



## Rule discovery to identify patterns contributing to overrepresentation and severity of run-off-the-road crashes

Alfonso Montella <sup>a,\*</sup>, Filomena Mauriello <sup>a</sup>, Mariano Pernetti <sup>b</sup>, Maria Rella Riccardi <sup>a</sup>

<sup>a</sup> University of Naples Federico II, Department of Civil, Architectural and Environmental Engineering, Via Claudio 21, 80125, Naples, Italy

<sup>b</sup> University of Campania Luigi Vanvitelli, Department of Engineering, Via Roma 29, 81031, Aversa, CE, Italy

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### ABSTRACT

The main objective of this paper was to analyse the roadway, environmental, and driver-related factors associated with an overrepresentation of frequency and severity of run-off-the-road (ROR) crashes. The data used in this study refer to the 6167 crashes occurred in the section Naples–Candela of A16 motorway, Italy in the period from 2001 to 2011. The analysis was carried out using the rule discovery technique due to its ability of extracting knowledge from large amounts of data previously unknown and indistinguishable by investigating patterns that occur together in a given event. The rules were filtered by support, confidence, lift, and validated by the lift increase criterion. A two-step analysis was carried out. In the first step, rules discovering factors contributing to ROR crashes were identified. In the second step, studying only ROR crashes, rules discovering factors contributing to severe and fatal injury (KSI) crashes were identified. As a result, 94 significant rules for ROR crashes and 129 significant rules for KSI crashes were identified. These rules represent several combinations of geometric design, roadside, barrier performance, crash dynamic, vehicle, environmental and drivers' characteristics associated with an overrepresentation of frequency and severity of ROR crashes. From the methodological point of view, study results show that the *a priori* algorithm was effective in providing new information which was previously hidden in the data. Finally, several countermeasures to solve or mitigate the safety issues identified in this study were discussed. It is worthwhile to observe that the study showed a combination of factors contributing to the overrepresentation of frequency and severity of ROR crashes. Consequently, the implementation of a combination of countermeasures is recommended.

### 1. Introduction

Each year road crashes cause 1.35 million deaths and 50 million injuries worldwide (WHO, 2018). Currently, road crashes represent the 8th leading cause of death for people of all ages. Lane departures resulting in run-off-the-road (ROR) crashes account for far too great a portion of the total highway crashes. ROR crashes involve vehicles that leave the travel lane, encroach onto the shoulder and beyond, and hit one or more natural or artificial objects, fixed or not, such as ditches, poles, embankments, safety barriers, and trees. About thirty percent of the road fatalities are the result of a ROR crash (NHTSA, 2019). More studies of ROR crashes in relation to the roadside features, the vehicle types, and the environmental conditions would be helpful for the selection of appropriate safety countermeasures. Indeed, highway agencies are continually faced with decisions relating to roadside safety,

and it is important to ensure that the best use is made of the limited funds available (Montella, 2001). The European Directive 2019/1936 on road infrastructure safety management (European Parliament, 2019) provides guidance for the provision and maintenance of “forgiving roadsides” in the attempt of preventing serious injuries. So far, little progress has been made in this direction witnessed by the still high number of serious and fatal ROR crashes and inadequate knowledge has been achieved regarding the characteristics of ROR crashes in terms of circumstances, causes, and consequences. Thus, further studies are required.

To date, researchers have used an extensive variety of methodological approaches, ever more sophisticated over time, to handle and explore crash data striving to investigate the many less obvious features in the data and hoping to uncover important new inferences relating to road safety (Mannering and Bhat, 2014). Most studies of ROR crashes

\* Corresponding author.

E-mail addresses: [alfonso.montella@unina.it](mailto:alfonso.montella@unina.it) (A. Montella), [filomena.mauriello@unina.it](mailto:filomena.mauriello@unina.it) (F. Mauriello), [mariano.pernetti@unicampania.it](mailto:mariano.pernetti@unicampania.it) (M. Pernetti), [maria.rellariccardi@unina.it](mailto:maria.rellariccardi@unina.it) (M. Rella Riccardi).



used discrete outcome models treating injury severity as either a nominal or ordered variable. Most common nominal (un-ordered) models used in the literature were multinomial logit models (Schneider et al., 2009), nested logit models (Holdridge et al., 2005; Lee and Mannering, 2002) and random parameters (mixed) logit models (Al-Bdairi et al., 2018; Rezapour et al., 2019) which allowed parameters to vary across observations and can potentially capture unobserved heterogeneity among data. Most common ordered regression models were ordered logit models (Russo and Savolainen, 2018), random parameters (mixed) ordered logit models (Gong and Fan, 2017), generalized ordered logit models (Eustace et al., 2016), partial proportional odds (PPO) logit models (Gong et al., 2016), ordered probit models (Shawky et al., 2016; Zhou and Chin, 2019), and random parameters (mixed) ordered probit models (Al-Bdairi and Hernandez, 2017; Anarkooli et al., 2017). Recent studies used advanced machine learning techniques, such as association rules (Das et al., 2019; Montella, 2011), Bayesian networks (Prati et al., 2017), classification and regression tree (CART) models (Huang et al., 2018; Montella et al., 2020; Moral-García et al., 2019), cluster analysis (Chang et al., 2019), neural networks (Zeng and Huang, 2014), random forests (Chen and Chen, 2020), structural equation models (Lee et al., 2018), and support-vector machine (Chen et al., 2016), in order to conduct the non-trivial process of identifying valid, potentially useful, and comprehensible patterns among large quantities of crash data.

Among the different methods used in the literature, association rules have the advantage of providing valuable insights on the interdependence among the several roadway, environmental, and driver-related factors contributing to the frequency and severity of crashes. Identifying an effective approach to investigate ROR crashes can provide valuable insights into how to decrease ROR fatal and severe injuries. This study used the rule discovery tool to investigate contributory factors ROR crashes since this methodology does not require analysis on the correlation between explanatory variables, demonstrates powerful ability in extracting knowledge, and allows to handle noisy and missing data.

The main objective of this paper is to analyse the roadway, environmental, and driver-related factors that are associated with ROR crashes contributing to fill in the gap of their influence on overrepresentation of frequency and severity of ROR crashes. Moreover, based on study results, a discussion on safety countermeasures to most efficiently reduce ROR injuries and fatalities is provided.

## 2. Literature review

Evidence of the dangerous features of the roadway and its roadsides had already been provided by many researchers. To date, researchers have focused their commitment trying to raise awareness on critical road design characteristics. Below, we tried to retrace their exertions through an in-depth literature review in the attempt to summarize the main findings about potential risk factors.

### 2.1. Crashes on terminals of safety barriers

Experience of crashes on the untreated safety barrier ends has shown the high severity of crashes against unprotected terminals, as they can penetrate the passenger compartment or cause the vehicle rollover (Igharo et al., 2004; La Torre et al., 2012). In the U.S., in the late 90 s the Federal Highway Administration has formalized the evaluation and certification process for roadside safety hardware, meaning that all guardrail terminals used on the National Highway System must satisfy the full-scale crash test and evaluation requirements of NCHRP Report 350 (AASHTO, 1998). In the deliverable 6 of the EU RISER project (Chalmers University of Technology, 2005), safety barrier ends are recognized as point hazards if not fulfilling the requirements of EN 1317 or NCHRP 350 standards as well as blunt ends of safety barriers. In addition to barrier terminals and blunt-ends, ramped ends of guardrails parallel to the road also lead to severe consequences as they can easily

cause a vehicle vault or rollover. In RISER detailed crash database, in 41 crashes the barrier was the only obstacle involved. In 14 cases, the barrier termination was impacted; in 4 of those cases, the vehicle travelled along the top of the barrier until it came to a stop or impacted another object whereas in 10 cases, the vehicle was launched into the air.

Griffin (1991) analysed the performance of turned-down guardrail terminals in the state of Texas. The study aimed at assessing the cost-effectiveness of replacing turned-down end treatments with different end treatments by examining the frequency of vehicle overturn and the severe consequences associated with turned-down end. The study highlighted an overrepresentation of fatal collisions at turned-down guardrail terminals. In the study performed by Ray et al. (2001) in Connecticut, Iowa and North Carolina, the in-service crash performance data for the breakaway cable guardrail terminals (BCT) and modified eccentric loader breakaway cable guardrail terminals (MELT) indicate that these terminals perform reasonably well. Over 60 % of crashes involving BCT and MELT resulted in only property damage, and only 5% involved severe occupant injuries. In the study performed by Igharo et al. (2004) in Washington State, the installation characteristics measured for BCT and Slotted Rail Terminals (SRT), along with the related crash data for these devices, showed acceptable performance when struck as 63 % of the BCT and SRT crashes resulted in only property damage. Holdridge et al. (2005) developed multivariate statistical injury severity models for fixed-object crashes to analyse the in-service performance of roadside hardware on urban State Route system in Washington State. The results showed that leading ends of guardrails and bridge rails increase the probability of fatal injury. Recently, Molan and Ksaibati (2020) carried out a study on end treatment crashes in Wyoming especially occurred in rural areas. Turned-down and blunt end terminals were found to strongly affect severe crashes.

### 2.2. Crashes on safety barriers

Traffic barriers are installed to keep vehicles on the roadways to prevent severe vehicle collisions with fixed obstacles such as trees and walls. However, such devices are also an obstacle and a not negligible proportion of severe injuries and fatalities occur when vehicle collide with safety barriers. Several studies have been conducted in the attempt of evaluating barrier potential hazard basing on their characteristics.

Li et al. (2018a,b) found that hitting guardrails leads a statistically significant reduction in fatal and severe injuries (about 45%–50%).

Zou et al. (2014) studied the performance of W-beam guardrails, concrete walls, and cable barriers in terms of crash severity and found 43 % of decrease in the odds of injury when striking a guardrail compared to striking a large-offset median concrete barrier wall. This reduction achieves 65 % if compared to hitting a small-offset median concrete barrier wall whereas hitting a near-side cable barrier and far-side cable barrier decrease the odds of injury by 57 % and 37 %, respectively, when compared to hitting a guardrail.

In France, Martin (2000) collected detailed information on all crashes (injury or property damage only) occurred in the period 1986–1995 on 224 km of the motorway between Paris and Perpignan to compare crash severity for vehicles impacting against steel and concrete safety barriers. A first impact on a concrete New Jersey safety barrier increases the risk of personal injury by a factor of 1.9 compared to a steel safety barrier. Similar results were found in a subsequent study relative to a 2'000 km French motorway network by Martin and Quincy (2001).

Ray et al. (2001) conducted in-service performance evaluations and assessments of the in-service performance of several types of longitudinal barrier systems: the concrete median barrier (CMB), the G2 weak-post W-beam guardrail, and the G1 weak-post cable guardrail. Only property damage resulted from approximately 80 % of the flexible guardrail (84 % for the W-beam guardrail, 79 % for the cable guardrail) crashes, whereas 68 % crashes resulted in only property damage with

rigid CMB. The difference between the property damage only rate for the CMB and W-beam guardrails resulted statistically significant at the 90 % confidence level meaning that the more flexible barriers lead to a lower proportion of injury crashes.

Tarko et al. (2008) investigated the impact of median design on crash frequency and severity. In their study, crashes were classified as single-vehicle, multiple-vehicle same direction, and multiple-vehicle opposite direction. Their results highlighted that a reduced median width with concrete barriers can eliminate opposite direction crashes. However, reducing the median width, the frequency of single vehicle crashes doubles as well as crash severity tends to increase.

Alluri et al. (2015) carried out a study on freeways in Florida to compare the safety performance of G4 strong-post median W-beam guardrails and cable median barriers. The barrier performance was assessed basing on the percentages of errant vehicles prevented from crossing the barrier. Guardrails performed slightly better than cable barriers in terms of barrier and median crossover crashes. However, cable median barriers were found to result in fewer severe injury crashes (the odds of severe injury were 0.56 times lower than the odds of severe injury when a vehicle hits a guardrail).

Recently, Rezapour et al. (2019) found that the odds of severe crash colliding a traffic barrier increased for rollover crashes, being improperly buckled, cut side slope other than level, non-normal driver condition, and being an older driver.

