Powered two-wheeler crash scenario development

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Abstract

Powered two wheeler (PTW) riders are a group of vulnerable road users that are overrepresented compared to other road user groups with regards to crash injury outcomes. The understanding of the dynamics that occur before a crash benefits in providing suitable countermeasures for said crashes. A clearer interpretation of which factors interact to cause collisions allows an understanding of the mechanisms that produce higher risk in specific situations in the roadway.

Real world in-depth crash data provides detailed data which includes human, vehicular and environmental factors collected on site for crash analysis purposes. This study used macroscopic on-scene crash data collected in the UK between the years 2000 – 2010 as part of the "Road Accident In-depth Study" to analyse the factors that were prevalent in 428 powered two-wheeler crashes.

A descriptive analysis and latent class cluster analysis was performed to identify the interaction between different crash factors and develop PTW scenarios based on this analysis. The PTW rider was identified as the prime contributor in 36% of the

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multiple vehicle crashes. Results identified seven specific scenarios, the main types of which identified two particular 'looked but failed to see' crashes and two types of single vehicle PTW crashes. In cases where the PTW lost control diagnosis failures were more common, for road users other than the PTW rider detection issues were of particular relevance.

Keywords

Powered two-wheelers, Human behavior, Human functional failure, Crash causation

1. Introduction

Riders of powered two-wheelers (PTW) form an increasingly important part of the traffic casualty population. Despite accounting for only 1% of traffic in the UK in 2014 PTW riders represented 19% of fatalities, 23% of seriously injured casualties and 10% of slightly injured road users from traffic crashes (DfT 2015). The risks of fatal and serious injury for PTW riders are over 55 times higher than for car occupants. In 2009 there were 140 deaths and 1,709 people killed and seriously injured (KSI) per billion vehicle miles for motorcycle riders. The corresponding figures for car drivers were 3 killed and 30 KSI per billion vehicle miles (DfT 2010). The reduction in PTW casualties is therefore an important objective of road safety policy due both to the frequency and also the severity of casualties. The prevention and mitigation of PTW casualties is therefore a priority for road safety policymakers.

Effective casualty reduction strategies are typically based on an understanding of the magnitude and nature of specific groups of collisions for each road user group. Technology-based countermeasures in particular rely on a detailed description of individual risk factors and how they interact. Previous research has identified a number of common risk factors amongst PTW riders. Males comprise 85% of the crash population (Bjørnskau et al. 2012). PTW crash involvement decreases with increasing rider age (Yannis et al. 2005). Alcohol and excessive speed are common factors and left turns while failure to yield were common factors in multi-vehicle collisions (Preusser et al. 1995).

Attitudes to riding and previous behaviour are also risk factors. In a sample of 1381 UK PTW riders it was found that past behaviour, control beliefs, attitudes, moral norm, normative beliefs, age and self-identity explained 60% of the variance in motorcyclists' intention to exceed the speed limit on motorways (Chorlton et al. 2012). Distinctions between clusters of PTW crashes have been made, motorcyclists were less likely to be at-fault during crashes that occurred at night time or at locations where surveillance cameras were present (Haque et al. 2009). Younger motorcyclists are more likely to be at-fault in the event of a collision, as are riders who are under the influence of alcohol (Seiniger et al. 2012).

Many studies have found that intersection collisions with the PTW having priority are common (Clarke et al. 2007)(Hurt, H. H., Ouellet, J. V., & Thom 1981)(MAIDS 2009)(Peek-Asa & Kraus 1996)(Williams & Hoffmann 1979)(Wulf et al. 1989). Furthermore, these crashes appear to be characterised by an often high level of injury severity (Pai & Saleh 2008)(Pai 2009)(Peek-Asa & Kraus 1996)(Williams & Hoffmann 1979). Motorcycle visibility is the prime cause in 65% of motorcycle to car crashes, with particular importance being placed on the front of the motorcycle (Williams & Hoffmann 1979), this category of crash has been termed 'looked but failed to see' crashes (Brown 2002). In France these collisions were related to high PTW speeds in urban areas but there was no difference in equivalent rural collisions (Clabaux et al. 2012).

Certain collision types are identified with higher risk of fatality and serious injury. Crashes occurring on bends are some of the most dangerous types of crashes with double the risk of rider or passenger fatality and a dominant factor in these crash types was found to be rider inexperience (Clarke et al. 2007).

Studies that examine the effect of combinations of risk factors on crash involvement are less common. Using an Age-Period-Cohort (APC) modelling approach it was identified that 15-19 year old PTW riders had substantially elevated risk as did the 10-year cohorts born 1949–1958, 1954–1963, 1959–1968 and 1964–1973 (Langley et al. 2013). Classification and Regression Tree methods were used to find area type, land use, and injured part of the body (head, neck, etc.) are the most influential factors affecting the fatality of motorcycle passengers (Kashani et al. 2016). Motorcyclists who tend to have dangerous attitudes and behaviours as well as younger motorcyclists are more likely to have been involved in a crash (Theofilatos & Yannis 2014). A mixed logit analysis was used to evaluate the factors that affected two-vehicle collisions involving PTWs and found roadway surface condition, clear vision, speed limit, light conditions and helmet use to be among the key factors influencing severe injury crashes (Shaheed et al. 2013). Chang et al. (2016) also using a mixed logit analysis identified that PTW riders being older than 60, roadway slope conditions, contributing equally to a crash occurrence and colliding with heavy goods vehicles in darkness was associated with an increase in injury levels. Injury levels for this study decreased when a crash occurred during the daytime or at night in the presence of light, this was in contrast to Shaheed et al. (2013) where fatal crashes were more likely to occur during the daytime and Kumar and Toshnival (2017) where fatal and serious injury crashes occurred most commonly at night in the presence of no light.

