginal effects in Table 5 offers more information regarding each of the four categories (gender of the driver, age of the driver, alcohol indicator, and safety equipment use). The male driver parameter was found statistically significant and negative in the learner model. The likelihood of male drivers of getting injured decreased by −0.129. This finding is similar to several previous studies on driver injury severity (Evans, 2004; Kockelman and Kweon, 2002; Li et al., 2019; Shaheed et al., 2016; Zubaidi et al., 2020). However, in this study, the finding is only related to the learner drivers, which means that the results did not show any significant effect between gender among the drivers who have provisional and full licenses. The male physical characteristics could explain the decrease of likelihood among the male learner drivers. Also, males reported that it was easier for them to obtain supervised practice than females, and females were more likely than males to require multiple attempts to pass the driving tests from learner to provisional phase (Bates et al., 2018).

Regarding the influence of driver age, the study found that drivers aged 35–64 years old have a higher probability of possible injury in the full model. The possibilities of the age of the driver were resulting in an injury outcome increased by 0.039. This is expected since most of the full licensed drivers usually fall in this range. The increase in the injury outcome could be interpreted as the middle-aged drivers are accustomed to driving and tend to show less cautious behaviors as reported by (Adebisi et al., 2019).

Looking at the effect alcohol indicator; this factor describes drivers' state of consciousness, the probabilities of resulting injury are increased by 0.207 and 0.108 for only provisional and full licensed drivers, respectively. This result is expected and consistent with previous studies (Behnood et al., 2014; Behnood and Mannering, 2017). This could be attributed to the fact that provisional and full licensed drivers are independent. In contrast, learner drivers are accompanied by full licensed supervisors, so it is unlikely to see this spectrum of drivers under the effect of alcohol.

For the impact of driver characteristic, the analysis indicated that the estimated parameter of the safety equipment uses (i.e., not using a seatbelt) was found to be statistically significant and random, with a mean of 1.61 and standard deviation of 1.47. This indicates that 14% of drivers who did not use seatbelt have a value of less than zero, which means that they are less likely to bring about injury outcome; this might be related to slow speed or light accident in the roundabouts. In contrast, 86% of them have a value greater than zero, which means they have an increased probability of a possible injury outcome. Furthermore, for safety equipment not used the likelihood of involvement in injury severity, the marginal effects indicated that safety equipment did not use increases in chances the probability of injury by 0.427 for provisional drivers only. Several studies suggest that violations become more common in the early stages of independent driving (Roman et al., 2015; Rowe et al., 2013). The protective effect of seatbelts has been verified and evaluated in abundant studies (Chen et al., 2015, 2016).

4.2. Vehicle movement

For vehicle movement, the marginal effect results in Table 5 show a decrease in the probability of being injured for swerving and turning right by −0.174 and −0.078, respectively, in the full model. This might be related to the speed reduction while entering the roundabout.

Table 2
Descriptive statistics of mean and the standard deviation of the selected variables.