### 2.3. Fixed object crashes

The presence of fixed objects, e.g. trees, ditches and unprotected drainage channels (depending upon their profile), wall, the end of walls and rock cuttings (especially if they are too close to the travelled path) on highway roadsides may strongly influence the crash severity. Crash severity derived by collisions with fixed object is closely related to impact speed and angle (Singleton et al., 2010). Budzynski et al. (2017) stated that the main consequence of a roadside hazard is not the likelihood of a crash itself but its severity, confirming that the roadside environment and its components (embankments, ditches, poles, etc.) are very critical when ROR crashes occur. Height and side slope of the embankment are factors that contribute to the severity (Austroads, 2015). Steep and high embankments represent a hazardous roadside feature for errant vehicles and have the potential to cause vehicle roll-over, often resulting in severe outcomes. Viner (1995) analysed the nature of ROR and vehicle rollover and found that side slopes and ditches are the leading cause of ROR fatalities.

### 2.4. Motorcycle crashes

Several studies identified powered-two-wheeler (PTW) ROR crashes as a major safety issue. Furthermore, motorcyclists are dramatically overrepresented in the fatalities resulting from guardrail impacts (Atahan et al., 2018; Daniello and Gabler, 2011; Jama et al., 2011; Russo and Savolainen, 2018). EuroRAP (2008) reported that PTW drivers are 15 times more likely to be killed than car occupants because of collision with roadside barrier. On the Spanish regional road network of Castilla y León (CyL), ROR constituted 43 % of the fatal motorcycle crashes (Perandones et al., 2008). In the U.S., motorcycles compose only 2% of the vehicle fleet, but account for 42 % of all fatalities resulting from guardrail collisions and one in ten motorcyclists striking a guardrail were fatally injured – a fatality risk nearly 100 times higher than for car occupants involved in a collision with a guardrail (Gabler, 2007). In Australia and New Zealand, Jama et al. (2011) highlighted that fatalities of motorcyclists predominantly involve W-beams barrier (72.7 %).

## 3. Study data

### 3.1. Geometric data

The study site is the section Naples–Candela of the motorway A16 Naples–Canosa ( $L = 255.0$  km, i.e., 127.5 km per carriageway), in Italy. A16 Motorway is a divided highway with two lanes for each direction (lane width = 3.75 m, right shoulder width = 0.50–3.50 m, median width = 2.00 m), access control, and interchanges. Median safety barriers include W-beam, double W-beam, thrie-beam, and concrete New Jersey shaped barriers. Roadside safety barriers include W-beam, thrie-beam, bridge rails, and bridge steel New Jersey barriers. The motorway has a bending alignment, with several low radius curves and many design inconsistencies, and by sections with high longitudinal grades (Montella, 2009; Montella et al., 2008, 2014). The corridor is connected to the road network by 11 interchanges. Part of the route is on mountainous terrain with 11 tunnels ( $L = 4.03$  km) and 38 bridges ( $L = 8.11$  km). Statutory speed limit is 130 km/h but posted speed limits equal to 80 km/h are installed in both travel directions ( $L = 50.25$  km in east carriageway,  $L = 26.60$  km in west carriageway). Radius of the horizontal curves varies between 245 and 4'000 m. Spiral transitions are not present. Deflection angle varies between 5 and 109 gon. Superelevation mean is equal to 3.25 %. Maximum longitudinal grade is equal to 6.35 %.

### 3.2. Crash data

Since the Italian national crash database maintained by the National Institute of Statistics presents major issues related to the crash report form, the crash classification, the crash location, and the crash severity, a new database was developed according to a framework based on the critical review of the crash databases in Australasia, the European Union and the United States (Montella et al., 2013, 2019). Crash data were collected through analysis of police reports in the eleven year period 2001–2011 and were integrated with detailed site inspections. Crashes at the interchange ramps, at rest areas, and at tollbooths were excluded from the study because of the poor location descriptions of the police reports. The final dataset consisted of 6167 crashes (see Table 1). Variables considered in the analysis were: 1) alignment, 2) curve direction, 3) curve radius, 4) deflection angle, 5) grade, 6) pavement, 7) weather, 8) lighting, 9) involved vehicles, 10) driver gender, 11) driver age, 12) driver behaviour, 13) crash type, 14) crash dynamics, 15) ROR direction, 16) most harmful impacted object, 17) point of first impact, 18) barrier performance, and 19) severity.

Each crash was classified according to the alignment (tangent and curve). Then, each curve was additionally classified in relation to curve direction (left and right), curve radius (small, less than or equal to 400 m, and large, greater than 400 m), and deflection angle (small, less than or equal to 45 gon, and large, greater than 45 gon). Longitudinal slope was classified according to the grade: downgrade (longitudinal slope less than -2%), level (longitudinal slope between -2% and 2%), upgrade (longitudinal slope greater than 2%). Collision type variable was classified in ROR crashes and other crashes. Furthermore, for each crash, the involved vehicles and drivers were reported. The study analysed environmental conditions to highlight the effects of road surface conditions (dry, wet, slippery, and snowy/frozen), weather conditions (clear, cloudy, rainy, and snow/foggy/windy), and lighting conditions (daytime and nighttime). Severity was classified according to the most severe injured person involved in the crash: a crash fatality was every single person that dies in the crash or within the 30 days following it. As far as non-fatal injuries, two levels were considered: severe injuries and slight injuries. A severe injury was a person detained in hospital or suffering any of the following injuries whether or not detained in hospital: significant burns (second and third degree burns over 10 % or more of the body), fractures, concussion, internal injuries, severe cuts and lacerations, or the injuries causing death 30 or more days after the crash. Slight

**Table 1**  
Descriptive statistics of total crashes.

Variable	Code	Count	%	KSI	
				Count	%
<b>Total</b>	–	6167	100.00	302	4.90
<b>Crash type</b>					
Run off the road	ROR	2762	44.79	210	7.60
Other	Ot	3405	55.21	92	2.70
<b>Geometric design factors</b>					
<b>Alignment</b>					
Curve	Cu	3013	48.86	167	5.54
<b>Curve direction</b>					
Left	L	1666	27.01	101	6.06
Right	R	1347	21.84	66	4.90
<b>Curve radius</b>					
R > 400 m	Large	2050	33.24	109	5.32
R ≤ 400 m	Small	963	15.62	58	6.02
<b>Deflection angle</b>					
Angle > 45 gon	Large	1397	22.65	76	5.44
Angle ≤ 45 gon	Small	1586	25.72	90	5.67
Missing	Missing	30	0.49	1	3.33
Tangent	Tan	3154	51.14	135	4.28
<b>Grade</b>					
G > 0.02	Up	2576	41.77	113	4.39
-0.02 ≤ G ≤ 0.02	Level	2016	32.69	113	5.61
G < -0.02	Down	1575	25.54	76	4.83
Missing	Missing	13	0.21	11	84.62
<b>Environmental factors</b>					
<b>Pavement</b>					
Dry	D	4260	69.08	205	4.81
Slippery	Sl	46	0.75	4	8.70
Snowy/Frozen	Sw/Fr	37	0.60	1	2.70
Wet	W	1738	28.18	81	4.66
Missing	Missing	86	1.39	11	12.79
<b>Weather</b>					
Clear	Cl	3733	60.53	171	4.58
Cloudy	Cloudy	1143	18.53	73	6.39
Rainy	Rn	1076	17.45	46	4.28
Snow/Foggy/Windy	Sw/Fg/Wd	88	1.43	1	1.14
Missing	Missing	127	2.06	11	8.66
<b>Lighting</b>					
Day	D	4312	69.92	212	4.92
Night	N	1833	29.72	79	4.31
Missing	Missing	22	0.36	11	50.00
<b>Vehicle factors</b>					
<b>Involved vehicles</b>					
PTW SV	PTW	36	0.58	20	55.56
PTW-PTW	PTW	4	0.06	2	50.00
PTW-Car	PTW	21	0.34	10	47.62
PTW-Truck	PTW	3	0.05	1	33.33
Car SV	Car	4220	68.43	156	3.70
Car-Car	Car	649	10.52	38	5.86
Car-Other	Car	2	0.03	–	0.00
Truck SV	Truck	570	9.24	12	2.11
Truck-Car	Truck	496	8.04	34	6.85
Truck-Truck	Truck	164	2.66	29	17.68
Truck-Other	Truck	2	0.03	–	–
<b>Driver factors</b>					
<b>Driver gender</b>					
Female	F	400	5.33	19	4.75
Male	M	3973	52.92	185	4.66
Missing	Missing	3135	41.76	212	6.76
<b>Driver age</b>					
≤18	≤18	15	0.20	1	6.67
19–25	19–25	489	6.51	30	6.13
26–45	26–45	2416	32.18	95	3.93
46–65	46–65	1172	15.61	60	5.12
>65	>65	263	3.50	13	4.94
Missing	Missing	3153	42.00	217	6.88
<b>Driver behaviour</b>					
Alcohol or drug use	Alcohol/ Drug	64	1.04	8	12.50
Distraction	Distract	356	5.77	26	7.30
Speeding	Speed	1827	29.63	150	8.21
Inappropriate manoeuvre	Inappropri	447	7.25	41	9.17
Overtaking	Overtake	138	2.24	3	2.17

**Table 1 (continued)**

Variable	Code	Count	%	KSI	
				Count	%
Sleeping	Sleep	89	1.44	16	17.98
Normal	Normal	3212	52.08	54	1.68
Other	Ot	34	0.55	4	11.76
<b>Severity</b>					
PDO	PDO	4757	77.14	–	–
Slight	Sl	1108	17.97	–	–
KSI	KSI	302	4.90	302	100.00

injuries were all the injuries not classified as serious. Finally, crash severity was classified in three levels: fatal and severe injuries (KSI, n = 302; 4.90 %), slight injuries (Sl, n = 1108; 17.97 %), and property damage only (PDO, n = 4757; 77.14 %). To gain better performance of the association rules, severe and fatal injuries were considered a unique level (KSI) because of the low number of fatal injuries. Data related to drivers involved in the crash were gender (male or female), age (≤18, 19–25, 26–45, 46–65, >65), and behaviour (alcohol or drug use, distraction, speeding, inappropriate manoeuvres, overtaking, sleeping, normal, other). In the dataset, crashes involving more than one vehicle were considered as two-vehicle crashes (n = 196, 3.18 %). Then, observing vehicles involved in the crash and the resulting crash severity, it was possible to highlight three vehicle macro-categories: 1) PTW (n = 64), 2) truck (n = 1232), and 3) car (n = 4871). Consequently, the code used for involved vehicle reports one vehicle type basing on the following order: 1) PTW, 2) truck, and 3) car. Thus, if a PTW and a truck were involved in the crash, the variable involved vehicle was classified as PTW, if a truck and a car were involved in the crash, the variable involved vehicle was classified as truck, and so on. Moreover, it was decided to do not use variables related to the use of seatbelts and helmets because of their poor quality and a considerable proportion of missing information.

Data related only to ROR crashes (n = 2762; 44.79 % of the total crashes) are reported in Table 2. To provide a clearer picture of ROR crashes, a crash tree was provided (Fig. 1). 88.6 % of ROR crashes were single-vehicle ROR crashes (SV ROR) and ROR crashes followed by another collision (ROR + Event). 11.4 % of ROR crashes were crashes with a first event (e.g., rear-end crashes) followed by a vehicle leaving the carriageway (Event + ROR). In the first group (SV ROR and ROR + Event), 61.2 % of the crashes occurred on curves while the remaining 38.8 % occurred on tangents. As expected, most ROR crashes on left curves occurred on the roadside (57.5 %). On the contrary, most ROR crashes on right curves occurred on the median (54.8 %).

Table 3 provides detailed information related only to ROR crashes: 1) crash dynamics (ROR SV, ROR + second event, Event + ROR), 2) ROR direction (median, roadside, not applicable used for event + ROR because the ROR direction depends on the first crash), 3) most harmful impacted object (ditch, foreslope, median w beam, median New Jersey, median thrie beam, roadside or bridge w beam, roadside or bridge New Jersey or redirective profile, roadside or bridge thrie beam, wall, other), 4) point of first impact (blunt-end or bull nose, longitudinal section), and 5) barrier performance (overriding, overturning, penetrated, redirected, stopped in contact).

Fig. 2 provides further information on crash dynamics. Single-vehicle ROR crashes were 70.7 % of ROR crashes, ROR + event crashes were 17.9 % of ROR crashes, and event + ROR crashes were 11.4 % of ROR crashes. The event after the ROR crash was a ROR crash in 56 % of the cases, a rear-end crash in 17.3 % of the cases, an angle crash in 7.5 % of the cases, and a side-swipe crash in 6.6 % of the cases. The event before the ROR crash was a rear-end crash in 50.0 % of the cases, and a side-swipe crash in 34.4 % of the cases.