The scarcity of in-depth collision data precludes much understanding of the rider behaviours as riding deviates from a normal range. A methodology based on Bayesian Networks derived from naturalistic riding data has been proposed (Vlahogianni et al. 2013). A preponderance of older drivers with relatively high levels of driving experience was observed amongst road users who had problems detecting approaching motorcycles. The most common error of PTW riders identified within German in-depth collision data was in information evaluation although planning errors were most frequent amongst serious injury crashes (Otte et al. 2012).

Much of the previous research into the causation of PTW collisions is based on analyses of macroscopic data in the form of macroscopic statistics. While this type of data may frequently provide information about crash conditions they contain limited information about the behaviours of the road users that initiate the collision nor the manner in which road user, infrastructure and other factors may interact. The understanding of the role of human errors and the circumstances contributing to those errors will enhance the repertoire of road safety practitioners who wish to change road user behaviour. Road safety strategies can be improved when target groups are disaggregated into distinct sub-groups that have meaningful differences in causation. The previous research that examines individual risk factors in isolation does not readily support new countermeasures that address a designated target population yet it is considered likely that more focussed interventions could have improved effectiveness.

The objective of the present research is therefore to establish a new segmentation of the PTW crash population on the basis of rider, vehicle and infrastructure factors in combination using a recently developed model of human functional failure.

2. Methodology

2.1 Crash injury data

In-depth collision data gathered in the UK under the "Road Accident In-depth Study" (RAIDS) was used for the analysis. The data was recorded using on-the-spot methods where specialist teams attended the scene of the collision to inspect vehicles, the road environment and to interview crash participants and witnesses. The sampling regions were selected to ensure the data was representative of the UK (Hill & Cuerden 2005). At the time of analysis the study had investigated a total of 4,004 crashes involving 12,749 vehicles and 527 pedestrians. Within this dataset there were 428 crashes involving a PTW which were selected for this analysis. Typically over 3,000 variables were recorded for each of these collisions.

2.2 Classification of road user behaviours

A Human Functional Failure model (Van Elslande & Fouquet 2007) was used to classify the behaviours of the active road users prior to the collision. The model treats driving as a series of functions that are continuously repeated during travel (Figure 1).

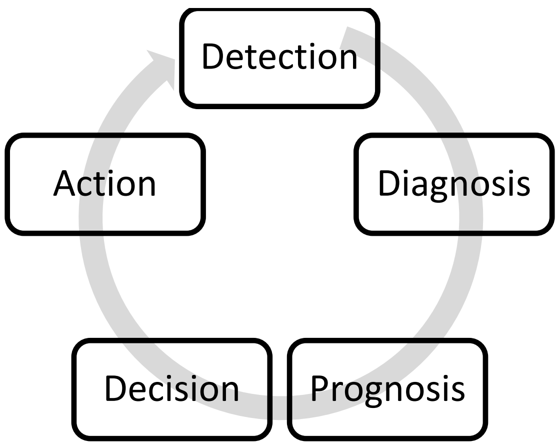

Figure 1: Continuous driving functions (Van Elslande & Fouquet 2007)

The road user first perceives (stage 1) the information from the environment, then diagnoses (stage 2) the situation, prognosticates (stage 3) how events will unfold, makes a decision (stage 4) and then performs an action (stage 5). These five stages continually operate in a cyclic manner. Violations both deliberate and as a result of the situation are made in the decision stage (4). The effective understanding of the dynamic traffic environment can be seen in two stages, in the diagnosis (stage 2) and the prognosis (stage 3) stages where a lapse in awareness can result in error or behaviours that will lead to the triggering of a crash. Overall failures can be referred to as any failures that result in a loss, impairment or exceeding of a road user's capabilities.

Road users can make errors while conducting each stage of driving behaviour. Van Elslande and Fouquet (2007) has further classified a series of failure types from in-depth French crash data that demonstrates the most common types of human failures that lead to crashes, illustrated in Figure 2. This methodology allows for similar types of collisions to be grouped together for analysis purposes and scenario development.