Variables	Descriptive Statistics			
	Learner Model Mean (S.D)	Provisional Model Mean (S.D)	Full Model Mean (S.D)	All Data Model Mean (S.D)
Driver Characteristics				
Gender of driver (1 if male, 0 otherwise)	0.68 (0.47)	–	–	–
Age of the driver (1 if 35 < middle age < 65, 0 otherwise)	–	–	0.52 (0,0.9)	0.04 (0.19)
Alcohol indicator (1 if that participant had been drinking, 0 otherwise)	–	0.04 (0.19)	0.03 (0.17)	–
Safety Equipment Use (1 if seatbelt is not used, 0 otherwise)	–	0.98 (0.13)	–	0.99 (0.11)
Vehicle Movement				
Vehicle movement (1 if swerving, 0 otherwise)	–	–	0.04 (0.14)	0.32 (0.14)
Vehicle movement (1 if turning right, 0 otherwise)	–	–	0.09 (0.29)	0.08 (0.29)
Crash Characteristics				
Crash Type (1 if side-swap crash, 0 otherwise)	–	0.06 (0.24)	–	–
Crash Type (1 if right angle crash, 0 otherwise)	0.39 (0.49)	–	–	0.53 (0.49)
Crash Type (1 if hit motorcycle, 0 otherwise)	0.28 (0.45)	–	0.03 (0.17)	0.03 (0.18)
Crash Type (1 if rear-end crash, 0 otherwise)	–	0.24 (0.43)	0.25 (0.43)	–
Number of involved vehicles *(continuous)*	–	2.13 (0.42)	–	–
Temporal Characteristics				
Time of the crash (if during nighttime between 12am-6am, 0 otherwise)	–	0.04 (0.19)	–	–
Time of the crash (if at morning between 6 am-12 pm, 0 otherwise)	–	–	0.29 (0.45)	0.28 (0.45)
Weekdays indicator (1 if the crash happened during the weekdays, 0 otherwise)	–	0.78 (0.42)	0.81 (0.39)	0.79 (0.41)
Spatial Characteristics				
Stats Area (1 if the crash occurred within city, 0 otherwise)	–	–	0.03 (0.18)	0.03 (0.15)
Stats Area (1 if the crash occurred within metropolitan, 0 otherwise)	–	–	0.87 (0.33)	0.88 (0.33)
Vehicle Characteristics				
Vehicle age (1 if age < 20 yrs., 0 otherwise)	–	0.61 (0.48)	–	0.61 (0.49)
Vehicle type (I if passenger car, 0 otherwise)	–	–	–	0.71 (0.45)
Roadway Characteristics				
Surface condition (1 if dry, 0 otherwise)	0.89 (0.32)	0.83 (0.38)	–	–
Vertical Alignment (1 if level road, 0 otherwise)	0.93 (0,26)	–	–	–
Horizontal Alignment (1 if curved road, 0 otherwise)	0.18 (0.38)	–	–	–
Horizontal Alignment (1 if straight road, 0 otherwise)	–	0.83 (0.37)	–	–
Posted Speed Limit (1 if the speed limit more than 50 kph (31 mph), 0 otherwise)	–	–	0.61 (0.49)	0.57 (0.49)

Table 3
Chi-square statistics and degrees of freedom for driver injury severity regarding driver license type transferability test.

M_1	M_2		
	Learner Model	Provisional Model	Full Model
Learner Model	–	112.6 (11)	98.1 (12)
Provisional Model	104.03 (7)	–	102.5 (12)
Full Model	98.41 (7)	105.7 (11)	–

Besides, this range of experienced drivers has more awareness and quicker time reaction towards danger than other inexperienced drivers.

4.3. Crash characteristics

Results of the random parameters binary probit model suggest that the marginal effect of side-swap crashes was significantly negative and associated with a driver of motor vehicle injury severity by −0.354 in the provisional model. This may be explained by the driver with provisional license get more experience and become more responsible while driving. This finding is not in line with (Isebrands, 2009). Moreover, the right-angle crash in motor vehicle crashes decreases the likelihood of an injury outcome by −0.104 in the learner model. One potential explanation for this result may be associated with drivers with learner licenses are always aware and supervised. The new learner drivers have the safest period of driving at the first early stage when risk exposure is mitigated by an in-vehicle supervisor (Bates et al., 2009).

Concerning crash characteristics, hit motorcycle show a significant effect in increasing the risk of an injury outcome by 0.376 and 0.355 for learner and full model, respectively. Motorcyclists usually do not slow down before they enter a roundabout (Baker, 2020). Moreover, drivers with learner licenses might not have enough information about motorcycle rules, and they might have a lack of experience to deal with such situations. On the other hand, the drivers with a full license have more mile's trip; therefore, they are more exposed to crashes with road users (Adebisi et al., 2019).

