Backpropagation – Artificial Neural Network (BP-ANN): Understanding gender characteristics of older driver accidents in West Midlands of United Kingdom

Amin, S.

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Backpropagation - Artificial Neural Network (BP-ANN): Understanding Gender Characteristics of Older Driver Accidents in West Midlands of United Kingdom

Abstract
Older people are vulnerable road users with higher rate of casualties in traffic accidents. The commonly cited causes of accidents for older people are poor attention and decision making at critical locations of road, poor visibility in extreme weather, poor road surface condition and unpredictability of other road users, particularly young drivers. Female drivers are often labelled as being precarious drivers and having higher accident risk comparing to male drivers. This paper applies Backpropagation - Artificial Neural Network (BP-ANN) with a Generalized Delta Rule (GDR) learning algorithm to model the factors affecting traffic accidents of both older female and male drivers. The BP-ANN can construct the causation model of traffic accidents with greater accuracy and define the proportion of errors contributed by each factor to traffic accidents. This paper studies a total of 95,092 accident records in West Midlands of the United Kingdom during the period of 2006 to 2016. This paper determines journey purpose, lighting condition, pedestrian crossing with physical interventions, complex roadway geometry, extreme weather and time severity as the most significant factors of older driver accidents. The accident risk of older drivers can be improved by providing accessible routes, affordable, reliable and convenient public transport, timely warning of unexpected situations and changes in roadway geometry; increasing use of assistive technology in cars, driverless cars and encouraging active transports into sociable activities. The findings help the transport authorities and city councils to develop strategies and measures promoting public and active transports to ensuring the safety of older drivers.

Keywords: accident; gender; older drivers; neural network; backpropagation algorithm; modelling errors

Introduction
The world's population is ageing and almost every country is experiencing growth in the number of elderlies. It is arbitrary to define the age of older drivers because biological age varies from person to person. Most developed countries define the chronological age of 65 years as an older person, however, the United Nations as well as the Department for Transport (UK) refer people aged 60 years and over as the older population (World Health Organization 2002; Department for Transport 2017). This UK classification is supported by UK statistics reporting a significantly higher number of accident and emergency (A&E) attendances by people aged 60 years and over (NHS England data 2015). Therefore, this paper considers drivers aged 60 and over as the older drivers.

The World Population Prospects: the 2019 Revision projected that one in six people in the world will be over age 65 (sixteen percent) by 2050, up from one in eleven in 2019 (nine percent). In the UK, people aged 65 and above will be twenty percent of total population by 2026 that will make up eight to ten percent of all license holders (Hayter 2019; RAC Foundation 2019). Older persons are mostly dependent on their cars because of convenience and lack of accessibility by public transports. The increasing number of older drivers on the streets raises new challenges for road safety as studies show that older drivers give up driving because of health conditions (Holley-Moore and Creighton 2015). The AgeUK study observed that forty-three percent drivers aged 60 and over would stop driving because of health concerns while only one percent of this age group would stop driving because of their age (Holley-Moore and Creighton 2015).

In the UK, the casualty rates were higher amongst the youngest (aged 0-15) and oldest drivers (aged 60 and over), Department for Transport (2017). Drivers aged 60 and over were contributing thirty percent of total deaths in traffic accidents (Department for Transport 2017). In New South Wales of Australia, older drivers were found to be more likely to be killed or seriously injured in road accidents compared to younger drivers (Boufous et al. 2008). McKnight and McKnight (1999) also investigated that drivers aged over 62 were seventeen times more likely to be killed in traffic accident per mile of travel. Lotfipour et al. (2013) found that older drivers had higher fatality ratio than middle-aged drivers in the Orange County at California and drivers over 80 were more fragile. Similar findings were observed in the fatal accidents in Utah studied by Cook et al. (2000).

There are many factors leading to accidents, these are reviewed in Section 2 and exploited in the approach described in Section 3. This paragraph reviews methods that have been applied to investigate the cause of road accidents to justify the approach proposed in this paper. Mannering and Bhat (2014) briefly discussed the statistical methodologies applied in road safety studies to extract accurate information from accident database. El-Basyouny and Sayed (2009) also discoursed the standard models used by safety researchers and practitioners in assessing and investigating factors of road accidents. The modelling errors jeopardise the prediction ability of statistical analytical methods using accident database. There are groups of studies that applied regression (Abu-Zidan and Eid 2015), negative binomial (Lord and Mannering 2010; Amin et al. 2014; Naghawi 2018; Malyshkina and Mannering 2010), logit (Santos et al. 2017; Michalaki et al. 2015; Li et al. 2013), probit (Garrido et al., 2014), multivariate (Boufous et al. 2008; Zhang et al. 2000), Bayesian networks (de Oña et al. 2011; de Oña et al. 2013) and Artificial Neural Network (ANN) (Abdulhafedh 2016) to draw the relationship between accident characteristics and severity. Negative binomial is the most frequently used model for accident-frequency modelling, but it is adversely influenced by low sample mean and small sample size and is susceptible to under dispersion (Lord and Mannering, 2010). Lord (2006) investigated the impact of low sample mean on the estimation of dispersion to determine the effects of unreliable dispersion parameter on highway studies. Lord (2006) indicated that dispersion parameter was seriously affected by low sample mean and small sample size, and the probability of dispersion parameter increased when the sample size and mean decreased. Similarly, Bayesian networks are sensitive to small and imbalanced dataset (Oña et al. 2013). The prediction ability of probit models cannot be undeniably verified by the goodness-of-fit measures because the marginal effects in probit models can be misleading for categorical variables (Garrido et al., 2014).

Abdulhafedh (2016) applied the Poisson and negative binomial models to analyse the accident frequency and validated the results with ANN. Abdulhafedh (2016) concluded that ANN predicted results with greater accuracy and determined the importance of explanatory variables without statistical estimates to interpret the accident dataset. The application of ANN requires to investigate the built-in functions and training parameters, including learning rate and momentum term. The inaccurate selection and application of ANN design parameters may affect the accuracy of ANN models (Amin 2015). The generalized delta rule (GDR)algorithm uses a constant negative gradient of the error surface that is paraboloid and determines the stability and speed of convergence of the weight vector towards the minimum error value.

This paper builds on the demonstrated benefits in using ANN for accident data modelling and combined it with GDR algorithm to overcome known issues associated with data sample size and ANN design parameter selection and tuning. It applies BP-ANN with a GDR learning algorithm to model the relationships between the factors affecting road accidents amongst different gender groups of older drivers.