**Table 2**  
Descriptive statistics of ROR crashes.

Variable	Code	Count	%	KSI	
				Count	%
<b>Total</b>	–	2762	100.00	212	7.64
<b>Geometric design factors</b>					
<i>Alignment</i>					
Curve	Cu	1638	59.30	136	8.30
<i>Curve direction</i>					
Left	L	952	34.47	78	8.19
Right	R	686	24.84	58	8.45
<i>Curve radius</i>					
$R > 400$ m	Large	939	34.00	85	9.05
$R \leq 400$ m	Small	699	25.31	51	7.30
<i>Deflection angle</i>					
Angle $> 45$ gon	Large	874	31.64	67	7.67
Angle $\leq 45$ gon	Small	745	26.97	68	9.13
Missing	Missing	19	0.69	1	5.26
Tangent	Tan	1124	40.70	74	6.58
<i>Grade</i>					
$G > 0.02$	Up	616	22.30	47	7.63
$-0.02 \leq G \leq 0.02$	Level	1199	43.41	88	7.34
$G < -0.02$	Down	947	34.29	75	7.92
<b>Environmental factors</b>					
<i>Pavement</i>					
Dry	D	1435	51.96	137	9.55
Slippery	Sl	38	1.38	3	7.89
Snowy/Frozen	Sw/Fr	22	0.80	–	–
Wet	W	1256	45.47	70	5.57
Missing	Missing	11	0.40	–	–
<i>Weather</i>					
Clear	Cl	1275	46.16	114	8.94
Cloudy	Cloudy	645	23.35	54	8.37
Rainy	Rn	783	28.35	41	5.24
Snow/Foggy/Windy	Sw/Fg/Wd	42	1.52	1	2.38
Missing	Missing	17	0.62	–	–
<i>Lighting</i>					
Day	D	1953	70.71	151	7.73
Night	N	806	29.18	59	7.32
Missing	Missing	3	0.11	–	–
<b>Vehicle factors</b>					
<i>Involved vehicles</i>					
PTW SV	PTW	23	0.83	16	69.57
PTW-PTW	PTW	3	0.11	2	66.67
PTW-Car	PTW	1	0.04	1	100.00
PTW-Truck	PTW	1	0.04	–	–
Car SV	Car	2078	75.24	139	6.69
Car-Car	Car	253	9.16	23	9.09
Truck SV	Truck	240	8.69	11	4.58
Truck-Car	Truck	131	4.74	11	8.40
Truck-Truck	Truck	32	1.16	7	21.88
<i>Driver factors</i>					
<i>Driver gender</i>					
Female	F	186	6.73	15	8.06
Male	M	1324	47.94	99	7.48
Missing	Missing	1252	45.33	98	7.83
<i>Driver age</i>					
$\leq 18$	$\leq 18$	5	0.16	–	–
19–25	19–25	257	9.30	19	7.39
26–45	26–45	821	29.73	51	6.21
46–65	46–65	345	12.49	35	10.15
$> 65$	$> 65$	78	2.82	8	10.26
Missing	Missing	1256	45.47	97	7.72
<i>Driver behaviour</i>					
Alcohol or drug use	Alcohol/ Drug	57	2.06	7	12.28
Distraction	Distract	230	8.33	20	8.70
Speeding	Speed	1569	56.81	120	7.65
Inappropriate manoeuvre	Inapprop	146	5.29	16	10.96
Overtaking	Over	61	2.21	3	4.92
Sleeping	Sleep	81	2.93	12	14.81
Normal	Normal	600	21.72	28	4.67
Other	Ot	18	0.65	4	22.22
<i>Severity</i>					
PDO	PDO	1792	64.58	–	–
Slight	Slight	771	27.78	–	–
KSI	KSI	212	7.64	212	100.00

#### 4. Method

This study used association rule discovery, which is a descriptive analytic methodology for extracting and refining valuable knowledge from large datasets. The tool belongs to data mining techniques and has already shown its ability in discovering significant rules highlighting items that occur frequently together in a crash dataset. What is more, association rule is focused on the search and finding of patterns in data rather than the confirmation of hypotheses (Das et al., 2019) and is not affected by the absence of important data, which can potentially undermine traditional statistical analyses leading to biased and inconsistent results and erroneous safety engineering countermeasures. Association discovery was performed using the a priori algorithm (Agrawal et al., 1993). Each crash record contains different items (e.g., crash type, crash severity, alignment, grade, pavement conditions, etc.) and the dataset contains all the items of each crash. Basing on the relative frequency of times the item-sets occur alone and in combination in a dataset, the association rules were extracted with the form “A → B”, where A and B are disjoint item-sets: A is the antecedent and B is the consequent. The a priori algorithm uses simple and repetitive steps examining candidate item-sets to find frequent item-sets. Then, it uses the new candidate item-sets to find new frequent item-sets until no newer item-sets can be produced (Montella et al., 2020). The parameters support, confidence, and lift were used to assess the strength of each association rule. Support is the percentage of the entire data set covered by the rule, confidence measures the reliability of the inference of a generated rule, and lift is a measure of the statistical interdependence of the rule.

Supports are calculated as follows:

$$\text{Support } (A \rightarrow B) = \frac{\#(A \cap B)}{N}; \text{Support } (A) = \frac{\#(A)}{N}; \text{Support } (B) = \frac{\#(B)}{N} \quad (1)$$

where  $\text{support}(A \rightarrow B)$  is the support of the association rule,  $\text{support}(A)$  is the support of the antecedent,  $\text{support}(B)$  is the support of the consequent,  $\#(A \cap B)$  is the number of crashes where both the condition A (antecedent) and the condition B (consequent) occur,  $\#(A)$  is the number of crashes with A antecedent,  $\#(B)$  is the number of crashes with B consequent, and N is the total number of crashes in the dataset.

Confidence is calculated as follows:

$$\text{Confidence} = \frac{\text{Support } (A \rightarrow B)}{\text{Support } (A)} \quad (2)$$

Confidence is defined by the percentage of cases in which a consequent appears given that the antecedent has occurred. A high confidence for  $A \rightarrow B$  indicates that the presence of B as consequent is high in the crashes having A (single item or combination of more items) as antecedent.

Lift is calculated as follows:

$$\text{Lift} = \frac{\text{Support } (A \rightarrow B)}{\text{Support } (A) \times \text{Support } (B)} \quad (3)$$

The lift of the rule relates the frequency of co-occurrence of the antecedent and the consequent to the expected frequency of co-occurrence under the assumption of conditional independence. A lift value lower than 1 indicates negative interdependence between the antecedent and the consequent. A lift value equal to 1 designates independence, and a value greater than 1 indicates positive interdependence (i.e., the number of times the sets of items occur together is greater than they would if they were independent of each other). The higher the lift, the greater the strength and the interest of the association rule since it would indicate how more often the antecedent and the consequent are part of the same crash than if these events were statistically independent. It is desirable for the rules to have a high level of support, a large confidence, and a lift value considerably greater than one. Thus,

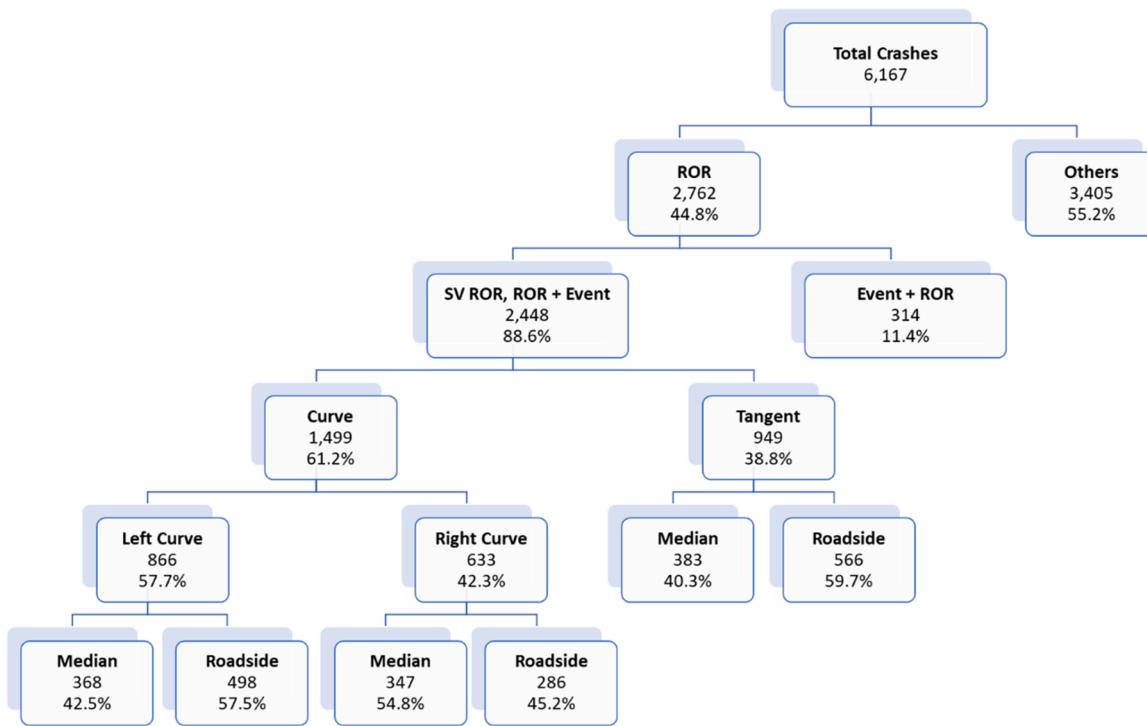


Fig. 1. Crash tree.

minimum values for support, confidence and lift are needed.

A rule with a single antecedent and a single consequent is defined as a 2-item rule; similarly, a rule with two antecedents and single consequent is defined as a 3-item rule. Each rule with  $n+1$  items is validated by verifying that each variable produces a lift increase (LIC). The LIC ensures that each additional item in the rules leads to an increase in terms of lift. The rules with only one item in the antecedent are used as a starting point, rules with more items are selected over simpler rules if the LIC condition satisfied the minimum threshold of 1.05 (López et al., 2014; Montella et al., 2011, 2012a, 2020).

LIC is calculated as follows:

$$\text{LIC} = \frac{\text{Lift}_{A_n}}{\text{Lift}_{A_{n-1}}} \quad (4)$$

where  $A_{n-1}$  is the antecedent of rule with  $n-1$  items, and  $A_n$  is the antecedent of rule with  $n$  items.

These criteria are further explained with an example. Let's suppose that a crash database consists of 1000 crashes and out of these crashes 100 were fatal. Out of the total crashes, 400 of them occurred on curve alignment and 80 of them were fatal. Now consider the rule "curve alignment → fatal crashes" for this database. In this rule, "curve alignment" is the antecedent while "fatal crashes" is the consequent. The support for the rule is defined as the percentage of all crashes that were both fatal and occurred on a curve alignment. For the aforementioned hypothetical rule, support would be 8% ( $80/1000 = 0.08$ ). Confidence for the rule is defined as the percentage of fatal crashes among all crashes that occurred on curve alignment. The number of such crashes is 400 and hence in this database, the confidence for the aforementioned rule would be 20% ( $80/400 = 0.20$ ). The lift is the ratio between the support of the rule (equal to  $80/1000 = 0.08$ ) and the expected support under the assumption of conditional independence (support of curve alignment, equal to  $400/1000 = 0.40$ , multiplied for the support of fatal crashes, equal to  $100/1000 = 0.10$ ;  $0.40 \times 0.10 = 0.04$ ) and is equal to 2 ( $0.08/0.04 = 2$ ). Now, let's make a new assumption. Out of the 400 crashes occurred on curves, in 100 crashes drivers were speeding and 30 of these crashes were fatal. The new rule is "curve alignment & speeding → fatal

crashes". This is a 3-item rule with support equal to 0.03 ( $30/1000 = 0.03$ ), confidence equal to 0.30 ( $30/100 = 0.30$ ), and lift equal to 3 ( $0.03/(0.10 \times 0.10) = 0.03/0.01 = 3$ ). The parent rule (curve alignment → fatal crashes) has a lift equal to 2 and the lift increase of the 3-item rule (curve alignment & speeding → fatal crashes) is 1.5 ( $3/2 = 1.5$ ). It means that the proportion of fatal crashes for "curve alignment & speeding" is 1.5 times the proportion for "curve alignment".