The indicator for rear-end crash was found to have a random and normally distributed estimated parameter in full model with a mean of −0.15 and a standard deviation of 0.42. The result suggests that about 64% of drivers in this license group decreases the likelihood of being an injury. While for 36%, the opposite is accurate, and this is compatible with the results of the driver with the provisional license. It might be related to high-speed driving or driver behavior. The marginal effects show that rear-end crashes significantly decrease the likelihood of injury by −0.155. Opposite finding for the driver with full license and compatible with driver with a provisional license has been highlighted in a previous study, which showed that in rear-end crash driver had a less chance of being involved in an injury crash (Isebrands, 2009).

The number of involved vehicles in a crash variable was found to be random and normally distributed, with a mean of −0.55 and a standard deviation of 0.39 in the provisional model only. This suggests that about 92% of crashes involved many vehicles have a mean less than zero, while about 8%% of them have a mean more than zero. In other words, 92% of the number of involved vehicles are less likely to result in injury outcome, whereas 8% are more likely to do so. This might be related to location, sometimes slow speed or high-speed effect. Marginal effects show the number of involved vehicles significantly decreases, getting injured crash by −0.124.

4.4. Temporal characteristics

Nighttime between 12 am-6 am was found to be significant in the provisional model, with negative coefficients indicating that the likelihood of injury is decreased by −0.305, this finding is not in line with some of the previous work (Doherty et al., 1998; Yu and Abdel-Aty, 2014). Bham et al. (2012) also showed that severe crashes are more

Table 4
Comparison of random parameter binary probit model results of the learner, provisional, full and all data models.

Variables	Learner Model		Provisional Model		Full Model		All Data Model	
	Coefficient	*t*-test	Coefficient	*t*-test	Coefficient	*t*-test	Coefficient	*t*-test
Constant	1.69	6.48	−3.38	−3.76	−0.95	−9.80	−1.19	−5.22
Standard Deviation of Parameter, Normally Distributed	−1.64	−1.92	1.44	12.31	–	–	–	–
Driver Characteristics								
Gender of driver (1 if male, 0 otherwise)	−0.64	−1.80	–	–	–	–	–	–
Age of the driver (1 if 35 < middle age < 65, 0 otherwise)	–	–	–	–	0.15	2.87	0.41	7.79
Alcohol indicator (1 if that participant had been drinking, 0 otherwise)	–	–	0.93	2.18	0.39	2.34	–	–
Safety Equipment Use (1 if seatbelt is not used, 0 otherwise)	–	–	1.61	2.62	–	–	0.21	1.00
Standard Deviation of Parameter, Normally Distributed	–	–	1.47	2.98	–	–	0.91	28.74
Vehicle Movement								
Vehicle movement (1 if swerving, 0 otherwise)	–	–	–	–	−0.64	−3.33	−1.06	−5.04
Vehicle movement (1 if turning right, 0 otherwise)	–	–	–	–	−0.29	−3.23	−0.52	−5.34
Crash Characteristics								
Crash Type (1 if side-swap crash, 0 otherwise)	–	–	−1.59	−3.72	–	–	–	–
Crash Type (1 if right angle crash, 0 otherwise)	−0.52	−1.67	–	–	–	–	0.33	6.56
Crash Type (1 if hit motorcycle, 0 otherwise)	1.87	4.43	–	–	1.31	9.06	0.93	8.77
Crash Type (1 if rear-end crash, 0 otherwise)	–	–	0.69	3.96	−0.15	−2.87	–	–
Standard Deviation of Parameter, Normally Distributed	–	–	–	–	0.42	4.76	–	–
Number of involved vehicles *(continues)*	–	–	−0.55	−2.82	–	–	–	–
Standard Deviation of Parameter, Normally Distributed	–	–	0.39	9.40	–	–	–	–
Temporal Characteristics								
Time of the crash (if during nighttime between 12am-6am, 0 otherwise)	–	–	−1.37	−2.63	–	–	–	–
Time of the crash (if at morning between 6 am-12 pm, 0 otherwise)	–	–	–	–	0.18	3.21	0.23	4.11
Weekdays indicator (1 if the crash happened during the weekdays, 0 otherwise)	–	–	0.54	2.98	0.09	1.39	0.20	3.35
Standard Deviation of Parameter, Normally Distributed	–	–	–	–	1.04	7.37	–	–
Spatial Characteristics								
Stats Area (1 if the crash occurred within city, 0 otherwise)	–	–	–	–	0.59	1.94	0.92	2.92
Stats Area (1 if the crash occurred within metropolitan, 0 otherwise)	–	–	–	–	0.23	2.84	0.31	4.04
Standard Deviation of Parameter, Normally Distributed	–	–	–	=	0.09	3.31	–	–
Vehicle characteristics								
Vehicle age (1 if age < 20 yrs., 0 otherwise)	–	–	0.41	2.71	–	–	−0.34	−6.14
Vehicle type (I if passenger car, 0 otherwise)	–	–	–	–	–	–	−1.37	−18.83
Standard Deviation of Parameter, Normally Distributed	–	–	–	–	–	–	3.25	33.59
Roadway characteristics								
Surface condition (1 if dry, 0 otherwise)	1.34	2.02	0.58	2.86	–	–	–	–
Vertical Alignment (1 if level road, 0 otherwise)	−0.93	−1.76	–	–	–	–	–	–
Horizontal Alignment (1 if curved road, 0 otherwise)	1.52	3.51	–	–	–	–	–	–
Horizontal Alignment (1 if straight road, 0 otherwise)	–	–	0.49	2.37	–	–	–	–
Posted Speed Limit (1 if the speed limit more than 50 km/hr., 0 otherwise)	–	–	–	–	−0.75	−2.87	−0.35	−6.88
Standard Deviation of Parameter, Normally Distributed	–	–	–	–	0.82	2.84	–	–
Log likelihood function	−95.24		−383.64		−2359.37		−3978.33	
Log likelihood at zero	−123.88		−507.23		−2933.08		−4619.20	
McFadden Pseudo R-squared	0.231		0.244		0.196		0.139	
AIC	206.5		795.3		4750.7		7988.7	
No. of observations	184		662		4017		6623	