Literature review

The aim of this section is to review the identified causes and factors leading to accidents in older drivers compared to younger drivers. Older drivers are often blamed for road accidents in mixed traffic where the interaction of drivers with different age groups may increase the frequency and severity of road accidents (Clarke et al. 2006). Clarke et al. (2010) argued that older drivers aged under 70 suffered as much from other crash-causing drivers crashing into them as they did by causing crashes themselves, however, the blameworthiness ratios appeared to rise with age after 70 years. Keskinen et al. (1998) assessed the behaviour of young and older drivers in Sendai Japan and concluded that there was no difference in attention between the age groups at familiar traffic situation, however, the older drivers had attention problems in new or demanding situations. Female drivers were often blamed for higher accident risks. Several studies argued that female drivers had less fatality rate in road accidents comparing to that of male drivers (WHO 2002; Laiou et al. 2016). There are also evidences that accident and fatality rates among older and female drivers are improving faster than that of younger drivers (Mitchell 2013; Laiou et al. 2016). However, an injury study of road accidents in Australia revealed that fatality rate of older female drivers was almost double comparing to that of younger drivers (Yee 2006). Royal National Institute of Blind People (RNIB 2013) also indicated that women, compared to men, are more susceptible to Age-related Macular Degeneration (AMD) problem. Amin et al. (2014) investigated that female drivers were more vulnerable to weather-accident severity compared to the male drivers and the accident severity could be increased by 2.4 to 3.7 percent for female drivers applying Poisson and Negative Binomial (NB) regression models, respectively. The AgeUK survey in (Holley-Moore and Creighton 2015) found that forty-three percents of drivers aged 60 and over would stop driving because of health concerns while only one percent of this age group would stop driving because of their age.

The cognitive impairment of older drivers slows the perception time and increases the difficulty to comprehend the complex traffic conditions resulting in higher casualty rate (Daigneault et al. 2002). McGwin Jr and Brown (1999) observed the characteristics of different age groups involved in traffic accidents in Alabama, USA, and stated that older drivers were involved in accidents at junctions failing to yield the right-of-way. This was due to difficulty in visualising moving objects and inability to notice stop signs and signals.

Other factors increasing the risk of accidents are age-related physical and medical conditions. Kent et al. (2005) analysed the fatal accidents and vehicle and occupant characteristics across age groups using Crashworthiness Data System (CDS) from the National Automotive Sampling System (NASS) and the Fatality Analysis Reporting System (FARS) in the USA. Kent et al. (2005) found that mortality rate from traffic accidents increased significantly with age and the older drivers were more likely to die from chest injury due to frontal impact points (Dissanayake 2004). Zhang et al. (2000) conducted a cross-sectional study of road accidents in Ontario, Canada and found that medical or physical conditions could increase the fatality risks of older drivers aged 75-79 and over 80 by five and three and half times, respectively. The physiological and pathological changes in older people such as stiffening of the heart and pericardium combined with atherosclerotic vessels, pulmonary parenchyma changes, osteoporosis, chronic bony changes and narrowing of the spinal canal increase the vulnerability towards rib fractures, pulmonary contusion, cord contusions and central cord syndrome during the accidents (Lotfipour et al. 2013; Branfronbrener et al. 1984). The subdural hematoma associated with a traumatic brain injury can occur more commonly among older victims compared to younger victims because of a smaller brain volume in a rigid skull (Timiras 2007).

The decrease in visual acuity results in poor perception of traffic signals and signs and stopping and overtaking sight distance in darkness (Groot, 1999). The reduction of pupil size and yellowing the lens are two age related causes to reduce the amount light reaching retina and cause the impaired night-time visual acuity (Olson et al. 1983; Olson 1993). In addition, older people are more vulnerable to disability glare because of sensitivity glare and the older drivers require more time to recover disability glare from the headlights of opposite vehicles and other reflecting sources (Kline and Scialfa 1997; Aizenberg and McKenzie 1997). Poor lighting condition also exaggerates the contrast sensitivity among older drivers resulting in difficulty to identify small details that is very dangerous specially to read traffic signs at junctions and critical road segments (such as slip roads). Moreover, contrast sensitivity impairs the perception of stopping distance and speed of moving objects that unable the older drivers to stop their cars safely at the signalised junctions and hit the stopped objects or breakdown vehicles (Shinar and Schieber, 1991; Holland, 2001). The accident risk among older drivers during night-time can be avoided by timely warnings (such as fixed lighting installations) of unexpected situations and changes in roadway geometry so that the perception-reaction time for older drivers can be increased (Staplin et al., 2001).

Several studies defined demographic characteristics, physical and mental conditions, road geometry, location, weather, lighting condition, and traffic management as the significant factors of older driver accidents (Table 2). Garrido et al. (2014) identified that female drivers were more likely to suffer serious or fatal injuries comparing to male drivers in road accidents. Physical and mental conditions of older drivers can impair the awareness, attention and reaction time (McKnight and McKnight 1999). Hakamies-Blomqvist et al. (2004) found that older drivers had issues filtering unrelated stimuli to distribute attention between various sub-tasks at urban junctions. Older drivers take a longer period to visually scan an area and spend a great percentage of their visual inspection time at a smaller area of a visual image in comparison to young drivers (Maltz and Shinar 1999). The narrow vision and deteriorated contrast sensitivity of older drivers decrease the perception times and increase their risk to road accidents (Horswill et al. 2008; Bohensky et al., 2008; Hancock and Manser 1997; Ni et al. 2010).

Several studies found that the location (rurality or urban environment), presence of complex junctions, road condition (dry or wet pavement), traffic volume, road geometry, traffic characteristics were significant factors of severe injuries for older drivers (Boufous et al. 2008; Santos et al. 2017; Garrido et al. 2014; Amin et al. 2014; Gray et al. 2008; Wang et al. 2009). Weather and lighting conditions in combination with other factors can augment the accident risk of older drivers (Amin et al. 2014; Bergel-Hayat et al. 2013; Naghawi 2018; Morgan and Mannering 2011; Gray et al. 2008).

This paper considers the journey purpose (journeypurpose), junction location (junctionlocation), pedestrian crossing (human interventions) (pedcrosssinghum), pedestrian crossing (physical interventions) (pedcrossingphy), lighting condition (light), weather condition (weather), road surface condition (roadsurface), level of carriage hazard (carriagehaz), time severity (timeseverity) and road or junction type (roadtype) as the factors of older driver accidents (Figure 1).