A two-step analysis was performed investigating two dependent variables: 1) crash type, and 2) crash severity. In the first step, the dataset consisted of total crashes and only rules with ROR crashes as consequent were investigated. The threshold values of support (S), confidence (C), and lift (L) were set as follows:  $S \geq 0.5\%$ ,  $C \geq 50\%$ , and  $L \geq 1.2$ . After assessing the actual LIC for each rule with more than two items, the first set of rules was extracted. In the second step, the dataset consisted of ROR crashes and only rules with fatal and severe injury (KSI) as consequent were investigated. Five variables related only to ROR crashes were introduced: 1) crash dynamics, 2) direction of the first crash, 3) most harmful impacted object, 4) point of first impact, and 5) barrier performance.

Due to the different number of consequents belonging to the two datasets, it is preferable to use different threshold values of support and confidence in the two steps. Conversely, as the lift is used to assess the dependence between the items in the item set, the threshold value depends on how much stronger the analyst wants the dependence and we used the same threshold value in the two steps. Consistently with previous studies (Li et al., 2018a,b; López et al., 2014; Montella et al., 2020), we set the lift value equal to 1.2. Finally, in the second step the threshold values of support (S), confidence (C), and lift (L) were set as follows:  $S \geq 0.2\%$ ,  $C \geq 10.0\%$ , and  $L \geq 1.2$ .

This study used the open source software R and the R packages 'arules' and 'arulesViz' to perform the analyses.

## 5. Results

All classes reported for each variable in the descriptive statistics (Tables 1–3) were investigated. The rules satisfying the predefined thresholds in terms of support, confidence, lift, and lift increase are

**Table 3**  
Descriptive statistics of variables related only to ROR crashes.

Variables	Code	Count	%	KSI	
				Count	%
<b>Total</b>	–	2762	100.00	212	7.64
<b>Crash dynamic factors</b>					
<b>Crash dynamics</b>					
ROR SV	ROR SV	1953	70.71	136	6.96
ROR + second event	ROR + event	495	17.92	40	8.08
Event + ROR	Event + ROR	314	11.37	34	10.83
<b>ROR Direction</b>					
Median	Median	1098	39.75	58	5.28
Roadside	Roadside	1350	48.88	118	8.74
Na	na	314	11.37	34	10.83
<b>Roadside factors</b>					
<b>Most harmful impacted object</b>					
Ditch	Ditch	119	4.31	14	11.76
Foreslope	Slope	63	2.28	15	23.81
Median W-Beam	MWBeam	590	21.36	27	4.58
Median New Jersey Barrier	MNJ	469	16.98	31	6.61
Median Thrie Beam	MTBeam	91	3.29	1	1.10
Roadside\Bridge W-Beam	WBeam	688	24.91	53	7.70
Roadside\Bridge New Jersey Barrier	NJ	135	4.89	10	7.41
\Redirective profile					
Roadside\Bridge Thrie Beam	TBeam	184	6.66	13	7.07
Wall	Wall	379	13.72	41	10.82
Other	Ot	10	0.36	–	0.00
Missing	Missing	26	0.94	2	7.69
na	na	8	0.29	3	37.50
<b>Point of first impact</b>					
Blunt-end or Bull nose	Blunt-end/Bull nose	44	1.59	10	22.73
Longitudinal section	Longit	2186	79.15	132	6.04
Missing	Missing	7	0.25	–	–
na	na	525	19.01	68	12.95
<b>Barrier performance factors</b>					
<b>Barrier performance</b>					
Overriding	Override	35	1.27	11	31.43
Overturning	Overturn	286	10.35	42	14.69
Penetrated	Penetrated	72	2.61	10	13.89
Redirected	Redirected	1349	48.84	71	5.26
Stopped in contact	Stopped	931	33.71	60	6.44
Missing	Missing	26	0.94	2	7.69
na	na	63	2.28	14	22.22

reported in Tables 4–11. In Tables 4–11, both the strongest rules as well as the rules emphasized in the discussions are marked in bold. The rules were ordered by the decreasing value of lift. For each two-item rule, the three-item rules having the same antecedent of the parent rule were ordered again by the decreasing value of the lift, and so on. Furthermore, the rules were grouped and discussed in different sections according to the strongest 2-item parent rules. To highlight the relationship among

the different items of the rules, a graph for each group of rules was created (Figs. 3–10). In the graphs, the antecedents are in the external area while the consequent is the central node. The other nodes represent the rule and the arrows link the rules with the antecedents and the consequent. Two different node layouts were used: colour and size. The intensity of the blue colour represents the lift of the rule, while the size of the node represents the support. The number of arrows connected to each item shows the number of rules containing the item.

The a priori algorithm identified 94 significant rules with ROR crashes as consequent and 129 significant rules with KSI crashes as consequent.

### 5.1. Run-off-the-road crashes

Based on the variables identified as ROR contributory factors, rules were divided in three different groups: geometric design factors, environmental factors, and driver factors.

#### 5.1.1. Geometric design factors

The first group of rules (Table 4, Fig. 3) was characterised by the curve alignment as antecedent in a two-item rule and in further rules obtained adding one or more items to this rule. Overall, thirty-four rules were identified (rules 1–34). The twelve items contained in the rules are shown in the peripheral area of Fig. 3. The items are curve alignment, small radius curve, left direction of the curve, large deflection angle, level grade, wet pavement, daytime, cloudy weather, distract driving, female driver, driver age in the range 19–25, and vehicle type equal to car.

Along the curves, the proportion of ROR crashes was 54 % while in the total sample the proportion of ROR crashes was 45 %. Curve radius had a very relevant effect on the overrepresentation of ROR crashes (rules 2–9). Lift increase for small radius curves, i.e. curves with radius smaller or equal to 400 m, was 1.33. In wet pavement conditions and small radius curves, the proportion of ROR crashes was 88 %. It means that in driving conditions requiring high values of friction, such as driving in motorways with small radius curves, the presence of wet pavement, which is associated to a reduced friction, gives rise to a higher proportion of ROR crashes. Pavement friction helps to keep vehicles on the road when navigating curves and this is particularly important in wet weather (Elvik et al., 2009; Intini et al., 2020; Cafiso et al., 2021) when only a thin film of water on the surface of the pavement can reduce contact between the tire and pavement surface, the level of pavement friction is reduced, and this may lead to skidding or hydroplaning. In small radius curves and wet pavement conditions, 94 % of crashes with female drivers were ROR crashes, indicating a greater propensity of female drivers to leave the carriageway in these difficult driving conditions. Other significant factors related to the driver were the young age (19–25) and the distracted driving behaviour. A greater propensity to ROR crashes was associated also to large deflection angle (rules 10–22),

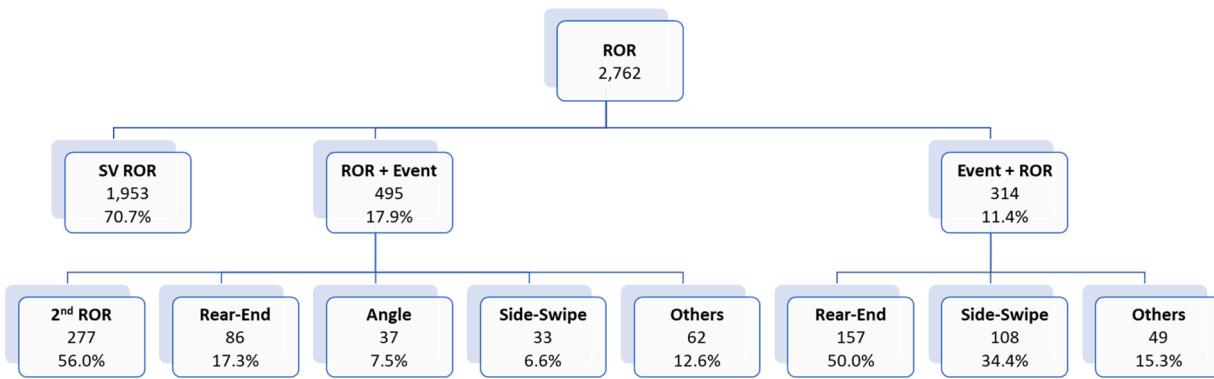


Fig. 2. ROR dynamics tree.

**Table 4**

Rules with geometric design factors as antecedent and ROR crash type as consequent.

Rule ID	Association Rule Antecedent	Consequent	S %	C %	Lift	LIC
1	Alignment = Cu	ROR	26.56	54.36	1.21	n.a.
2	Alignment = Cu & Curve Radius = Small	ROR	11.32	72.63	1.62	1.33
3	Alignment = Cu & Curve Radius = Small & Pavement = W	ROR	8.01	88.37	1.97	1.21
4	Alignment = Cu & Curve Radius = Small & Pavement = W & Driver Gender = F	ROR	0.55	94.44	2.11	1.07
5	Alignment = Cu & Curve Radius = Small & Driver Age = 19–25	ROR	1.14	86.42	1.93	1.19
6	Alignment = Cu & Curve Radius = Small & Driver Gender = F	ROR	0.75	80.70	1.80	1.11
7	Alignment = Cu & Curve Radius = Small & Grade = Level	ROR	5.19	80.81	1.80	1.11
8	Alignment = Cu & Curve Radius = Small & Grade = Level & Weather = Cloudy	ROR	1.43	86.27	1.93	1.07
9	Alignment = Cu & Curve Radius = Small & Driver Behaviour = Distract	ROR	0.50	79.49	1.77	1.10
10	Alignment = Cu & Deflection Angle = Large	ROR	14.17	62.56	1.40	1.15
11	Alignment = Cu & Deflection Angle = Large & Weather = Cloudy	ROR	3.97	76.09	1.70	1.21
12	Alignment = Cu & Deflection Angle = Large & Weather = Cloudy & Involved Vehicle = Car	ROR	3.63	81.45	1.82	1.07
13	Alignment = Cu & Deflection Angle = large & Weather = Cloudy & Involved Vehicle = Car & Lighting = D	ROR	2.45	87.28	1.95	1.07
14	Alignment = Cu & Deflection Angle = Large & Weather = Cloudy & Grade = Level	ROR	1.88	81.12	1.81	1.07
15	Alignment = Cu & Deflection Angle = Large & Driver Gender = F	ROR	0.94	73.42	1.64	1.17
16	Alignment = Cu & Deflection Angle = Large & Driver Gender = F & Lighting = D	ROR	0.76	78.33	1.75	1.07
17	Alignment = Cu & Deflection Angle = Large & Driver Age = 19–25	ROR	1.30	72.73	1.62	1.16
18	Alignment = Cu & Deflection Angle = Large & Driver Age = 19–25 & Grade = Level	ROR	0.57	81.40	1.82	1.12
19	Alignment = Cu & Deflection Angle = Large & Driver Age = 19–25 & Direction = L	ROR	0.63	78.00	1.74	1.08

**Table 4 (continued)**

Rule ID	Association Rule Antecedent	Consequent	S %	C %	Lift	LIC
20	Alignment = Cu & Deflection Angle = Large & Grade = Level	ROR	6.75	69.57	1.55	1.11
21	Alignment = Cu & Deflection Angle = Large & Grade = Level & Direction = L	ROR	4.26	74.29	1.66	1.07
22	Alignment = Cu & Deflection Angle = Large & Involved Vehicle = Car	ROR	7.31	70.03	1.56	1.12
23	Alignment = Cu & Curve Direction = L	ROR	15.44	57.73	1.29	1.06
24	Alignment = Cu & Curve Direction = L & Driver Gender = F	ROR	0.96	68.60	1.53	1.18
25	Alignment = Cu & Curve Direction = L & Grade = Level	ROR	6.78	60.58	1.35	1.05
26	Alignment = Cu & Curve Direction = L & Grade = Level & Weather = Cloudy	ROR	1.72	68.39	1.53	1.13
27	Alignment = Cu & Curve Direction = L & Grade = Level & Weather = Cloudy & Lighting = D	ROR	1.25	76.24	1.70	1.11
28	Alignment = Cu & Curve Direction = L & Grade = Level & Lighting = D	ROR	5.03	65.13	1.45	1.07
29	Alignment = Cu & Curve Direction = L & Grade = Level & Involved Vehicle = Car	ROR	6.16	64.63	1.44	1.07
30	Alignment = Cu & Curve Direction = L & Weather = Cloudy	ROR	3.89	65.22	1.46	1.14
31	Alignment = Cu & Curve Direction = L & Weather = Cloudy & Lighting = D	ROR	2.84	71.14	1.59	1.09
32	Alignment = Cu & Curve Direction = L & Weather = Cloudy & Lighting = D & Involved Vehicle = Car	ROR	2.42	77.20	1.72	1.09
33	Alignment = Cu & Curve Direction = L & Involved Vehicle = Car	ROR	13.46	61.03	1.36	1.07
34	Alignment = Cu & Curve Direction = L & Involved Vehicle = Car & Lighting = D	ROR	9.83	64.74	1.45	1.06

i.e. deflection angle greater than 45 gon, and to left direction of the curves (rules 23–24), i.e. counterclockwise curves. Significant environmental conditions were cloudy weather and daytime. Probably, in these environmental conditions the curve perception is reduced, and this has a strongest effect on ROR crashes.