probable to happen during nighttime. This can be attributed to the drivers with a provisional license who do not have enough experience so that they might be avoid driving at night. Also, Table 1 showed it is illegal to drive during this period while being younger than 25 years of old and holding provisional licensure. Therefore, it could be those drivers who broke this role and tended to drive with awareness to avoid any traffic troubles.

Moreover, in general, there are no jam density inroads between 12 am-6 am. Looking at the effect of the crash in the morning between 6 am-12 pm, the results indicated that the probability of driver being injured increases by 0.048 in the full model. This finding is consistent with previous studies that explored the effect of the crash in the morning on injury (Yu and Abdel-Aty, 2014).

Crashes happening during weekdays were found to be random with normal distribution in the full model. With a mean of 0.09 and a standard deviation of 1.04, the results indicated that 47% of drivers in these crashes have less likelihood of being involved in injury outcomes, whereas 53% of them have more likelihood, which was similar to the result found by (Behnood and Mannering, 2019; Islam and Hernandez, 2013). The marginal effects indicated that crashes in weekdays increase the chances for the driver of being injured by 0.120 and 0.024 in the provisional and full model, respectively. This result can be mainly related to numerous trips during weekdays for school and works trips.

4.5. Spatial characteristics

The crash occurred within the city are found to increase the likelihood of an injury by 0.161 in the full model. The other significant association established was crash occurred within metropolitan, the indicator variable for it was found to be statistically significant with a random parameter that is normally distributed in the full model, with mean 0.23 and standard deviation of 0.09. This indicates that about 99% experienced more injury whereas about 1% (less than zero) of the crash has a lower level of injury, The results for crash occurred within metropolitan might be due to the large cities has jam density which leads to reduce speed; as a result, reducing in injury. The marginal effects indicated that the crash occurred within metropolitan increases the probability of injury by 0.061 in the full model.