Table 2: Literature matrix on factors influencing older driver accidents

Literature	Factors influencing road traffic accidents										
	Drivers’ error	Physical health	Mental health	Road condition	Lighting	Weather	Road geometry	Traffic condition	Vehicle characteristics	Location	Demographic characteristics
Kowalski et al. 2014		√				√					
Boufous et al. 2008	√						√	√		√	√
Santos et al. 2017				√	√					√	√
Garrido et al. 2014				√				√	√		√
Amin et al. 2014				√		√	√				
McKnight and McKnight 1999		√									√
Naghawi 2018	√			√		√		√	√		√
Morgan and Mannering 2011						√					√
Gray et al. 2008				√	√		√	√		√	√
Wang et al. 2009							√	√			
Hakamies-Blomqvist et al. 2004		√									
Horswill et al. 2008		√									
Bohensky et al., 2008		√									
Hancock and Manser 1997		√						√			
Hakamies-Blomqvist et al. 2004		√								√	
Ni et al. 2010		√				√					

Methodology

This study applies BP-ANN networks with GDR learning algorithm that considers non-linear and multidimensional relationship and minimises the uncertainty of modelling parameters (Amin and Amador-Jiménez 2016). The BP-ANN network has two forms of activation functions: hyperbolic tangent and sigmoid function. This study applies sigmoid function given that the output of the model (e.g. accident risk of older drivers) is a positive value and the logistic function results in positive outputs in the unitary range of (0, 1) (Amin and Amador-Jiménez 2016). Figure 1 shows the input, hidden and output layers of the BP-ANN networks for older driver accidents. The journey purpose (*journeypurpose*), junction location (*junctionlocation*), pedestrian crossing (human interventions) (*pedcrosssinghum*), pedestrian crossing (physical interventions) (*pedcrossingphy*), lighting condition (*light*), weather condition (*weather*), road surface condition (*roadsurface*), level of carriage hazard (*carriagehaz*), time severity (*timeseverity*) and road or junction type (*roadtype*) are the neurons in the input layer. The first and second hidden layers have seven and five hidden neurons (synapse layers), respectively, that are represented by the synaptic weights yielding towards the decision boundary (Figure 1). Synaptic weights in Figure 1 are the strength of connectivity metric between nodes and approximation of multiple processes combined in the BP-ANN networks (Figure 1). The backpropagation algorithm is designed to strengthen the connectivity between layers for optimal solution. The magnitude of a synaptic weight equivalent to a combination of increased resembling connections between different components of layers (such as input variables and synapse layers of hidden layers). The positive weights (grey colour) increase the prospect of receiving cell with an action potential, while negative weights (blue colour) have the opposite action (Figure 1). The outputs are predicted applying a two-phase propagate-adapt cycle and compared with the desired outputs to estimate the errors (bias). These errors are transferred backward from the output layer to synapse layers in hidden layers based roughly on the relative contribution the synapse layers made to the estimated output. This process was repeat layer-by-layer until each neuron in the network received an error representing its relative contribution to total errors.

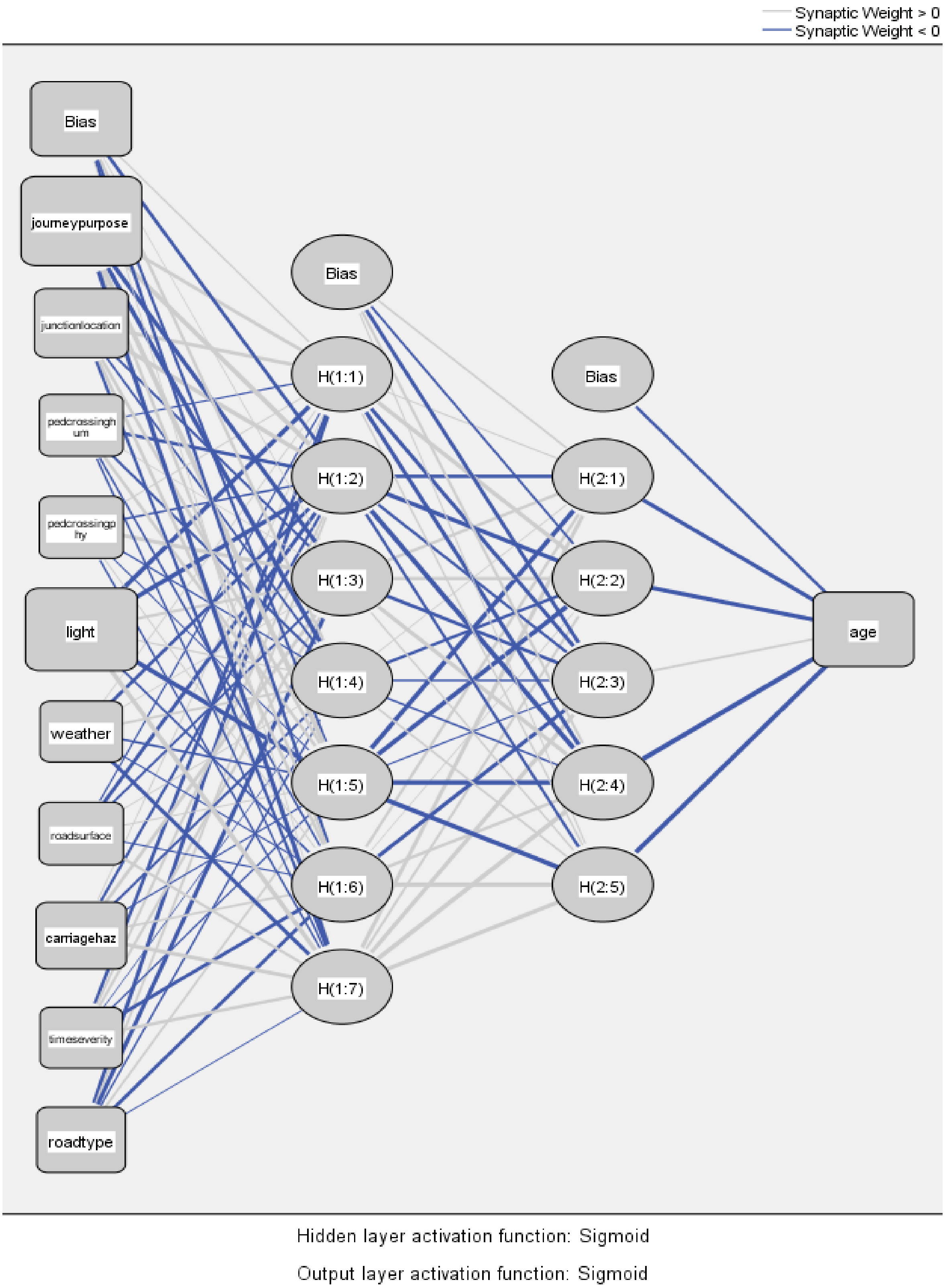


Figure 1: BP-ANN Diagram for factors affecting road traffic accidents involving older drivers