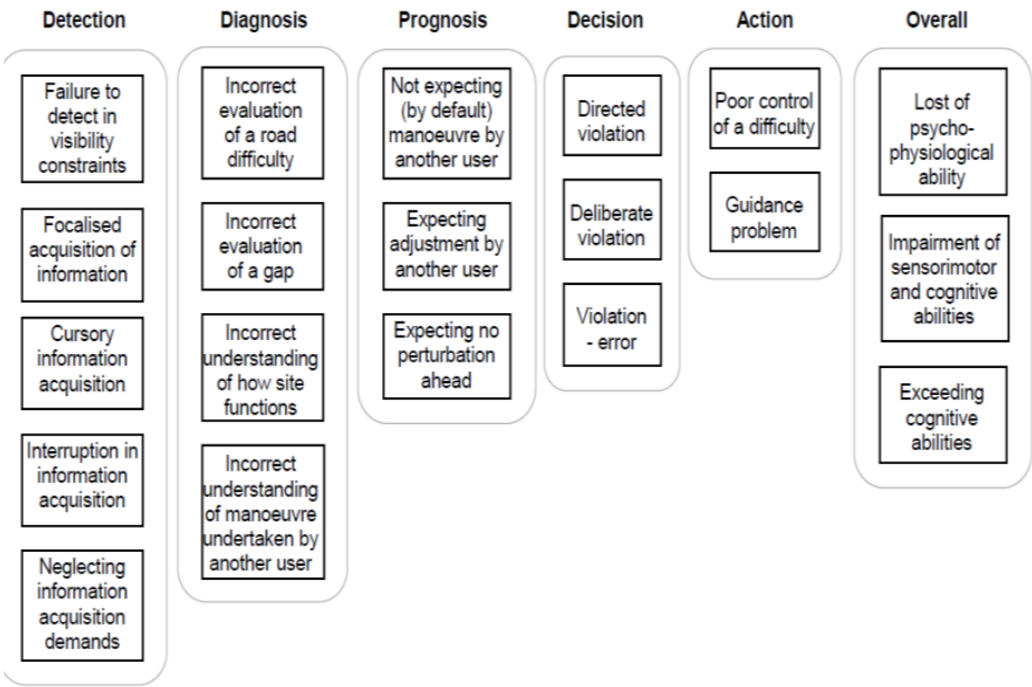

Figure 2: Perceptual stages and failure types for road user (Adapted from Van Elslande & Fouquet 2007)

2.3 Analysis methodology

The data analysis comprised two stages, (1) a descriptive analysis to present the underlying variable distributions and (2) a scenario building approach using latent cluster analysis to group crashes into similar types. Cluster analysis is most commonly used to maximise the similarities between in-cluster elements and the differences between inter-cluster elements (Fraley & Raftery 2002). When data has a number of categorical variables it is often of interest to identify cases that contain similar aspects and identify whether these similarities hold over different variables (Linzer 2008). The crash injury data is of this nature with many categorical variables so a latent class cluster analysis was selected for this analysis, as it does not assume any underlying probability distribution of the variables and so is particularly suitable for use with a large number of categorical variables. The poLCA package with the r language combined with SPSS 22® was used for the cluster analysis. A further test of independence was carried out to identify overrepresented values within the factors for individual cluster comparison purposes.

2.4 Cluster method

The latent class clustering was run thirty times for each individual cluster with the repetition with the lowest goodness of fit value being kept. The goodness of fit of the clusters were analysed using the Akaike information criterion (AIC), Bayesian information criterion (BIC), “adjusted” Bayesian information criterion (aBIC) and “consistent” Akaike information criterion (CAIC). The different fits based on these measures for one to ten clusters was calculated and compared. This method was used for estimation purposes and to limit the error in the cluster analysis by keeping the cluster with the highest likelihood measures. The measures indicated a seven cluster model for the AIC, a two cluster model for the BIC, a ten cluster model for the aBIC and a four cluster model for the CAIC. These measures and models were compared and taken into consideration when selecting the appropriate measure for model identification.

The AIC provides a better goodness of fit measure for the cluster analysis when using real life data with a smaller number of cases compared to the other measures, which tend to underfit the number of selected clusters (Dziak et al. 2012), and so was selected for this research. Seven clusters of crash cases were identified using the AIC as a measure of goodness of fit. Figure 3 demonstrates the different goodness of fit values for the clusters using the AIC, BIC, aBIC and CAIC measures.