4.6. Vehicle characteristics

This research found that the probability of driving a modern car <20 years of age increased an injury outcome by 0.091 in the provisional model. A possible explanation might be that people with this type of license are getting more experienced, but sometimes they might be overestimating their ability. Also, several studies indicate that violations become more common in the early stages of independent driving

Table 5
Comparison of marginal effects between the learner, provisional, full and all data models.

Variables	Marginal Effects			
	Learner Model	Provisional Model	Full Model	All Data Model
Driver Characteristics				
Gender of driver (1 if male, 0 otherwise)	−0.129	–	–	–
Age of the driver (1 if 35 < middle age < 65, 0 otherwise)	–	–	0.039	0.048
Alcohol indicator (1 if that participant had been drinking, 0 otherwise)	–	0.207	0.108	–
Safety Equipment Use (1 if seatbelt is not used, 0 otherwise)	–	0.427	–	0.025
Vehicle Movement				
Vehicle movement (1 if swerving, 0 otherwise)	–	–	−0.174	−0.124
Vehicle movement (1 if turning right, 0 otherwise)	–	–	−0.078	−0.061
Crash Characteristics				
Crash Type (1 if side-swap crash, 0 otherwise)	–	−0.354	–	–
Crash Type (1 if right angle crash, 0 otherwise)	−0.104	–	–	0.039
Crash Type (1 if hit motorcycle, 0 otherwise)	0.376	–	0.355	0.110
Crash Type (1 if rear-end crash, 0 otherwise)	–	0.155	−0.115	–
Number of involved vehicles	–	−0.124	–	–
Temporal Characteristics				
Time of the crash (if during nighttime between 12am-6am, 0 otherwise)	–	−0.305	–	–
Time of the crash (if at morning between 6 am-12 pm, 0 otherwise)	–	–	0.048	0.027
Weekdays indicator (1 if the crash happened during the weekdays, 0 otherwise)	–	0.120	0.024	0.023
Spatial Characteristics				
Stats Area (1 if the crash occurred within city, 0 otherwise)	–	–	0.161	0.108
Stats Area (1 if the crash occurred within metropolitan, 0 otherwise)	–	–	0.061	0.037
Vehicle Characteristics				
Vehicle age (1 if age < 20 yrs., 0 otherwise)	–	0.091	–	−0.040
Vehicle type (I if passenger car, 0 otherwise)	–	–	–	−0.161
Roadway Characteristics				
Surface condition (1 if dry, 0 otherwise)	0.269	0.128	–	–
Vertical Alignment (1 if level road, 0 otherwise)	−0.187	–	–	–
Horizontal Alignment (1 if curved road, 0 otherwise)	0.304	–	–	–
Horizontal Alignment (1 if straight road, 0 otherwise)	–	0.111	–	–
Posted Speed Limit (1 if the speed limit more than 50, 0 otherwise)	–	–	−0.102	−0.041

(Roman et al., 2015); therefore, modern vehicles can be drove aggressively than old vehicles.

4.7. Roadway characteristics

The marginal effects in Table 5 indicated a 0.269 and 0.128 increase in the probability of driver getting injured when crashes occurred on a dry road surface in the learner and provisional model, respectively. The reason might be attributed to the combination of higher vehicle speeds under dry conditions and lack of driver experience, as argued in previous researches (Kockelman and Ma, 2007; Leard and Roth, 2015). Besides, the crash risks peak during the first few months of unsupervised driving upon obtaining their provisional license (Bates et al., 2009).

According to the vertical alignment feature, the level approaches of the roundabout drivers are less likely to be involved in an injury crashes, with probability decreasing by −0.187 in the learner model. This specifically refers to the driver with a learner model are more awareness and the sight distance for level alignment always clear.

Driving on a horizontal curve increases the probability of injuries by 0.304 for the learner model. The drivers with the learner model can explain this have less experience to negotiate the driving around the curve. Additionally, horizontal curves reduce the visibility and maneuverability of the drivers. Also, driving around bends has high crash risk situations for inexperienced drivers (Clarke et al., 2006). It is also noted that horizontal straight roads increase the likelihood of injuries by 0.111 for the provisional model. This might be attributed to the failure of reducing speed or yielding while entering the roundabouts.