#### 5.1.2. Environmental factors

The second group of rules (Table 5, Fig. 4) was characterised by environmental factors (slippery pavement, rainy weather, wet pavement, and cloudy weather) as antecedent in two-item rules and in further rules obtained adding one or more items to these rules. Overall, twenty-two rules were identified (rules 35–56). The fourteen items contained in the rules are shown in the peripheral area of Fig. 4. The items are the same items shown in Fig. 3 with the exclusion of distracted driving and the addition of clear weather, rainy weather, and slippery

**Table 5**

Rules with environmental factors as antecedent and ROR crash type as consequent.

Rule ID	Association Rules Antecedent	Consequent	S %	C %	Lift	LIC
35	Pavement = Sl	ROR	0.62	82.61	1.84	n.a.
36	Pavement = Sl & Alignment = Cu	ROR	0.52	86.49	1.93	1.05
37	Pavement = Sl & Alignment = Cu & Involved Vehicle = Car	ROR	0.50	93.94	2.10	1.09
38	Weather = Rn	ROR	12.70	72.77	1.62	n.a.
39	Weather = Rn & Driver Age = 19–25	ROR	1.25	87.50	1.95	1.20
40	Weather = Rn & Driver Gender = F	ROR	0.88	85.71	1.91	1.18
41	Weather = Rn & Alignment = Cu	ROR	8.55	79.25	1.77	1.09
42	Weather = Rn & Alignment = Cu & Curve Radius = Small	ROR	5.11	89.49	2.00	1.13
43	Weather = Rn & Alignment = Cu & Deflection Angle = Large	ROR	5.12	83.82	1.87	1.06
44	Weather = Rn & Alignment = Cu & Grade = Level	ROR	3.73	83.64	1.87	1.06
45	Weather = Rn & Alignment = Cu & Curve Direction = L	ROR	5.58	80.94	1.81	1.11
46	Pavement = W	ROR	20.37	72.27	1.61	n.a.
47	Pavement = W & Driver Gender = F	ROR	1.31	88.04	1.97	1.22
48	Pavement = W & Driver Age = 19–25	ROR	2.01	86.71	1.94	1.20
49	Pavement = W & Driver Age = 19–25 & Grade = Level	ROR	0.71	97.78	2.18	1.13
50	Pavement = W & Alignment = Cu	ROR	13.91	79.08	1.77	1.09
51	Pavement = W & Alignment = Cu & Deflection Angle = Large	ROR	8.51	85.09	1.90	1.08
52	Pavement = W & Weather = Cl	ROR	1.44	78.76	1.76	1.09
53	Weather = Cloudy	ROR	10.46	56.43	1.26	n.a.
54	Weather = Cloudy & Alignment = Cu	ROR	6.36	65.55	1.46	1.16
55	Weather = Cloudy & Alignment = Cu & Lighting = D	ROR	4.33	70.45	1.57	1.07
56	Weather = Cloudy & Alignment = Cu & Involved Vehicle = Car	ROR	5.59	69.56	1.55	1.06

pavement.

It is worthwhile to observe that environmental factors giving rise to difficult driving conditions were associated to ROR crashes. As far as pavement is concerned, both slippery pavement and wet pavements, which are characterised by low friction, were associated to ROR crashes. As far as weather is concerned, cloudy and rainy, which are characterised by reduced visibility, were both associated to ROR crashes.

The environmental factor giving rise to the highest lift value was the slippery pavement (rule 35, lift = 1.84) while the environmental factor with the lowest lift was the cloudy weather (rule 53, lift = 1.26). In most cases, the environmental factors were combined with the curve alignment. These rules were classified in the environmental factors group since the rules with only the environmental factors as antecedent (rules 35, 38, 46, 53) had lift values greater than the rule with only the curve alignment as antecedent (rule 1). Environmental factors were combined also with small curve radius, large deflection angle, left curve, young drivers, and female drivers.

**Table 6**

Rules with driver factors as antecedent and ROR crash type as consequent.

Rule ID	Association Rules Antecedent	Consequent	S %	C %	Lift	LIC
57	Driver Behaviour = Sleep	ROR	1.31	91.01	2.03	n.a.
58	Driver Behaviour = Sleep & Involved Vehicle = Car	ROR	0.99	98.39	2.20	1.08
59	Driver Behaviour = Alcohol/Drug	ROR	0.92	89.06	1.99	n.a.
60	Driver Behaviour = Alcohol/Drug & Involved Vehicle = Car	ROR	0.88	96.43	2.15	1.08
61	Driver Behaviour = Alcohol/Drug & Lighting = N	ROR	0.55	94.44	2.11	1.06
62	Driver Behaviour = Speed	ROR	25.44	85.88	1.92	n.a.
63	Driver Behaviour = Speed & Weather = Rn	ROR	8.68	94.02	2.10	1.09
64	Driver Behaviour = Speed & Weather = Rn & Driver Age = 19–25	ROR	0.88	100.00	2.23	1.06
65	Driver Behaviour = Speed & Weather = Rn & Driver Gender = F	ROR	0.57	100.00	2.23	1.06
66	Driver Behaviour = Speed & Pavement = W	ROR	13.82	93.73	2.09	1.09
67	Driver Behaviour = Speed & Pavement = W & Driver Gender = F	ROR	0.86	100.00	2.23	1.07
68	Driver Behaviour = Speed & Involved Vehicle = Car	ROR	22.39	90.97	2.03	1.06
69	Driver Behaviour = Speed & Driver Gender = F	ROR	1.54	90.48	2.02	1.05
70	Driver Behaviour = Speed & Alignment = Cu	ROR	16.33	90.07	2.01	1.05
71	Driver Behaviour = Distract	ROR	3.73	64.61	1.44	n.a.
72	Driver Behaviour = Distract & Involved Vehicle = Car	ROR	2.93	79.39	1.77	1.23
73	Driver Behaviour = Distract & Involved Vehicle = Car & Alignment = Cu	ROR	1.57	84.35	1.88	1.06
74	Driver Behaviour = Distract & Involved Vehicle = Car & Alignment = Cu & Grade = Level	ROR	0.63	90.70	2.03	1.08
75	Driver Behaviour = Distract & Alignment = Cu	ROR	1.98	71.35	1.59	1.10
76	Driver Behaviour = Distract & Alignment = Cu & Grade = Level	ROR	0.75	82.14	1.83	1.15
77	Driver Behaviour = Distract & Alignment = Cu & Deflection Angle = Large	ROR	0.68	79.25	1.77	1.11
78	Driver Behaviour = Distract & Alignment = Cu & Deflection Angle = Large & Involved Vehicle = Car	ROR	0.52	88.89	1.98	1.12

(continued on next page)

**Table 6 (continued)**

Rule ID	Association Rules	S %	C %	Lift	LIC	
	Antecedent	Consequent				
79	Driver Behaviour = Distract & Alignment = Cu & Lighting = N	ROR	0.52	78.05	1.74	1.09
80	Driver Behaviour = Distract & Lighting = N	ROR	1.04	70.33	1.57	1.09
81	Driver Age = 19–25	ROR	4.17	61.93	1.38	n.a.
82	Driver Age = 19–25 & Weather = Cloudy	ROR	1.05	74.71	1.67	1.21
83	Driver Age = 19–25 & Weather = Cloudy & Alignment = Cu	ROR	0.65	81.63	1.82	1.09
84	Driver Age = 19–25 & Alignment = Cu	ROR	2.61	68.80	1.54	1.11
85	Driver Age = 19–25 & Alignment = Cu & Grade = Level	ROR	1.01	76.54	1.71	1.11
86	Driver Age = 19–25 & Alignment = Cu & Grade = Level & Curve Direction = L	ROR	0.62	86.36	1.93	1.26
87	Driver Age = 19–25 & Alignment = Cu & Curve Direction = L	ROR	1.56	75.00	1.67	1.09
88	Driver Age = 19–25 & Alignment = Cu & Lighting = N	ROR	0.99	74.39	1.66	1.08
89	Driver Age = 19–25 & Grade = Level	ROR	1.57	67.83	1.51	1.10
90	Driver Age = 19–25 & Lighting = N	ROR	1.61	67.81	1.51	1.09
91	Driver Age = 19–25 & Driver Gender = F	ROR	0.55	66.67	1.49	1.08
92	Driver Gender = F	ROR	3.00	57.28	1.28	n.a.
93	Driver Gender = F & Weather = Cloudy	ROR	0.55	75.56	1.69	1.32
94	Driver Gender = F & Alignment = Cu	ROR	1.65	63.35	1.41	1.11

A very particular rule is the rule 52, with wet pavement and clear weather as antecedent. Probably the combination of wet pavement and clear weather gives rise to driving speed inappropriate in relation to the reduced friction in wet pavement, thus contributing to ROR crashes overrepresentation.

### 5.1.3. Driver factors

The third group of rules with ROR crashes as consequent (Table 6, Fig. 5) was characterised by driver factors (sleeping, alcohol or drug use, speeding, distraction, young age, and female gender) as antecedent in two-item rules and in further rules obtained adding one or more items to these rules. Overall, thirty-eight rules were identified (rules 57–94). The fifteen items contained in the rules are shown in the peripheral area of Fig. 5. The items are driver factors (speeding, sleeping, driving under the influence of alcohol-drug, distract driving, driver age in the range 19–25, female gender), geometric design factors (curve alignment, left direction of the curve, large deflection angle, level grade), environmental factors (nighttime, wet pavement, cloudy weather, rainy weather), and vehicle factors (car). Rules with large support (in dark blue) are shown in the upper left part of the graph.

The rules with the highest lift were the rules with sleeping, alcohol or drug use, or speeding as antecedent (rules 57–70). In these rules, the proportion of ROR crashes was greater than 85 % and the lift value was about 2. It means that almost all crashes with sleeping, alcohol or drug use, or speeding were ROR crashes. Most rules were the rules with distracted driving, young driver age or female driver as antecedent (rules 71–94), even if these rules exhibited smaller lift values.

**Table 7**

Rules with roadside factors as antecedent and KSI crashes as consequent.

Rule ID	Association Rule	S %	C %	Lift	LIC
	Antecedent	Consequent			
95	Most harmful impacted object = Slope	KSI	0.54	23.81	3.13
96	Most harmful impacted object = Slope & Crash Dynamics = Event + ROR	KSI	0.22	40.00	5.26
97	Most harmful impacted object = Slope & Pavement = D	KSI	0.47	37.14	4.89
98	Most harmful impacted object = Slope & Weather = Cl	KSI	0.40	36.67	4.82
99	Point of first impact = Blunt-end/Bullnose	KSI	0.40	22.22	2.92
100	Most harmful impacted object = Ditch	KSI	0.51	11.76	1.55
101	Most harmful impacted object = Ditch & Weather = Cl	KSI	0.43	17.39	2.29
102	Most harmful impacted object = Ditch & Pavement = D	KSI	0.43	15.38	2.02
103	Most harmful impacted object = Wall	KSI	1.48	10.82	1.42
104	Most harmful impacted object = Wall & Driver Age = 46–65	KSI	0.25	15.56	2.05
105	Most harmful impacted object = Wall & Driver Age = 46–65 & ROR	KSI	0.22	17.65	2.32
106	Direction = Roadside	KSI	0.62	15.04	1.98
107	Most harmful impacted object = Wall & Weather = Rn & ROR	KSI	0.62	17.53	2.31
108	Direction = Roadside	KSI	0.76	12.00	1.58
109	Pavement = D	KSI	0.69	12.93	1.70
110	Weather = Cl	KSI	1.34	11.71	1.54
	Most harmful impacted object = Wall & ROR				
	Direction = Roadside				

### 5.2. Fatal and serious injury crashes

Severity was classified in three categories: KSI which includes fatal and serious injury crashes (7.64 %), Slight which includes slight injury crashes (27.78 %), and PDO which includes property damage only crashes (64.58 %). Rule discovery identified 129 rules with KSI as consequent, which satisfied the threshold values of support ( $S \geq 0.2\%$ ), confidence ( $C \geq 10.0\%$ ), lift ( $L \geq 1.2$ ), and lift increase ( $LIC \geq 1.05$ ). Based on the variables identified as KSI contributory factors, rules were divided into five different groups: roadside factors, barrier performance factors, driver factors, vehicle factors, and crash dynamic factors.