Case study – road accidents at West Midlands, UK

Road accident records in West Midlands for the period of 2006 to 2016 were collected from the Department for Transport. A total of 95,092 accident records were analysed in this study. Figure 2 shows that accident rates of older drivers per year were almost constant despite the reduction of road accidents during the ten-year period. Older drivers were involved in eleven percent of road accidents of whom seventy-two percent drivers were male and twenty-eight percent were female (Table 1). On the contrary, female drivers aged less than 60 were involved in twenty-six percent of road accidents during the same period (Table 1). This study has taken nine domains of input layers of older driver accidents such as journey purposes, junction locations, pedestrian crossing, lighting, weather, road surface, carriage hazards, time severity and road or junction types (Figure 3). The risk levels of each domain are categorised based on accident potential and vulnerability of different input variables. For example, pupils are more vulnerable to traffic accidents comparing to commuters. Drivers in darkness with unknown frequency or location of street lights are more prone to traffic accidents than driving in complete darkness because of drivers' eyes can get weak when overworked.

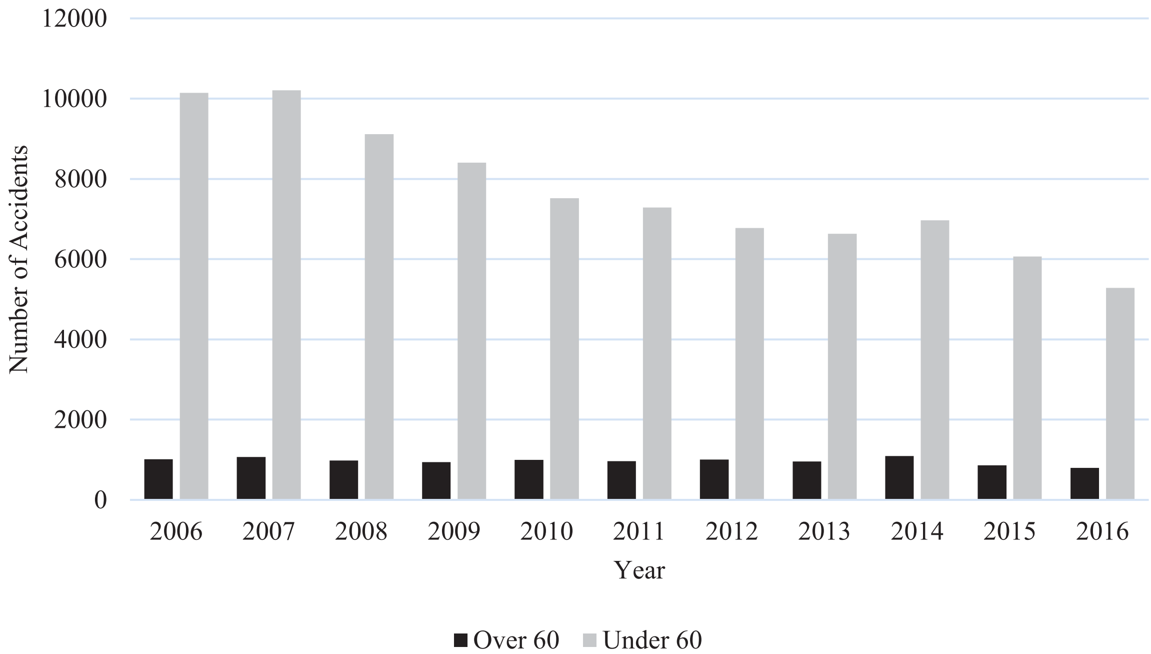


Figure 2: Number of accidents for drivers over and under the age of 60 per year

Table 1: Gender-age profile of road traffic accident records during the period of 2006-2016

Age Groups	Male		Female		Others		Total	
	No.	%	No.	%	No.	%	No.	%
Others (< 60)	57904	60.89%	22395	23.55%	4106	4.32%	84405	88.76%
Older driver (≥60)	7723	8.12%	2960	3.11%	4	0.00%	10687	11.24%
Total/gender group	65627	69.01%	25355	26.66%	4110	4.32%	95092	100