Finally, the estimated parameter for crashes because of speed limit more than 50 km/hr (31 mph) was found to have a random parameter that was normally distributed. With a mean of −0.75 and a standard deviation of 0.28, the results indicated that crashes involving speed limit more than 50 km/hr have a decrease in injury outcome probability, and 82% have an increase in injury outcome probability. In contrast, 18% have the opposite situation. These results are consistent with previous studies (Lu et al., 2010; Zhu and Srinivasan, 2011; Cerwick et al., 2014; Osman et al., 2016). This marginal effect shows that this factor is significantly negative. This is expected since the speed limits at roundabouts are generally low.

5. Summary and conclusions

Identifying factors that increase or decrease the risk of driver injury severity is one of the fundamental tasks required to enhance the safe operation of roundabouts in South Australia. The first step in this study was to select an appropriate statistical model to analyze the dataset. A random parameter binary probit model was used to identify the significant factors that contribute to 6623 driver injury severity in different crashes sustained by different driving experiences at 4-legs roundabouts in South Australia. Four models were estimated based on seven years of crash data from 2013 to 2018. The four estimated models were based on different levels of driver experience considering the type of the driving license: learner model (learner licensure), provisional model (provisional licensure), full model (full licensure), and all data model (a combination of the learner, provisional, full licensure, and another unknown type). The dependent variables of all the models comprised of two outcomes: (1) injury and (2) no injury.

The results showed that crashes at the 4-legs roundabouts need to be modeled separately according to the driving license type with well over 99% confidence. It was found that there are significant differences in driver-injury severities resulting from the different driving experience. The explanatory variables of the model estimates are categorized into the driver, crash, temporal, spatial, vehicle, roadway characteristics, and vehicle movements. Several parameters were found to be random and normally distributed: safety equipment, crash type (rear-end crash), number of involved vehicles, weekdays indicator, stats area (crash occurred within metropolitan), vehicle type (passenger car), and posted speed limit (more than 50 km/hr.).

The main findings show that the male driver was found statistically significant and negative in the learner model only. The male physiology characteristics could explain the decrease of likelihood among the male learner drivers; they might be feeling more confident while driving as a learner driver. Drivers aged 35–64 years old have a higher probability of possible injury in the full model. Alcohol effect increased the likelihood of possible injuries among provisional and full licensed drivers. Safety equipment uses (i.e., not using a seatbelt) was found to increase the probability of injury by 0.427 for provisional drivers only. This is explained as violations become more common in the early stages of independent driving. The marginal effects show that rear-end crashes significantly decrease the likelihood of injury by −0.155. Crashes in weekdays were found to increase in chances of injuries by 0.120 and 0.024 in the provisional and full model, respectively. This result can be mainly related to numerous trips during weekdays for school and works trips. The level approaches of the roundabouts are less likely to be involved in injury crashes in the learner model. This specifically refers to the driver with the learner model are more awareness and the sight distance for level alignment always clear. While driving on a horizontal curve increases the probability of injuries by 0.304 for the learner model, this is because driving around bends has high crash risk situations for inexperienced drivers.

Several low-cost mitigation measures can reduce the number of crashes at roundabouts. First, improving pavement marking and signage to guide the motorist better and enhance driver expectancy. Furthermore, educating the public, including public–private partnerships between law enforcement agencies, driver's education instructors, transportation engineering groups, and insurance companies.

This study has several limitations. There are around 1760 crashes with an unknown type of driver license could have a significant impact if added to the current results. Also, missing some crucial variables could give more insight into the driver injury severity like the number of lanes, AADT, presence of streetlights, impaired driver situation, presence of the mini-roundabouts, age of the roundabout, and the location of the crash for example; in the entrance, at the circulating or the exit.

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