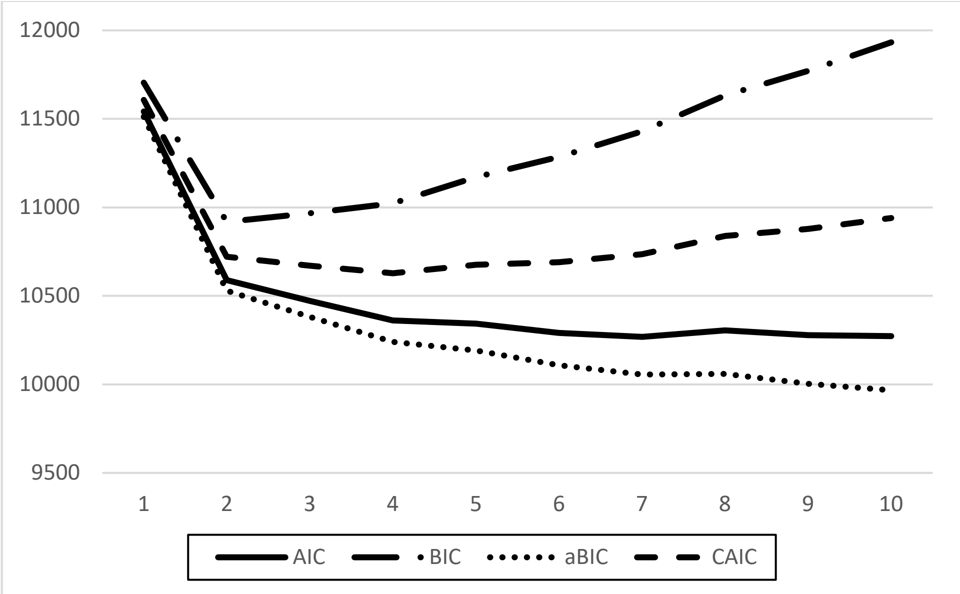

Figure 3: AIC, BIC, aBIC and CAIC values for the PTW cluster analysis

3. Results

3.1 Descriptive analysis

Table 1 shows the functional failures made by PTW riders and the other active road users in the same crash for the 449 single and multi-vehicle collisions. There were 216 (48%) PTW riders who made prognosis errors and 156 of these were in combination with a detection error made by the other road user. Similarly 71 (16%) of the riders made detection errors with 41 (9%) in combination with prognosis errors of the other road user. Amongst the 110 (24%) single vehicle crashes there were 34 (8%) riders who made diagnosis errors however all other types of error except prognosis were also common.

Table 1: Functional failures – PTW riders and other road users

		Other road user						
	Failure	Detection	Diagnosis	Prognosis	Decision	Overall	Single PTW crash	Total
Rider	Detection	7	1	41	4	1	17	71
	Diagnosis	3	1	24	1	0	34	63
	Prognosis	156	13	5	28	5	9	216
	Decision	11	1	18	6	0	16	52
	Action	1	1	3	1	0	17	23
	Overall	0	0	7	0	0	17	24
	Total	178	17	98	40	6	110	449

Table 2 shows the distribution of each type of human functional failure mode and the association with a range of collision factors describing the pre-crash conditions and PTW rider factors in multi-vehicle collisions. Some factors, labelled ** allow multiple coding and so may add to more than 100%. Points of note are indicated below.

Speed, denoted by contributory factors “Speed” and “In a hurry” was the most common factor associated with all types of human failure. 51 (15%) of the PTW riders were classified as speeding and 72 (21%) were recorded as in a hurry. Only 3 (0.9%) collisions were recorded where alcohol was a factor for the rider and 10 (2.9%) were distracted.

The most common age group of rider was 26-45 years (33%) followed by 19-25 (17%) and 0-18 (15%). However riders aged up to 18 years were significantly over-represented amongst the group making detection errors as were riders aged 19-25 in the group making diagnosis errors.

54% of the riders did not actively contribute to the crash causation sequence, the other road user being responsible in these cases. However the rider was the primary contributor in 86% of the cases with detection errors and 90% of diagnosis errors, while when they made prognosis errors 84% were non-contributory.

Table 2: Collision factors and PTW rider functional failure

Factor	Detection N=55	Diagnosis N=29	Prognosis N=207	Decision N=36	Action N=5	Overall N=7	N 339
Contributory factor**							
Speed	14.5	27.6	5.3	55.6	20.0	42.9	15.0
Alcohol	0.0	0.0	0.0	0.0	0.0	42.9	0.9
Distraction	12.7	0.0	0.0	8.3	0.0	0.0	2.9
In a hurry	34.5	55.2	5.3	55.6	0.0	85.7	21.2
Inexperience	29.1	10.3	2.9	5.6	40.0	100.0	10.3
Age range							
0-18	29.1	13.8	9.7	19.4	20.0	28.6	14.7
19-25	9.1	37.9	15.5	22.2	20.0	28.6	17.4
26-45	29.1	34.5	32.9	33.3	40.0	42.9	32.7
46-65	3.6	6.9	10.1	2.8	0.0	14.3	10.9
66+	1.8	0.0	3.4	2.8	0.0	0.0	2.7
Missing	5.5	6.9	28.5	22.2	20.0	0.0	21.5
Engine size							
⩽ 50cc	23.6	10.3	12.1	22.2	40.0	14.3	15.3
51> cc ⩽ 250	16.4	17.2	15.9	44.4	0.0	42.9	16.5
> 250	50.9	72.4	48.8	52.8	60.0	42.9	51.6
Missing	5.5	0.0	23.2	16.7	0.0	14.3	17.1
Day/Night							
Day	83.6	79.3	67.1	88.9	60.0	71.4	73.5
Night	10.9	17.2	22.2	8.3	40.0	28.6	18.9
Missing	1.8	3.4	10.6	5.6	0.0	0.0	7.7
Other road user emergency manoeuvre							
Yes	9.4	20.7	16.5	22.9	50.0	28.6	17.3
No	90.6	79.3	83.5	77.1	50.0	71.4	82.7
Injury severity							
Fatal	9.1	10.3	2.9	13.9	0.0	28.6	5.3
Serious	23.6	34.5	23.2	36.1	40.0	28.6	26.0
Slight	25.5	48.3	56.5	38.9	40.0	57.1	53.7
Non-injury	5.5	3.4	7.7	8.3	20.0	0.0	7.7
Level of involvement							
Primary	85.5	89.7	6.3	61.1	40.0	100.0	36.3
Secondary	3.6	0.0	10.1	25.0	20.0	0.0	9.7
Not-contributory	7.3	10.3	83.6	2.8	40.0	0.0	54.0

Table 3 shows the distribution of functional failure groups for each group of pre-crash manoeuvre. Since each crash could involve several failure types and total cases may exceed 100% in each group no measures of association are presented. The table indicates that detection failures are most frequently associated with rear end collisions (51.9%) in which either road user initiated the conflict situation whereas the most common group of diagnosis failures were overtaking collisions (44.4%). Prognosis failures most often occurred in turning manoeuvres (60.7%) while decision failures most commonly occurred in either overtaking (25.7%) or turning manoeuvres (22.9%).