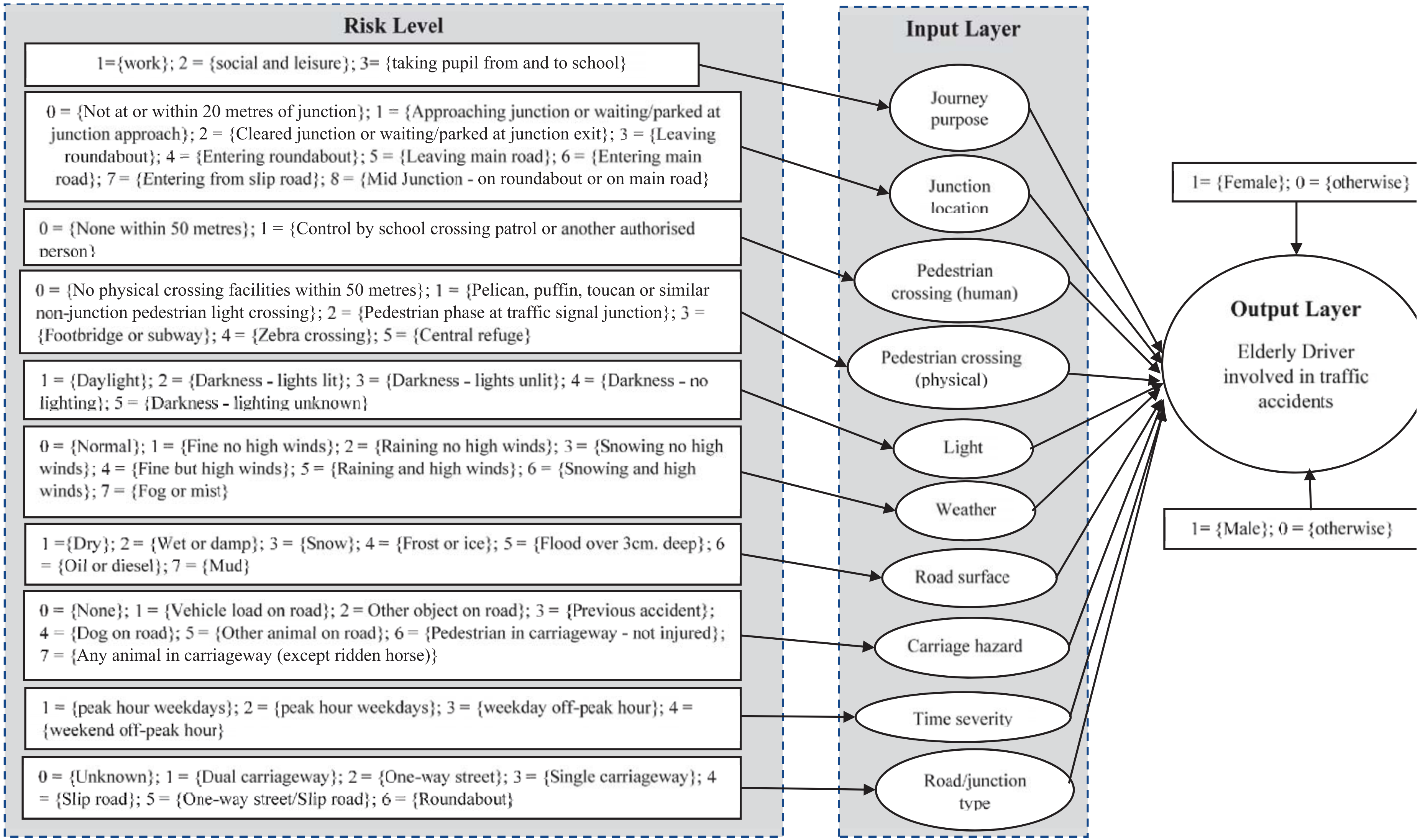


Figure 3: Risk levels of variables for older driver accidents

Data analysis

Road accident database for both older female and male drivers were partitioned into training, testing and validation datasets to construct BP-ANN models (Table 3). Fifty-eight and seventy-four percent data were assigned to define the BP-ANN processes, twenty-eight percent and twenty-one percent data were used to train the BP-ANN networks minimising the errors that prevents the overtraining of BP-ANN models, and fifteen percent and five percent of data were used to assess the overall BP-ANN models and predict the accuracy for female and male drivers, respectively (Table 3). The performance of BP-ANN models was assessed by the Sum of the Squares the Error (SSE) and the Relative Error (RE) (Table 4). The SSE is the cross-entropy error when the sigmoid activation function is applied to the output layer. The BP-ANN models for both older female and male drivers minimise the SSE function during dataset training (Table 4). The RE is the percentage of incorrect predictions that is the ratio of SSE for prediction and null models and is associated with output variable (Amin and Amador-Jiménez 2016). Estimation of BP-ANN models shows negligible difference between observed and predicted values for training data (Table 4). The Insignificant errors for testing and validation data explain the accurate prediction ability of constructed BP-ANN models for accidents of both older female and male drivers (Table 4). The variations of predicted and residual values for male older drivers in Figure 4 and 5 are marginally higher than that for female older drivers because of larger dataset for the male older drivers, respectively.

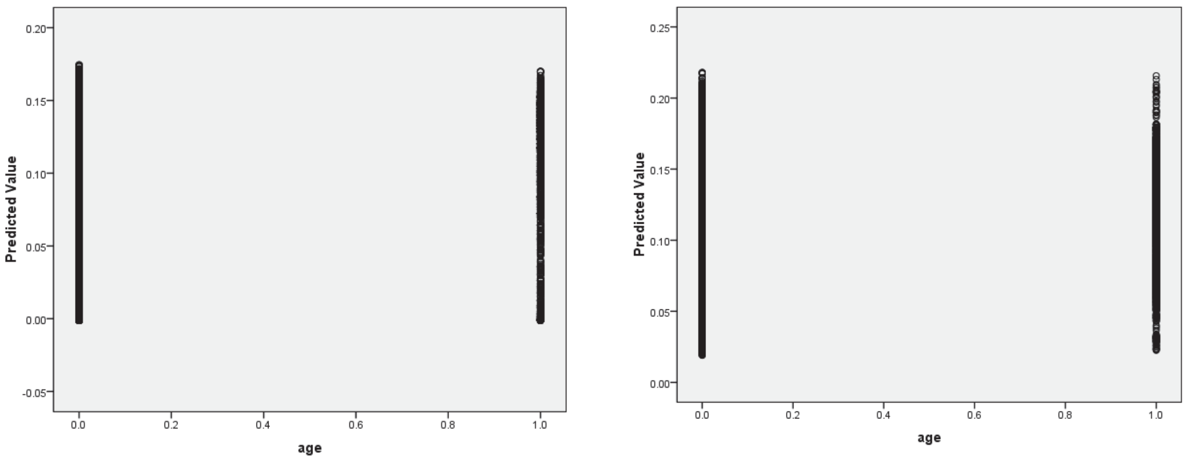
Table 3: BP-ANN optimisation algorithm summary

Samples	Female		Male	
	Data	Percentage	Data	Percentage
Training	17017	57.8	48730	74.3
Testing	8046	27.3	13972	21.3
Holdout	4402	14.9	2925	4.5
Total	29465	100	65627	100