#### 5.2.1. Roadside factors

This group of rules (Table 7, Fig. 6) was characterised by roadside factors (foreslope, blunt-end terminal or bullnose, ditch, and wall) as antecedents in two-item rules and in further rules obtained adding one or more items to these rules. Overall, sixteen rules were identified (rules

**Table 8**

Rules with barrier performance factors as antecedent and KSI crashes as consequent.

Rule ID	Association Rule Antecedent	KSI Consequent	S %	C %	Lift	LIC
111	Barrier perf = Override	KSI	0.40	31.43	4.13	n.a.
112	Barrier perf = Override & Pavement = D	KSI	0.33	42.86	5.64	1.36
113	Barrier perf = Override & Driver Behaviour = Speed	KSI	0.22	35.29	4.64	1.12
114	Barrier perf = Overturn	KSI	1.52	14.69	1.93	n.a.
115	Barrier perf = Overturn & Crash Dynamics = Event + ROR	KSI	0.22	30.00	3.95	2.04
116	Barrier perf = Overturn & Crash Dynamics = Event + ROR & Lighting = N	KSI	0.22	54.55	7.17	1.82
117	Barrier perf = Overturn & Crash Dynamics = Event + ROR & Lighting = N & Involved Vehicle = Car	KSI	0.22	66.67	8.77	1.22
118	Barrier perf = Overturn & Crash Dynamics = Event + ROR & Involved Vehicle = Car	KSI	0.22	37.50	4.93	1.25
119	Barrier perf = Overturn & Driver Age = 46–65	KSI	0.22	22.22	2.92	1.51
120	Barrier perf = Overturn & Driver Age = 46–65 & Involved Vehicle = Car	KSI	0.22	24.00	3.16	1.08
121	Barrier perf = Overturn & Most harmful object = WBeam	KSI	0.47	19.70	2.59	1.34
122	Barrier perf = Overturn & Most harmful object = WBeam & Grade = Level	KSI	0.33	27.27	3.59	1.38
123	Barrier perf = Overturn & Most harmful object = WBeam & Grade = Level & Weather = Cl	KSI	0.22	33.33	4.38	1.22
124	Barrier perf = Overturn & Most harmful object = WBeam & Pavement = D	KSI	0.36	23.81	3.13	1.21
125	Barrier perf = Overturn & Most harmful object = WBeam & Pavement = D & Involved Vehicle = Car	KSI	0.33	25.71	3.38	1.08
126	Barrier perf = Overturn & Most harmful object = WBeam & Weather = Cl	KSI	0.29	23.53	3.09	1.19
127	Barrier perf = Overturn & Most harmful object = WBeam & Weather = Cl & Involved Vehicle = Car	KSI	0.25	25.93	3.41	1.10
128	Barrier perf = Overturn & Most harmful object = WBeam & Lighting = N	KSI	0.22	22.22	2.92	1.13
129	Barrier perf = Overturn & Most harmful object = WBeam & Involved Vehicle = Car	KSI	0.43	21.43	2.82	1.09
130	Barrier perf = Overturn & Pavement = D	KSI	1.09	19.11	2.51	1.30
131		KSI	0.25	24.14	3.17	1.26

**Table 8 (continued)**

Rule ID	Association Rule Antecedent	KSI Consequent	S %	C %	Lift	LIC
132	Barrier perf = Overturn & Pavement = D & Weather = Cloudy	KSI	0.87	17.52	2.30	1.19
133	Barrier perf = Overturn & Weather = Cl & Weather = Cl & Grade = Level	KSI	0.58	22.54	2.96	1.29
134	Barrier perf = Overturn & Weather = Cl & Grade = Level & ROR	KSI	0.43	29.27	3.85	1.30
135	Barrier perf = Overturn & Grade = Down	KSI	0.62	16.35	2.15	1.11
136	Barrier perf = Overturn & Grade = Down & Most harmful object = Wall	KSI	0.29	29.63	3.90	1.81
137	Barrier perf = Overturn & Grade = Down & Most harmful object = Wall & ROR Direction = Roadside	KSI	0.29	32.00	4.21	1.08
138	Barrier perf = Overturn & Grade = Down & Lighting = N	KSI	0.29	20.51	2.70	1.25
139	Barrier perf = Overturn & Grade = Down & Driver Gender = M	KSI	0.29	19.05	2.51	1.17
140	Barrier perf = Overturn & Grade = Down & Driver Gender = M & Pavement = D	KSI	0.22	25.00	3.29	1.31
141	Barrier perf = Overturn & Grade = Down & Pavement = D	KSI	0.36	18.18	2.39	1.11
142	Barrier perf = Overturn & Lighting = N	KSI	0.58	16.33	2.15	1.11
143	Barrier perf = Overturn & Lighting = N & Pavement = W	KSI	0.25	18.42	2.42	1.13
144	Barrier perf = Overturn & Grade = Level	KSI	0.80	16.18	2.13	1.10
145	Barrier perf = Overturn & Grade = Level & ROR	KSI	0.54	20.00	2.63	1.24
146	Barrier perf = Overturn & Grade = Level & ROR Direction = Roadside	KSI	0.98	16.07	2.11	1.09
147	Barrier perf = Penetrated	KSI	0.36	13.89	1.83	n.a.
148	Barrier perf = Penetrated & Most harmful object = WBeam	KSI	0.22	20.69	2.72	1.49
149	Barrier perf = Penetrated & Involved Vehicle = Car	KSI	0.33	19.57	2.57	1.41
150	Barrier perf = Penetrated & Weather = Cl	KSI	0.29	18.60	2.45	1.34
151	Barrier perf = Penetrated & Weather = Cl & Pavement = D	KSI	0.29	20.51	2.70	1.10
152	Barrier perf = Penetrated & Pavement = D	KSI	0.33	18.00	2.37	1.30
153	Barrier perf = Penetrated & Pavement = D & ROR Direction = Roadside	KSI	0.22	20.00	2.63	1.11
154	Barrier perf = Penetrated & ROR Direction = Roadside	KSI	0.25	17.07	2.25	1.23

**Table 9**

Rules with Driver related factors as antecedent and KSI as ROR crash consequence.

Rule ID	Association Rule Antecedent	KSI	S %	C %	Lift	LIC
155	<b>Driver Behaviour = Sleep</b>	KSI	<b>0.43</b>	<b>14.81</b>	<b>1.95</b>	n.a.
156	<b>Driver Behaviour = Sleep &amp; Grade = Level</b>	KSI	<b>0.22</b>	<b>18.18</b>	<b>2.39</b>	<b>1.23</b>
157	Driver Behaviour = Sleep & Involved Vehicle = Car	KSI	0.40	18.03	2.37	1.22
158	Driver Behaviour = Sleep & Involved Vehicle = Car & Lighting = N	KSI	0.25	20.59	2.71	1.14
159	Driver Behaviour = Sleep & Involved Vehicle = Car & ROR Direction = Roadside	KSI	0.29	19.05	2.51	1.06
160	Driver Behaviour = Sleep & Involved Vehicle = Car & Weather = Cl	KSI	0.29	19.05	2.51	1.06
161	Driver Behaviour = Sleep & ROR Direction = Roadside	KSI	0.33	16.67	2.19	1.13
162	Driver Behaviour = Sleep & Driver Gender = M	KSI	0.33	16.07	2.11	1.08
163	Driver Behaviour = Sleep & Weather = Cl	KSI	0.33	15.79	2.08	1.07
164	Driver Behaviour = Sleep & Lighting = N	KSI	0.25	15.56	2.05	1.05
165	<b>Driver Behaviour = Alcohol/Drug</b>	KSI	<b>0.25</b>	<b>12.28</b>	<b>1.62</b>	n.a.
166	Driver Behaviour = Alcohol/Drug & Driver Gender = M	KSI	0.22	13.33	1.75	1.09
167	Driver Behaviour = Inappropriate	KSI	0.58	10.96	1.44	n.a.
168	Driver Behaviour = Inappropriate & Most harmful object = Wall	KSI	0.22	37.50	4.93	3.42
169	Driver Behaviour = Inappropriate & Most harmful object = Wall & Pavement = D	KSI	0.22	46.15	6.07	1.23
170	<b>Driver Behaviour = Inappropriate &amp; Grade = Down</b>	KSI	<b>0.40</b>	<b>18.97</b>	<b>2.49</b>	<b>1.73</b>
171	Driver Behaviour = Inappropriate & Grade = Down & Crash Dynamics = Event + ROR	KSI	0.29	27.59	3.63	1.45
172	Driver Behaviour = Inappropriate & Grade = Down & Pavement = D	KSI	0.33	23.08	3.04	1.22
173	Driver Behaviour = Inappropriate & Crash Dynamics = Event + ROR	KSI	0.36	15.87	2.09	1.45
174	Driver Behaviour = Inappropriate & Crash Dynamics = Event + ROR & Involved Vehicle = Car	KSI	0.22	20.00	2.63	1.26
175	Driver Behaviour = Inappropriate & Lighting = N	KSI	0.22	15.00	1.97	1.37
176	<b>Driver Age = &gt;65</b>	KSI	<b>0.29</b>	<b>10.26</b>	<b>1.35</b>	n.a.
177	Driver Age = >65 & Pavement = D	KSI	0.25	12.28	1.62	1.20
178		KSI	0.25	13.46	1.77	1.10

**Table 9 (continued)**

Rule ID	Association Rule Antecedent	KSI	S %	C %	Lift	LIC
179	Driver Age = >65 & Pavement = D & Driver Gender = M	KSI	0.29	11.43	1.50	1.11
180	Driver Age = >65 & Driver Gender = M & Involved Vehicle = Car	KSI	0.29	12.90	1.70	1.13
181	<b>Driver Age = 46–65</b>	KSI	<b>1.27</b>	<b>10.14</b>	<b>1.32</b>	n.a.
182	Driver Age = 46–65 & ROR Direction = Roadside	KSI	0.83	14.56	1.91	1.43
183	Driver Age = 46–65 & ROR Direction = Roadside & Driver Behaviour = Distract	KSI	0.25	26.92	3.54	1.85
184	Driver Age = 46–65 & ROR Direction = Roadside & Pavement = D	KSI	0.51	16.87	2.22	1.16
185	Driver Age = 46–65 & ROR Direction = Roadside & Driver Behaviour = Speed	KSI	0.33	15.52	2.04	1.07
186	Driver Age = 46–65 & ROR Direction = Roadside & Driver Behaviour = Speed & Driver Gender = M	KSI	0.33	16.98	2.23	1.09
187	Driver Age = 46–65 & ROR Direction = Roadside & Grade = Down	KSI	0.29	15.38	2.02	1.06
188	Driver Age = 46–65 & Driver Behaviour = Distract	KSI	0.29	14.04	1.85	1.38
189	Driver Age = 46–65 & Driver Behaviour = Distract & Pavement = D	KSI	0.29	17.02	2.24	1.21
190	Driver Age = 46–65 & Driver Behaviour = Speed	KSI	0.58	13.01	1.71	1.28
191	Driver Age = 46–65 & Driver Behaviour = Speed & Weather = Rn	KSI	0.33	21.95	2.89	1.69
192	Driver Age = 46–65 & Driver Behaviour = Speed & Weather = Rn & Driver Gender = M	KSI	0.33	23.08	3.04	1.05
193	Driver Age = 46–65 & Driver Behaviour = Speed & Grade = Down	KSI	0.29	16.33	2.15	1.26
194	Driver Age = 46–65 & Driver Behaviour = Speed & Driver Gender = M	KSI	0.58	14.29	1.88	1.10
195	Driver Age = 46–65 & Driver Behaviour = Speed & Driver Gender = M & Pavement = W	KSI	0.33	15.52	2.04	1.09
196	Driver Age = 46–65 & Driver Behaviour = Speed & Pavement = W	KSI	0.33	14.29	1.88	1.10
197	Driver Age = 46–65 & Grade = Down	KSI	0.54	12.30	1.62	1.21
198	Driver Age = 46–65 & Grade = Down & Weather = Rn	KSI	0.22	14.63	1.92	1.19
199	Driver Age = 46–65 & Grade = Down & Pavement = D	KSI	0.33	13.24	1.74	1.08
200	Driver Age = 46–65 & Weather = Cloudy	KSI	0.25	12.28	1.62	1.21
201		KSI	0.36	11.63	1.53	1.15

(continued on next page)

**Table 9 (continued)**

Rule ID	Association Rule Antecedent	Consequent	S %	C %	Lift	LIC
202	Driver Age = 46–65 & Most harmful object = WBeam	KSI	0.25	16.28	2.14	1.40
203	Driver Age = 46–65 & Most harmful object = WBeam & Pavement = D	KSI	0.22	20.69	2.72	1.27
204	Driver Age = 46–65 & Most harmful object = WBeam & Pavement = D & Involved Vehicle = Car	KSI	0.40	11.34	1.49	1.12

**Table 10**

Rules with Involved vehicle factors as antecedent and KSI as ROR crash consequence.