Table 3: PTW rider failure and crash type

Crash Type	Detection N=52	Diagnosis N=27	Prognosis N=163	Decision N=35	Other N=24
Overtaking	21.1%	44.4%	22.0%	25.7%	8.3%
Loss of Control	9.6%	18.5%	4.9%	8.6%	29.1%
Rear End	51.9%	3.7%	12.3%	14.3%	4.1%
Turning	15.4%	7.4%	60.7%	22.9%	4.1%
Other	1.9%	29.6%	14.7%	2.6%	54.1%
Total	100%	100%	100%	100%	100%

3.2 Cluster analysis

The results of the cluster analysis are presented in Table 4 which includes both single and multi-vehicle PTW collisions. The distributions of the parameters are shown under “Total” and a value in bold indicates a statistically significant overrepresentation from the complete PTW sample. In order for a value to be overrepresented the value needed to have a statistically significant higher value than the overall sample. The methodology used aimed to establish interactions of factors rather than identify singular high risk factors such as in Table 2. The contributory factors in this analysis were based on different road user, vehicular or environmental groupings. This difference was reflected in the types of contributory factors used in the analysis.

Table 4: PTW causation factors – cluster specifications

Cluster	1	2	3	4	5	6	7	Total
Number of cases	122	77	75	45	42	36	31	428
Rider gender (%)								
Male	83	91	93	91	91	96	97	90
Female	**17**	9	7	9	10	5	3	10
Rider failure mechanism (%)								
Detection	3	3	1	**75**	**54**	4	13	16
Diagnosis	1	**51**	3	**25**	14	0	7	14
Prognosis	**97**	0	**96**	0	0	33	13	48
Decision	0	**25**	0	0	15	**63**	7	12
Action	0	0	0	0	5	0	**57**	5
Overall	0	**21**	0	0	**13**	0	4	5
Area type (%)								
Urban	**88**	42	26	62	**90**	**89**	35	63
Rural	12	**58**	**74**	38	10	12	**65**	38
Light conditions (%)								
Day	74	84	79	85	72	90	77	79
Night	26	17	21	15	28	10	23	21
Rider contributory factor (%)								
Physical/physiological	8	**34**	16	31	**36**	31	8	21
Risk taking	2	**58**	4	26	23	**50**	4	21
Inexperience	1	3	0	2	17	3	3	3
Distraction	1	1	0	**13**	3	0	7	3
Road condition	1	0	0	0	0	0	**35**	3
Traffic condition	**41**	5	**34**	9	8	3	0	20
Visibility impaired	**5**	0	0	2	**9**	6	3	3
Other environmental factors	0	0	0	0	0	0	19	1
Vehicle factor	0	0	0	0	5	0	**16**	2
No factor	**43**	0	**46**	18	0	8	7	23
Road user emergency manoeuvre (%)								
Yes	33	30	**47**	35	38	35	41	36
No	68	70	54	65	62	65	59	64

Cluster	1	2	3	4	5	6	7	Total
Number of cases	122	77	75	45	42	36	31	428
Level of involvement (%)								
Primary contributor	0	**100**	6	**100**	**93**	63	**81**	50
Secondary contributor	7	0	11	0	5	**34**	6	8
Not contributing	**93**	0	**83**	0	2	3	13	43
Road type (%)								
A road	37	44	**68**	63	24	**68**	52	49
B road	**23**	10	12	17	17	11	7	15
Motorway	0	1	**14**	4	0	0	**32**	5
Minor road	**40**	**44**	6	16	**59**	22	10	30
Rider age group (%)								
0-18	19	0	4	3	**88**	16	10	17
19-25	22	**35**	21	15	10	21	3	21
26-45	41	46	**52**	53	3	52	**76**	45
46-65	14	17	16	**29**	0	3	11	14
66+	4	2	**8**	0	0	8	0	4
Speed limit (%)								
0-30 mph	**76**	41	0	33	**84**	48	10	45
40-50 mph	24	13	**50**	33	16	**49**	29	29
60-70 mph	0	**46**	**50**	34	0	3	**61**	25
PTW engine capacity (cc) (%)								
50	**25**	5	6	0	**67**	7	7	17
51-250	23	20	16	16	28	17	13	20
250+	53	**76**	**78**	**84**	5	76	81	64
Opponent road user failure type (%)								
Detection	**76**	0	**80**	11	2	42	0	41
Prognosis	0	25	1	**80**	**64**	24	13	23
Decision	**14**	1	11	0	7	**28**	0	9
Single vehicle	0	**73**	0	9	24	4	**74**	22
Other	**10**	0	8	0	2	3	13	6
Crash type (%)								
Leaving lane	3	**84**	5	0	25	0	**77**	25
Rear end	4	0	8	**42**	**22**	0	6	10
Changing lane	2	0	**31**	9	7	15	3	9
Overtaking	3	6	10	**29**	9	11	0	9
Right turn	**54**	0	23	16	16	**49**	0	27
Left turn	**6**	0	7	0	0	5	0	4
Intersection	**13**	0	11	0	14	4	0	7
Other	15	11	5	4	7	18	13	11

The seven clusters were characterised on the basis of the variables with significant differences from the complete sample, these are summarised in Table 5. If there was no significant value for a specific variable this was left empty in the cluster, for example the factor light conditions did not include any values that were significantly overrepresented and so was left completely empty to demonstrate this.