Table 4: Error Estimation of BP-ANN Models

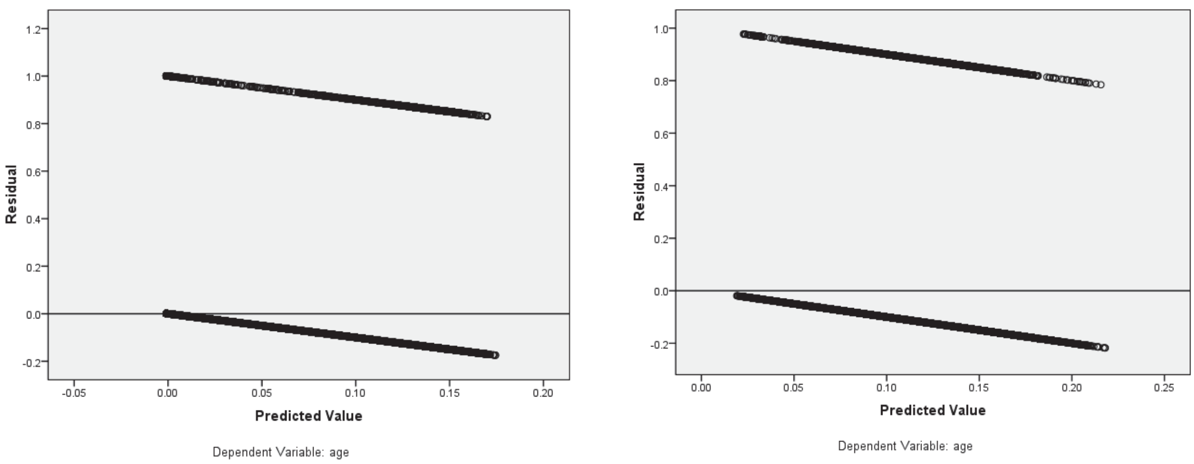
Cases	Statistical significance	Gender characteristics	
		Female	Male
Training	Sum of Squares Error	758.432	2309
	Relative Error	0.994	0.982
Testing	Sum of Squares Error	361.827	642.639
	Relative Error	0.988	0.982
Validation	Relative Error	0.996	0.981

The predicted-by-observed (Figure 4) and residual-by-observed (Figure 5) scatterplots were analysed to understand the relationship between predicted and observed outputs and residual and observed data, respectively. The scatterplots for both older female and male driver accidents show that the BP-ANN models can predict the factors influencing road accidents for both gender groups (Figure 4). Figure 4 shows that accident data cluster at 0 and 1 values because of the binary characteristics of driver's age. The predicted values of dependent variable range from 0 to 0.25 for both the older female and male drivers despite its binary characteristics (Figure 4). Similarly, the residuals form a horizontal band and plot randomly around the '0' and '1' lines with respect to 0 to 0.25 predicted values for younger and older drivers, respectively (Figure 5).



(a) Female (b) Male

Figure 4: BP-ANN predicted-by-observed scatterplot



(a) Female (b) Male

Figure 5: BP-ANN residual-by-observed scatterplot

Results

The predictive variables are initially applied as stimulus to the input layer of the network units that is propagated to the hidden (intermediate) layers in the BP-ANN models. This study applies a Multi-Layer Perceptron (MLP) network that is a function of predictors and estimates the number of hidden layers based on the minimum prediction errors and smallest Bayesian information criterion in the training data. The MLP estimates that the best number of hidden layers is two. The training and testing data are distributed into seven and five synapse layers of hidden layers 1 and 2, respectively.

For the older female drivers, journey purpose provides positive weight to most of the synapses (H(1:1), H(1:2), H(1:4), H(1:5) and H(1:7)) in the first hidden layer (Table 5). The older drivers who made social or leisure trips and transported pupils from and to school are susceptible to traffic accidents. The value increase of journey purposes produces the expected increase in traffic accidents of 0.276, 1.224, 5.5234, 0.637 and 2.691 in H(1:1), H(1:2), H(1:4), H(1:5) and H(1:7) synapse layers of first hidden layer (Table 5). On the contrary, human assisted pedestrian crossing facilities give negative weights to most of the synapse layers in the first hidden layer explaining that pedestrian crossings regulated by school patrol or other authorised person reduce the risk of traffic accidents for older drivers (Table 5). The existence of unsignalised pedestrian crossing, footbridge or subway and central refuge area near to the junctions increases the risk of traffic accidents for older drivers (Table 5). Similarly, extreme weather, hazardous condition of carriageway, time severity and roadway or junction types contribute positive synapses to the first synapse layer of the first hidden layer (Table 5). These explanatory variables increase the risk of older driver accidents. On the other hand, junction location and characteristics, pedestrian crossing with human and physical interventions, lighting condition and road surface condition give negative weights to the H(1:1) synapse layer (Table 5). The outputs of all synapses coming from explanatory variables to each synapse layers added along with a bias applying the sigmoid activation function to the weighted sum. The output of each synapse layer of hidden layer 1 was used as the input for the synapse layers of hidden layer 2.

The H(1:2), H(1:3), H(1:4), H(1:6) and H(1:7) synapse layers for the first hidden layer provide negative weights to H(2:2), H(2:3), H(2:4) and H(2:5) synapse layers in the second hidden layer (Table 5). Only H(1:1) and H(1:5) synapse layers contribute positive weights to the above synapse layers in the second hidden layer (Table 5). On the other hand, H(1:1), H(1:2), H(1:4), H(1:5) and H(1:7) synapse layers provide positive weight to H(2:1) synapse layer (Table 5). The H(2:1) and H(2:3) synapse layers in the second hidden layer give positive weights to the output layer while H(2:2), H(2:4) and H(2:5) synapse layers provide negative weights to the output layer (Table 5).

For the older male drivers, no explanatory variable of traffic accident dictates the synapse layers in the first hidden layer except in the case of road and junction types (Table 6). The accident risk of older male drivers significantly reduced at junctions, one-way streets and slip roads because they are very careful at these locations. Journey purpose and junction location have similar pattern of synaptic weight distribution among synapse layers in the first hidden layer. These explanatory variables result in positive and negative weights H(1:1), H(1:2), H(1:5) H(1:6) and H(1:3), H(1:4), H(1:7), respectively (Table 6). A unit increase of journey purpose, junction location, pedestrian crossing with physical interventions, extreme weather and hazardous carriageway causes the expected increase in traffic accidents of 0.383, 0.475, 0.042, 0.036 and 0.038 in the first synapse layers of the first hidden layer (Table 6). By contrast, pedestrian crossing with human interventions, lighting condition, road surface condition, and time severity give negative synaptic weights to the first synapse layer in the first hidden layer (Table 6). Accidents of older male drivers occurred less during off-peak periods on both weekdays and weekends.

The H(1:1), H(1:3), and H(1:6) synapse layers of the first hidden layer provide similar pattern of synaptic weights to the synapse layers in the second hidden layer. For instance, these synapse layers give positive weights to H(2:1), H(2:2), H(2:4) and H(2:5) synapse layers and negative weights to H(2:3) synapse layer in the second hidden layer, respectively (Table 6). The H(1:2) and H(1:5) synapse layers provide negative weights to all synapse layers in the second hidden layer (Table 6). All synapse layers in the second hidden layer give negative weights to output layer except in the case of H(2:3) synapse layer (Table 6).