Rule ID	Association Rule Antecedent	Consequent	S %	C %	Lift	LIC
205	Involved Vehicle = PTW	KSI	0.69	67.86	8.92	n.a.
206	Involved Vehicle = PTW & Most harmful impacted object = MWBeam	KSI	0.29	88.89	11.69	1.31
207	Involved Vehicle = PTW & ROR Direction = Median	KSI	0.36	76.92	10.12	1.13
208	Involved Vehicle = PTW & ROR Direction = Median & Driver Behaviour = Speed	KSI	0.33	81.82	10.76	1.06

95–110). The eleven items contained in the rules are shown in the peripheral area of Fig. 6. The items are roadside factors (blunt-end & bullnose, ditch, slope, wall), environmental factors (clear weather, rainy weather, dry pavement), crash dynamic factors (event + ROR, ROR direction equal to roadside), geometric design factors (large radius), and driver factors (driver age in the range 19–25).

Most harmful impacted objects were foreslopes (rules 95–98), ditches (rules 100–102), and walls (rules 103–110). Blunt-end terminals or bullnoses as point of first impact were a significant rule with low support but very high lift (rule 99, lift = 2.92).

While critical environmental conditions were antecedents in the rules with ROR crashes as consequent, favourable environmental conditions, such as clear weather and dry pavement, were antecedents in the rules with KSI crashes as consequent. It means that favourable environmental conditions do not contribute to an increase of crash frequency but influence the increase of crash severity.

### 5.2.2. Barrier performance factors

This group of rules (Table 8, Fig. 7) was characterised by barrier performance factors (override, overturn, and penetrated) as antecedents in two-item rules and in further rules obtained adding one or more items to these rules. Overall, forty-four rules were identified (rules 111–154). These rules contain eighteen items shown in the peripheral area of Fig. 7. The items are environmental factors (clear weather, cloudy weather, dry pavement, wet pavement, nighttime), barrier performance factors (override, overturn, and penetrated), driver factors (male driver, speeding, driver age in the range 46–65), roadside factors (roadside/bridge W-beam barrier, wall), crash dynamic factors (event + ROR, ROR direction equal to roadside), geometric design factors (level grade, downgrade), and vehicle factors (car).

Barrier override (rule 111) exhibited the highest lift (lift = 4.13),

**Table 11**

Rules with Crash dynamic factors as antecedent and KSI as ROR crash consequence.

Rule ID	Association Rule Antecedent	Consequent	S %	C %	Lift	LIC
209	Crash Dynamics = Event + ROR	KSI	1.23	10.83	1.42	n.a.
210	Crash Dynamics = Event + ROR & Lighting = N	KSI	0.80	21.36	2.81	1.97
211	Crash Dynamics = Event + ROR & Lighting = N & Most harmful object = MNJ	KSI	0.25	38.89	5.11	1.82
212	Crash Dynamics = Event + ROR & Lighting = N & Most harmful object = MNJ & Driver Gender = M	KSI	0.25	70.00	9.21	1.80
213	Crash Dynamics = Event + ROR & Lighting = N & Grade = Down	KSI	0.43	31.58	4.15	1.48
214	Crash Dynamics = Event + ROR & Lighting = N & Driver Gender = M	KSI	0.47	30.95	4.07	1.45
215	Crash Dynamics = Event + ROR & Lighting = N & Driver Gender = M & Pavement = D	KSI	0.47	39.39	5.18	1.27
216	Crash Dynamics = Event + ROR & Lighting = N & Alignment = Cu	KSI	0.36	27.03	3.56	1.27
217	Crash Dynamics = Event + ROR & Lighting = N & Alignment = Cu & Curve Direction = L	KSI	0.22	33.33	4.38	1.23
218	Crash Dynamics = Event + ROR & Lighting = N & Pavement = D	KSI	0.65	23.08	3.04	1.08
219	Crash Dynamics = Event + ROR & Grade = Down	KSI	0.54	12.82	1.69	1.18
220	Crash Dynamics = Event + ROR & Grade = Down & Pavement = D	KSI	0.43	14.29	1.88	1.11
221	Crash Dynamics = Event + ROR & Pavement = D	KSI	1.01	11.97	1.57	1.11
222	Crash Dynamics = Event + ROR & Alignment = Cu	KSI	0.58	11.51	1.51	1.06
223	Crash Dynamics = Event + ROR & Alignment = Cu & Curve Radius = Large	KSI	0.47	13.13	1.73	1.14

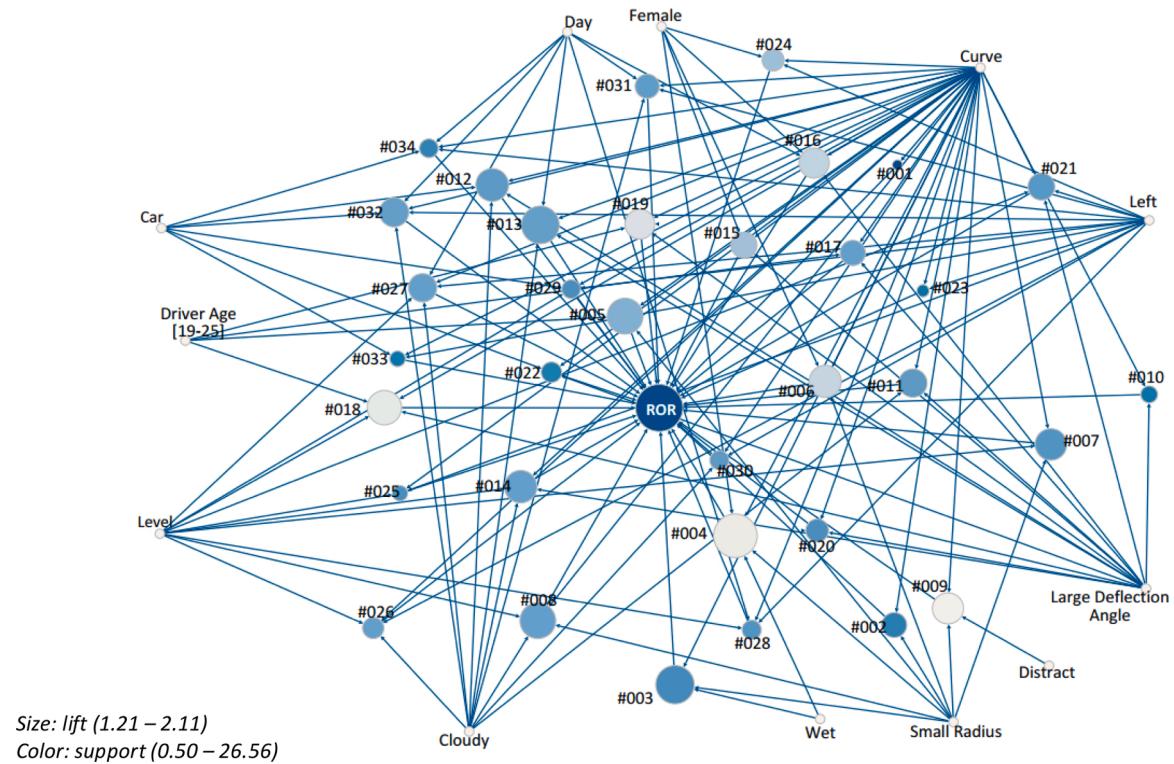
giving rise to a proportion of KSI crashes equal to 31.4 % (vs 7.4 % in the overall ROR crashes). The combination of barrier override and dry pavement (rule 112) as well as the combination of barrier override and speeding (rule 113) produced further increase in the lift value.

Overturn produced thirty-three rules (rules 114–146) with lift values ranging between 1.93 (two-items rule 114) and 8.77 (five-items rule 117). Main factors who resulted as antecedents combined with overturning were crash dynamics equal to event plus ROR, nighttime, most harmful object equal to W-beam or wall, level grade, downgrade, and male driver.

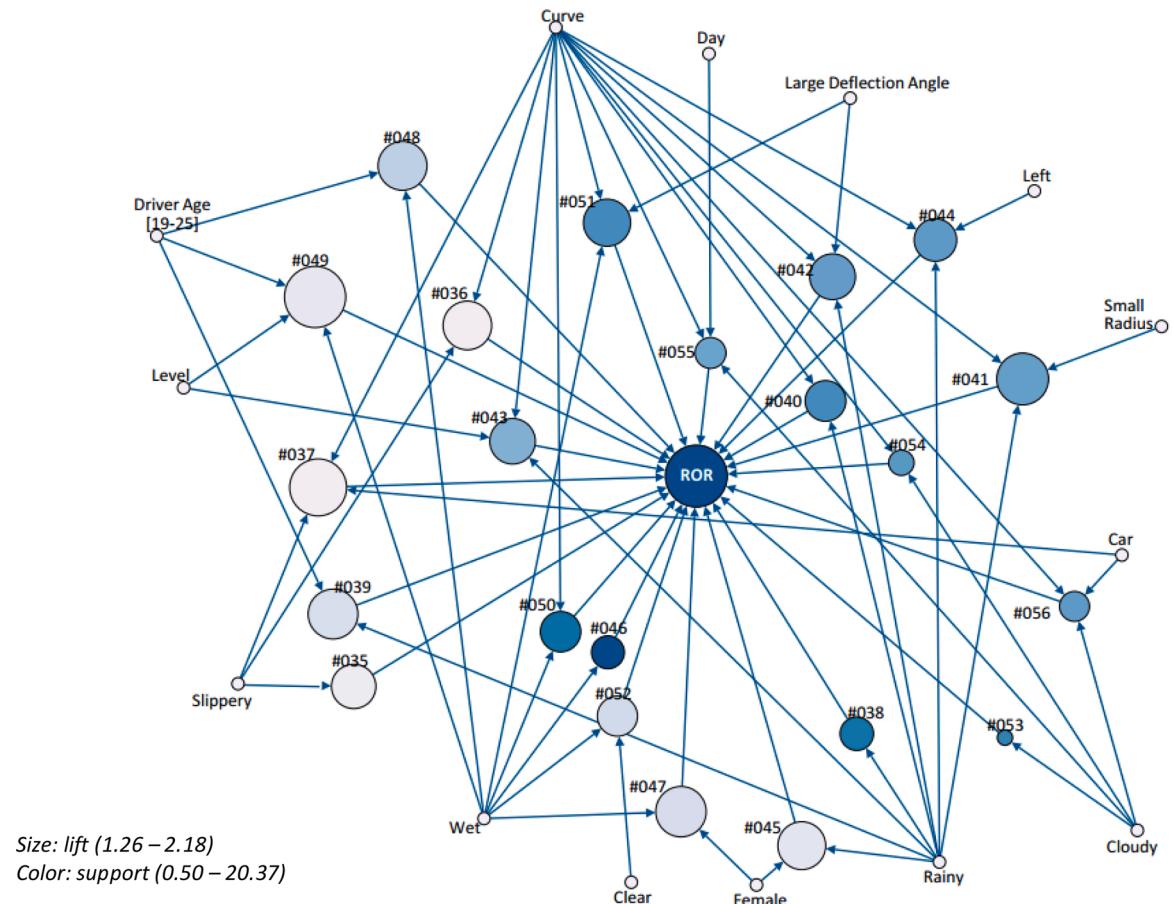
Barrier penetration produced eight rules (rules 147–154) with lift values ranging between 1.83 (two-items rule 147) and 2.72 (three-items rule 148). Main factor associated with barrier penetration and KSI crashes was the W-beam safety barrier (LIC = 1.49).