Table 5: Summary of overrepresented significant cluster factors

	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6	Cluster 7
Rider gender	Female						
Rider failure mechanism	Prognosis	Diagnosis, Decision and Overall	Prognosis	Detection and Diagnosis	Detection and Overall	Decision	Action
Area type	Urban	Rural	Rural		Urban	Urban	Rural
Light conditions							
Rider contributory factor	Adverse traffic conditions and No contributory factor	Physical/psychological and Risk taking	Traffic conditions and No factor	Distraction	Physical/psychological and Visibility impaired	Risk taking	Road conditions and Vehicle factors
Road user emergency manoeuvre			Emergency manoeuvre				
Rider Level of involvement	Non-contributory	Primary contributor	Non-contributory	Primary contributor	Primary contributor	Secondary contributor	Primary contributor
Road type	B road and Minor road	Minor road	A road and Motorway		Minor road	A road	Motorway
Rider age group			26-45, 66+	46-65	0-18		26-45
Speed limit	0-30 mph	60-70 mph	40-50 mph and 60-70 mph		0-30 mph	40-50 mph	60-70 mph
PTW engine capacity	50cc	250cc+	250cc+	250cc+	50cc		
Opponent road user failure	Detection, Decision and Other	Single vehicle	Detection	Prognosis	Prognosis	Decision	Single vehicle
Crash type	Turning and intersection	Leaving lane	Changing lane	Rear end and Overtaking	Rear end	Right turn	Leaving lane

4. Discussion

Effective road safety policies are increasingly data driven. A detailed understanding of the characteristics of crashes and their causation is the start of a sequence of development that leads to the implementation of targeted countermeasures followed by evaluation and subsequent revision of the crash analysis. A safety policy development cycle based on these premises is proposed in Figure 4.

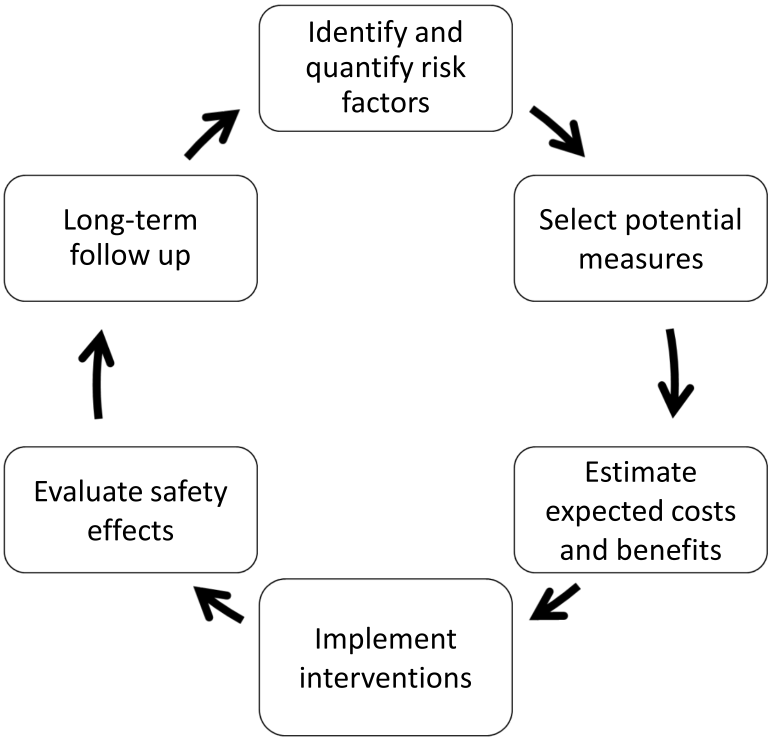

Figure 4: Safety policy development cycle

PTW training and education programmes will normally address rider behaviour in both frequent and high risk riding scenarios. Enforcement strategies in particular take the approach of allocating blame to road users involved in crashes having made high risk behaviours. Alcohol and speeding are examples of high risk behaviours that are commonly understood to be a factor in crash causation yet this analysis has shown that many PTW crashes are not influenced by these factors but occur in the presence of mistakes – human failures – on the part of the riders and other road users.

The Safe System Approach for Road Safety Management (Bliss & Breen 2009) has been adopted by many countries and international groups as the basis of casualty reduction policy-making. It is based on the premise that serious crashes are avoidable, humans routinely make mistakes and therefore the traffic system must be resilient and accommodating of error. There is no attribution of blame and the understanding of human functional failure is made with the exclusion of the judicial process. The Safe System Approach also considers that driving errors are an outcome of associated vehicle, infrastructure and traffic factors yet there has been little previous research that describes behaviours within this wider pre-crash traffic context.