Table 5: Parameter estimation of the independent variables for traffic collisions involving female older drivers

Parameter Estimates

Predictor		Predicted												
		Hidden Layer 1							Hidden Layer 2					Output Layer
		H(1:1)	H(1:2)	H(1:3)	H(1:4)	H(1:5)	H(1:6)	H(1:7)	H(2:1)	H(2:2)	H(2:3)	H(2:4)	H(2:5)	age
Input Layer	(Bias)	.532	-.595	1.345	-1.970	.108	-.677	-1.286						
	journeypurpose	.276	1.224	-4.377	5.534	.637	-.880	2.691						
	junctionlocation	-.116	.114	-1.544	2.117	.037	-.345	.651						
	pedcrossinghum	-.542	-.363	.175	-.590	-.321	-.433	-.245						
	pedcrossingphy	-.360	.060	2.091	-2.183	.423	.574	-1.657						
	light	-.383	-1.081	3.640	-4.683	.127	.669	-2.641						
	weather	.601	.632	-1.844	2.134	-.235	.249	1.103						
	roadsurface	-.357	.154	-.059	.501	.387	-.025	.228						
	carriagehaz	.236	-.104	.262	-.360	.407	.395	-.107						
	timeseverity	.596	.514	-1.166	2.086	-.579	-.464	.486						
	roadtype	.458	-.261	1.394	-1.342	.518	-.455	-1.149						
Hidden Layer 1	(Bias)								-.104	1.778	3.569	1.850	2.342	
	H(1:1)								.366	1.671	2.234	1.758	2.302	
	H(1:2)								.483	-3.896	-3.334	-3.953	-4.040	
	H(1:3)								-1.117	-.573	-1.084	-1.033	-1.336	
	H(1:4)								.597	-3.569	-2.958	-3.521	-3.598	
	H(1:5)								.345	.696	.772	.535	.096	
	H(1:6)								-.035	-2.551	-2.360	-2.365	-2.536	
	H(1:7)								.450	-4.917	-6.105	-6.824	-5.952	
Hidden Layer 2	(Bias)													-4.993
	H(2:1)													3.995
	H(2:2)													-6.691
	H(2:3)													1.018
	H(2:4)													-6.315
	H(2:5)													-7.057

Table 6: Parameter estimation of the independent variables for traffic collisions involving male older drivers

Parameter Estimates

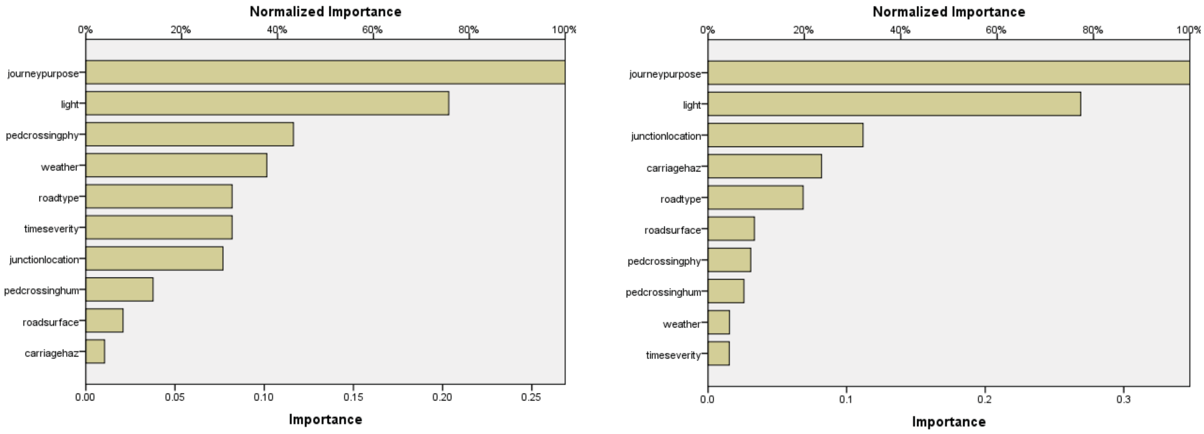
Predictor		Predicted												
		Hidden Layer 1							Hidden Layer 2					Output Layer
		H(1:1)	H(1:2)	H(1:3)	H(1:4)	H(1:5)	H(1:6)	H(1:7)	H(2:1)	H(2:2)	H(2:3)	H(2:4)	H(2:5)	age
Input Layer	(Bias)	.102	-.347	.015	.311	-.240	-.329	.024						
	journeypurpose	.383	1.326	-.597	-.724	1.607	.313	-.629						
	junctionlocation	.475	.724	-.206	-.162	.334	.337	-.274						
	pedcrossinghum	-.084	-.371	.015	-.223	.333	-.127	-.124						
	pedcrossingphy	.042	-.147	.594	-.095	-.045	.039	-.120						
	light	-.827	-.936	.314	.084	-1.266	-.151	.884						
	weather	.036	-.348	.026	.194	-.180	-.066	-.467						
	roadsurface	-.075	-.409	-.191	.040	.048	-.074	.255						
	carriagehaz	.038	-.240	.352	-.213	-.054	.187	.571						
	timeseverity	-.343	.218	.246	-.014	-.101	-.396	.345						
	roadtype	-.435	.185	-.548	-.120	.165	-.360	-.039						
Hidden Layer 1	(Bias)								.151	-.184	-.399	.233	.046	
	H(1:1)								.052	.641	-.448	-.521	.110	
	H(1:2)								-.410	-.724	-.262	-1.535	-.256	
	H(1:3)								.333	.341	-.370	.561	.112	
	H(1:4)								.036	-.323	-.142	-.126	.161	
	H(1:5)								-.986	-1.003	-.074	-1.777	-1.467	
	H(1:6)								.304	.024	-.500	.336	.712	
	H(1:7)								.480	.219	.619	1.155	.673	
Hidden Layer 2	(Bias)													-.318
	H(2:1)													-.578
	H(2:2)													-.779
	H(2:3)													.196
	H(2:4)													-2.114
	H(2:5)													-1.245