The present analysis uses UK in-depth collision data that incorporates a specific coding of functional failures made by PTW riders and other road users and that is available with sufficient cases to support multivariate, data mining analysis strategies.

The data indicates that PTW riders and the drivers of the opponent vehicles both have similar types of functional failure. Most commonly PTW riders make prognosis errors where the predicted traffic movements or road layout according to their world model do not transpire. On the other hand drivers of the opponent vehicles most frequently make detection errors and these situations are similar to the ‘looked but failed to see’ crashes reported in previous studies (Clarke et al. 2007)(Hurt, H. H., Ouellet, J. V., & Thom 1981)(MAIDS 2009)(Peek-Asa & Kraus 1996)(Williams & Hoffmann 1979)(Wulf et al. 1989). Most commonly these crashes involve the other road user not detecting the presence of the PTW while at the same time the rider has a false expectation that the other vehicle will undertake a different motion. A study that used video clips taken at a t junction to analyse the visual search patterns of other road users when faced with PTW riders demonstrated that drivers that had experience in using PTWs had better performance in identifying PTWs compared to experienced and novice drivers that had no experience in using PTWs (Crundall et al. 2012). These results combined with the present studies results indicate that the expectation of the driver at the junction, the reduced conspicuity of the PTW compared to other forms of travel and gaze patterns all play a part in the occurrence of these crashes.

Countermeasures related to road user visual search, PTW conspicuity and the environment at junctions providing a clearer guidance for search pattern needs are possible avenues to be pursued. In the UK PTW riders are advised to wear reflective clothing in the dark, though visibility aids are also beneficial during the daytime. The crash data indicated that a large number of crashes occurred during the day and measures to make the PTW rider more visible during these time periods is necessary. A study by Gershon et al. (2012) indicated that though reflective clothing is beneficial for PTW riders to be recognized earlier, in situations where the reflective clothing colours merged with the environment this could also decrease the possibility of recognition. Crundall et al. (2017) suggested that training other road users to be able to determine a PTW at a distance and identify differences in road user groups is important as the ‘looked but failed to see’ crash type implies that other road users cannot identify PTWs despite looking at them.

Two clusters also identified detection issues for the PTW rider which led to rear end collisions in urban areas. The first cluster included larger PTWs with older riders and the second cluster included younger riders on mopeds where impaired visibility was a contributing factor. The PTW to other road user detection issues were of a significantly lower number than the other road user to PTW detection crashes. The clusters in which PTW riders made detection errors also indicated that the high manoeuvrability of the PTW combined with rider risk taking behaviours leads to rear end collisions. Rider training is seen as a way to reduce risk taking behaviours, though previous studies provide conflicting results with regards to how effective training measures are for PTW riders (Savolainen & Mannering 2007)(Wali et al. 2018).

The drivers of the other vehicles also made prognosis errors and 42% of these were in association with PTW rider detection errors but rider diagnosis (24%) and decision (18%) errors were also commonplace. Certain types of failure were rare including action errors, where the rider was unable to make the intended manoeuvre, or overall failures caused by drowsiness, sleep or alcohol. This compares well with the avoidance of these errors being a primary target of driver/rider training and traffic enforcement. In other words the high risk driving behaviours associated with alcohol or fatigue were not commonly observed within this group, also the ability of riders to undertake their planned manoeuvre was high.

In contrast, although the subject of enforcement activities and a focus in basic rider training there were still 15% of riders who were speeding and 21% in a hurry, although the groups are not mutually exclusive. Risk taking behaviours for single PTW crashes were also indicated in two of the seven clusters. These clusters included a significant number of PTWs that had engine capacities above 250cc on minor roads in rural areas that ran off the road. Enforcement measures need to take into account the higher speeds and behavioural factors that increase the injury level of PTW riders on high speed rural roads.

Only 10 (3%) riders were judged to have been distracted at the time of the collision, a conclusion based on physical evidence at the scene and interviews with the riders. This contradicts the importance more widely attributed to distraction which is considered to be a frequent traffic safety risk factor (Neyens & Boyle 2008). Many simulator studies have shown distraction to have an impact on driving ability (Bunn et al. 2005)(Consiglio et al. 2003)(Donmez et al. 2006)(Hancock et al. 2003)(Laapotti & Keskinen 1998) yet there are far fewer assessments of prevalence in real-world collisions and none identified concerning PTW crashes. The relatively low frequency of distraction amongst PTW riders is therefore unexpected. Possible explanations of this include the nature of PTW riding which has the potential to keep riders more engaged with the riding process than drivers of other vehicles. It may also be an artefact from a comparison with simulator studies where the effects of distraction can be measured whereas in real-world crash investigations the occurrence of distraction is a subjective judgement on the part of the researcher. Nevertheless this result does not support distraction being a frequent factor in the causation of PTW collisions.

The present analysis concludes that the PTW rider and other road user broadly had an equal share of contribution to the crash in multi-vehicle collisions. In 54% the actions of the rider were judged to have made no contribution whereas the rider was the prime contributor in 36% and a secondary contributor in 10% of cases. However riders as the primary contributor were significantly overrepresented ($p=0.05$) when they made detection, diagnosis or decision failures and underrepresented when they made prognosis errors.

This analysis has shown that PTW collisions can be divided into seven distinct groups on the basis of information about the rider characteristics and behaviour, environmental and vehicle factors. The application of the Latent Class Cluster Analysis (LCA) groups cases according to the similarities of cases within a group and differences between groups on the basis of unobserved variables within the data. It is a powerful method that can be used to partition categorical data. All types of cluster analysis have an advantage that the case sample is grouped solely according to the relationships in the data and there is no subjective element in classifying cases. Since the classification is conducted on the basis of the latent variables the distributions of the observed variables may still show overlaps between clusters. Nevertheless an inspection of the observed variables may aid interpretation of the clusters and provide a reference for targeted road safety interventions. This analysis has focussed on parameters that differ significantly ($p=0.05$) from the distribution of the complete sample in order to characterise each cluster. The present analysis concludes that there are seven distinct types of PTW collision according to the associated causation factors. Each is described below.

Cluster 1: 112 cases (29%)

Female riders on local roads using PTWs with small engines who crash while turning across traffic or at intersections in adverse traffic conditions. They misjudge the evolving traffic situation but are not the primary contributor to the crash. Drivers of the opponent vehicle either fail to detect the PTW or select an inappropriate manoeuvre.

Cluster 2: 77 cases (18%)

Single vehicle crashes with large engine PTWs that occur on minor rural roads with 60 mph speed limits. Riders may be impaired and either incorrectly judge the situation or select an inappropriate manoeuvre, they are influenced by physical or psychological factors or are risk taking road users.

Cluster 3: 75 cases (18%)

Multi-vehicle collisions occurring on motorways and high speed rural A roads involving large engine PTWs while changing lanes. Riders with age groups 26-45 or 66+ misjudge the movements of other vehicles in adverse traffic conditions. Other drivers fail to detect the PTW.

Cluster 4: 45 cases (11%)

Riders of large engine PTWs aged 46-65 on all types of road involved in rear end or overtaking collisions. The riders are the primary contributor to the crash having made detection or prognosis errors as a result of distraction. Other drivers misjudge the expected PTW manoeuvres.

Cluster 5: 42 cases (10%)

Young riders of small engine PTWs on lower speed minor urban roads in rear end collisions. They are the primary contributor to the crash as a result of detection or overall failures that are influenced either by physical and psychological factors or by visibility obstructions. Other road users misjudge the PTWs manoeuvres.

Cluster 6: 36 cases (8%)

Riders of all PTW types on urban A roads with 40 or 50 mph speed limits involved in right turn collisions. They are secondary contributors to the crash and make decision errors as a result of risk taking. The other drivers also make decision errors.

Cluster 7: 31 cases (7%)

Riders of all PTW types on rural roads with 40 or 50 mph speed limits involved in single vehicle crashes. Aged 26-45 they make action errors as a result of adverse road conditions or vehicle factors.

5. Conclusions

This research has analysed in-depth collision data of PTW crashes occurring in the UK in order to identify the primary road user errors classified using a Human Functional Failure approach. This model describes driving errors and mistakes according to the series of cognitive steps that result in a driving action. This behaviour data was analysed in the context of associated vehicle, infrastructure and rider/driver factors.

The availability of in-depth crash injury data provides a greater depth of understanding of road user behaviour than is typically available within macroscopic, police reported crash data. The systematic collection of information about the perceptions, actions and motivations of the active road users can only be conducted by specialist teams and is not possible for routine police reporting. The present analysis has shown that an understanding of the role of PTW rider behaviour is enhanced when it is related to the behaviours of other drivers involved in the crash.

The analysis confirms that a systematic understanding of human functional failures within the framework of a comprehensive examination of pre-crash factors can result in new insights of crash causation. In particular the association between failure types and other crash factors may initiate the development of new countermeasures.

The application of latent class cluster analysis has segmented PTW collisions into seven distinct groups on the basis of the behaviour of all involved road users and their characteristics, vehicle and infrastructure factors. Some of these, such as ‘looked but failed to see’ have been identified in previous research however other groups are new.

6. Limitations

Like other investigations into the causes of traffic collisions this analysis incorporates an unavoidable subjective element. The identification of specific human functional failure modes was made on the basis of interviews, crash reconstructions and available scene evidence. While corroborating information was always sought the final classification of the failure types was inevitably subjective. The crash segmentation that was the result of the latent class cluster analysis was purely data driven however the interpretation of the clusters and the relevance of specific factors remained inherently subjective on the part of the investigator.

The availability of in-depth crash data presents new opportunities to develop a more detailed understanding of the role of road user, vehicle and infrastructure factors in crash causation. The analysis has identified statistically significant relationships between factors where there are deviations from the overall population distributions. Nevertheless it is beyond the scope of this analysis to examine the increase in crash risk deriving from these factors.

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The Road Accident In-Depth Studies (RAIDS) programme and associated database were commissioned by the United Kingdom Department for Transport in 2012 to consolidate data gathered from historic in-depth collision investigation programmes dating back to the year 2000. Data collection is ongoing and since 2012, 1200 new

cases have been investigated, the data is made available free of charge over the internet however conditional access is limited to those with a defined research need. For further information please contact RAIDS@dft.gov.uk.

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