Discussion

The BP-ANN models performed the sensitivity analyses to compute the importance of factors determining the accident risk for older drivers of both gender groups based on the combined training and testing data (Table 7). Figure 6 shows the normalised importance of factors affecting traffic accidents among older drivers. For both older female and male drivers, journey purpose is the highest contributor of accident risk with twenty-seven percent and thirty-five percent importance, respectively (Table 7 and Figure 6). Most of older people, who are at retirement and free from childcare, make social trips to avoid loneliness and isolation. Sometimes older people transport their grandchildren to and from the schools. Due to the decrease in cognitive and physical abilities, lack of accessibility to public transport from origin to destination of their trips and easy accessibility to cars, older people are highly dependent on driving cars. Moreover, there is a common belief among older driver is that giving up the driving is the sign of aging and loss of identify. The AgeUK surveyed that thirty-two percent people aged 65 and over never use public transport while twenty-seven percent use public transport once in a month or less (Holley-Moore and Creighton 2015). The tendency to use cars among older women was high with a twenty percent increase of holding driving licence among women over 70 during the period of 1995-2010 (Department for Transport 2010). The accessibility to cars and inconvenience in public transport persuade both older female and male to drive cars and expose them to traffic accidents. Therefore, the risk of involving in traffic accidents is high for both older male and female drivers with increase in social, shopping and recreational trips. The accessible, affordable and convenient public transport can ensure active lifestyle for older people (Coronini-Cronberg et al. 2012). Greener Journeys (2014) studied that £1 spent on concessionary bus travel for older and disabled people in the UK could benefit £2.87 in terms of fifty percent for older people, twenty percent to other bus passengers and other road users who share the road, and the remaining thirty percent to the wider economic community.

Table 7: Importance of explanatory variables to estimate the accident risk among older drivers in BP-ANN models

Input variables	Female	Male
Journey purpose	0.269	0.348
Junction location	0.077	0.112
Pedestrian crossing (human interventions)	0.038	0.026
Pedestrian crossing (physical interventions)	0.116	0.031
Lighting condition	0.203	0.269
Weather condition	0.101	0.016
Road surface condition	0.021	0.033
Level of carriage hazard	0.011	0.082
Time severity	0.082	0.015
Road or junction type	0.082	0.069



(a) Female (b) Male

Figure 6: Normalised importance of independent variables for older driver accidents

Lighting condition is the second most important factor (twenty percent for female and twenty-seven percent for male) of accident risk for older drivers due to decrease in visual acuity in poor light, sensitivity to glare and contrast sensitivity among older people (Table 7 and Figure 6).

Older female drivers are more susceptible to traffic accidents at pedestrian crossing with physical interventions such as non-junction pedestrian signal crossing (pelican, puffin, toucan signals), pedestrian phase at signalised junctions, footbridge or subway, zebra crossing and central refuge (Table 7 and Figure 6). Older male drivers are not at similar accident risk at pedestrian crossings but are at complex locations such as junctions and merging and diverging locations of slip roads. The complexity of road environment places increasing workload on both groups of older drivers and reduces the ability to perceive cognitive resources involving visuospatial and motor coordination that are critical for making turns or passing through junctions and making safe stopping distance (Oxley et al. 2010; Schweizer et al. 2013). The ability to control over vehicle speed, stopping distance and alignment of junctions indicates the strength of the driver's visual-motor coordination between eye movement and vehicle's steering (Chattington et al. 2007). Lack of proper visual-motor coordination is the major factor of traffic accidents at road curves particularly at junctions (Fitzsimmons et al. 2013). The extreme weather condition (such raining, storm, snowing and fog or mist) and darkness at night are also significant factors of older driver accidents for both gender groups because of the reduced ability to perceive cognitive resources (Table 7 and Figure 6). The ageing is related to decline in both perception and cognitive tasks such as difficulty in paying attention and remembering. Roberts and Allen (2016) stated that impaired perception and cognitive decline lead to higher load on cognition and reduce resources available for cognitive processing of older people.

The BP-ANN methods with a GDR learning algorithm overcome the prevailing statistical errors of widely practiced methods in analysing accident database ensuring stability and speed of convergence of the weight vector towards the minimum error value. However, the accident studies should also ensure sufficient reliability and sensitivity of accident data and have mechanisms in place to deal with prediction errors. Future studies should explore a variety of ways in which transport options could be improved for older drivers such as flexible transport services, age friendly infrastructure, use of assistive technology in cars, driverless cars, use of audio-visual announcements on public transports to increase older people's confidence, and community car sharing schemes.

Conclusions

The world population is ageing and the proportion of older drivers with reduced cognitive resources and mental impairment operating vehicles on the roads is also increasing. These results in safety challenges not only for the older drivers but also for other road users. Older persons are mostly dependent on their cars because of convenience and lack of accessibility to public transports. This paper applies BP-ANN network with a GDR learning algorithm to understand the factors affecting the older driver accidents of both gender groups. A total of 95,092 accident records in West Midlands of the UK during the period of 2006-2016 were collected from the Department for Transport. The BP-ANN models determine that journey purpose is the most important factor of older driver accidents for both gender groups. Older drivers are highly exposed to accidents because of decrease in cognitive and physical abilities, lack of accessibility to public transport from origin to destination of their trips and easy accessibility to cars.

Older drivers also suffer in decreased visual acuity in poor light, increased sensitivity to glare and contrast. This results in increased accidents at pedestrian crossing with physical interventions and at complex locations such as junctions and merging and diverging locations of slip roads. The extreme weather and darkness in combination with reduced ability to perceive cognitive resources increase the accident risk among both female and male older drivers. Road safety for older people can be improved with less driving and more using public and active transport. The accessible routes and affordable, reliable and convenient public transport are helpful for the active lifestyle of older people.

This study defines the older drivers aged 60 and above, however, previous studies (Clarke et al. 2010; Lotfipour et al. 2013; Kent et al. 2005) found that older drivers over 70 were more fragile. Further categorisation of older drivers within three groups: 60-70 years of age, 70-80 years of age and 80 over can provide in-depth causation models of accident severity for different gender groups. The BP-ANN methods with a GDR learning algorithm can reduce the prediction errors but accident data sensitivity and reliability is required to be addressed. Future studies should ensure the reliability and sensitivity of accident data along with dealing with statistical errors. It is also necessary to explore a variety of transport options such as flexible and reliable transport services, friendly infrastructure for active transport, use of assistive technology in cars, driverless cars, use of audio-visual announcements on public transports and community car sharing schemes to improve the safety of older drivers. The findings of this study will help the transport authorities and city councils to develop strategies and measures promoting public and active transports thereby improving road safety for older road users.

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