### 5.2.3. Driver factors

This group of rules (Table 9, Fig. 8) was characterised by driver factors (driver behaviour equal to sleep, alcohol, drug, or inappropriate;



**Fig. 3.** Network graph for rules with geometric design factors as antecedent and ROR crash type as consequent.



**Fig. 4.** Network graph for rules with environmental factors as antecedent and ROR crash type as consequent.

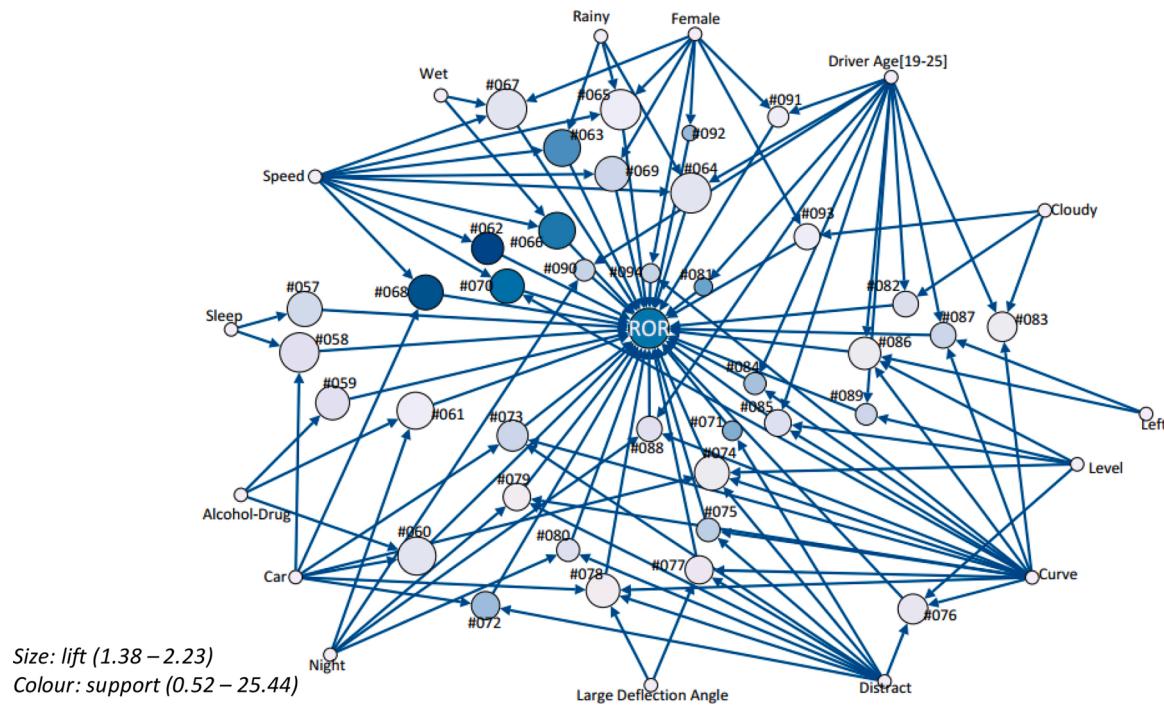


Fig. 5. Network graph for rules with driver factors as antecedent and ROR crash type as consequent.

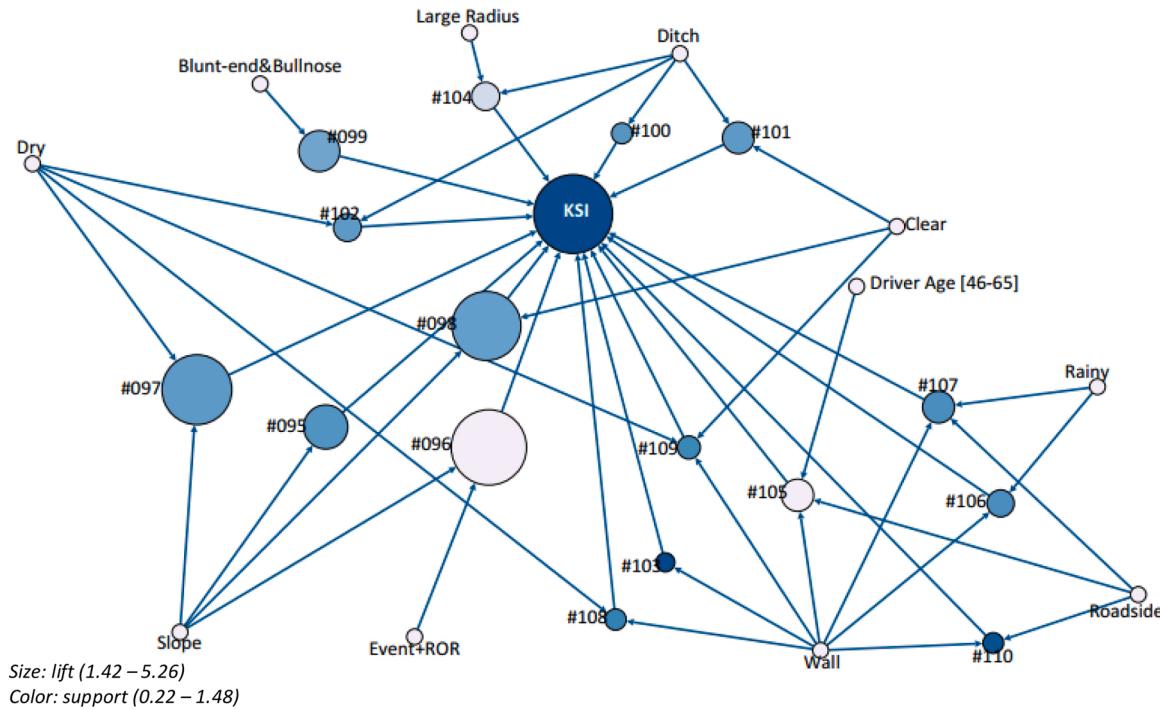
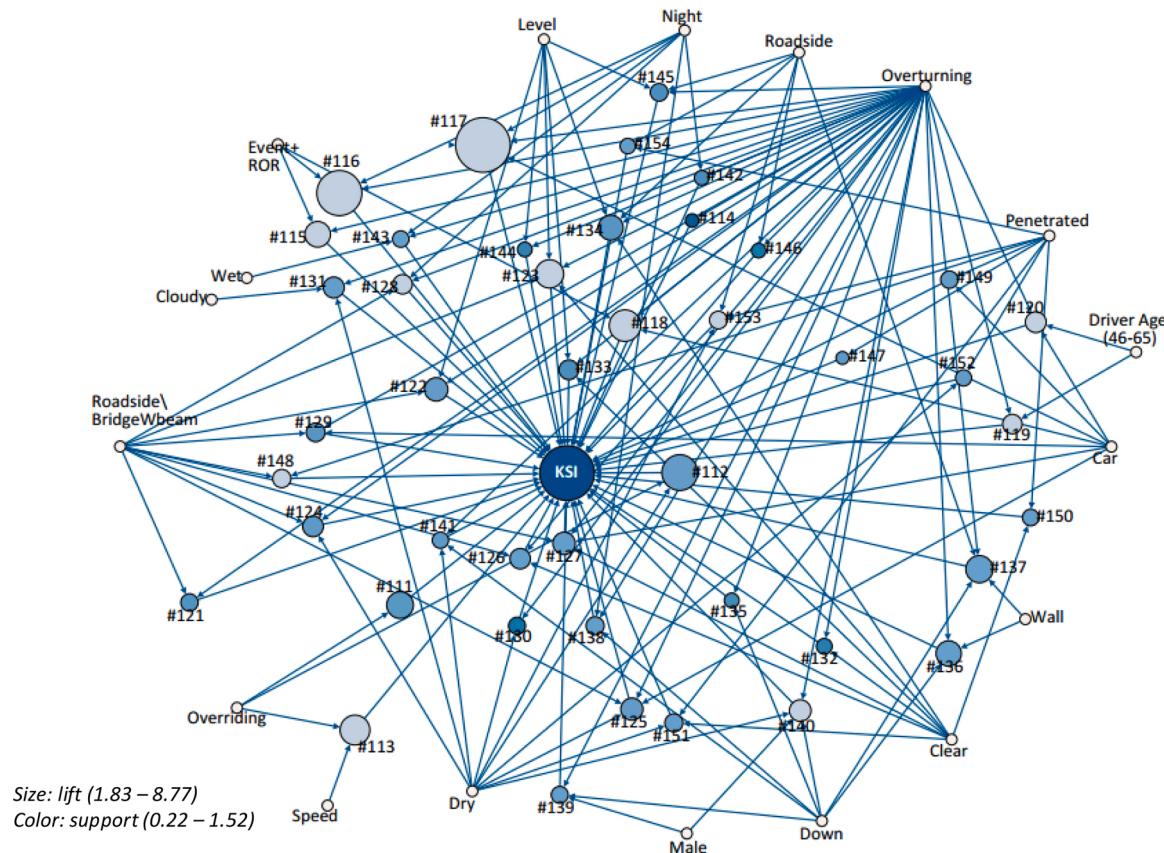


Fig. 6. Network graph for rules with roadside factors as antecedent and KSI crashes as consequent.

driver age greater than 65 or between 46 and 65) as antecedents in two-item rules and in further rules obtained adding one or more items to these rules. Overall, fifty rules were identified (rules 155–204). These rules contain twenty items shown in the peripheral area of Fig. 8. The items are driver factors (speeding, sleeping, driving under the influence of alcohol or drug, distraction, inappropriate behaviour, male driver, driver age greater than 65, driver age between 46 and 65), environmental factors (clear weather, cloudy weather, dry pavement, wet pavement, nighttime), roadside factors (roadside/bridge W-beam

barrier, wall), crash dynamic factors (event + ROR, ROR direction equal to roadside), geometric design factors (level grade, downgrade), and vehicle factors (car).

Sleeping (rules 155–164), alcohol and drug use (rules 165–166), and inappropriate manoeuvres, which include sudden braking, not respecting the minimum safety distance, and sudden lane changing (rules 167–175), were identified as the drivers' behaviour most contributing to KSI crashes. It is worthwhile to observe that sleeping and alcohol or drug use were also identified as contributory of ROR crashes



**Fig. 7.** Network graph for rules with barrier performance factors as antecedent and KSI crashes as consequent.

(rules 57–61). Other factors further contributed to an increase of crash severity. These factors include speeding, distraction, male drivers, level grade, downgrade, clear weather, dry pavements, nighttime, roadside direction, car involvement, most harmful object equal to wall, and crash dynamics equal to event plus ROR. As far as driver age was concerned, association rule discovery outlined two groups contributing to KSI crashes: older drivers (age greater than 65, rules 176–180) and middle-aged drivers (age between 46 and 65, rules 181–204).

#### 5.2.4. Vehicle factors

This group of rules (Table 10, Fig. 9) was characterised by vehicle factors (involved vehicle equal to PTW) as antecedent in a two-item rule (rule 205) and in further rules obtained adding one or more items to this rule (206–208). Proportion of KSI in ROR crashes involving PTWs was 68 % (rule 205, L = 8.92), thus showing a dramatic propensity towards severe crashes associated with PTWs. Speeding, encroachment towards the median, and median W-beam further contributed to higher crash severity.

### 5.2.5. Crash dynamic factors

This group of rules (Table 11, Fig. 10) was characterised by crash dynamic factors (event plus ROR) as antecedent in a two-item rule (rule 209) and in further rules obtained adding one or more items to this rule (210–223). These rules contain ten items shown in the peripheral area of Fig. 10. Other factors further contributing to an increase of crash severity were curve alignment, large curve radius, left curve direction, downgrade, dry pavement, median New Jersey barrier, nighttime, and male driver.

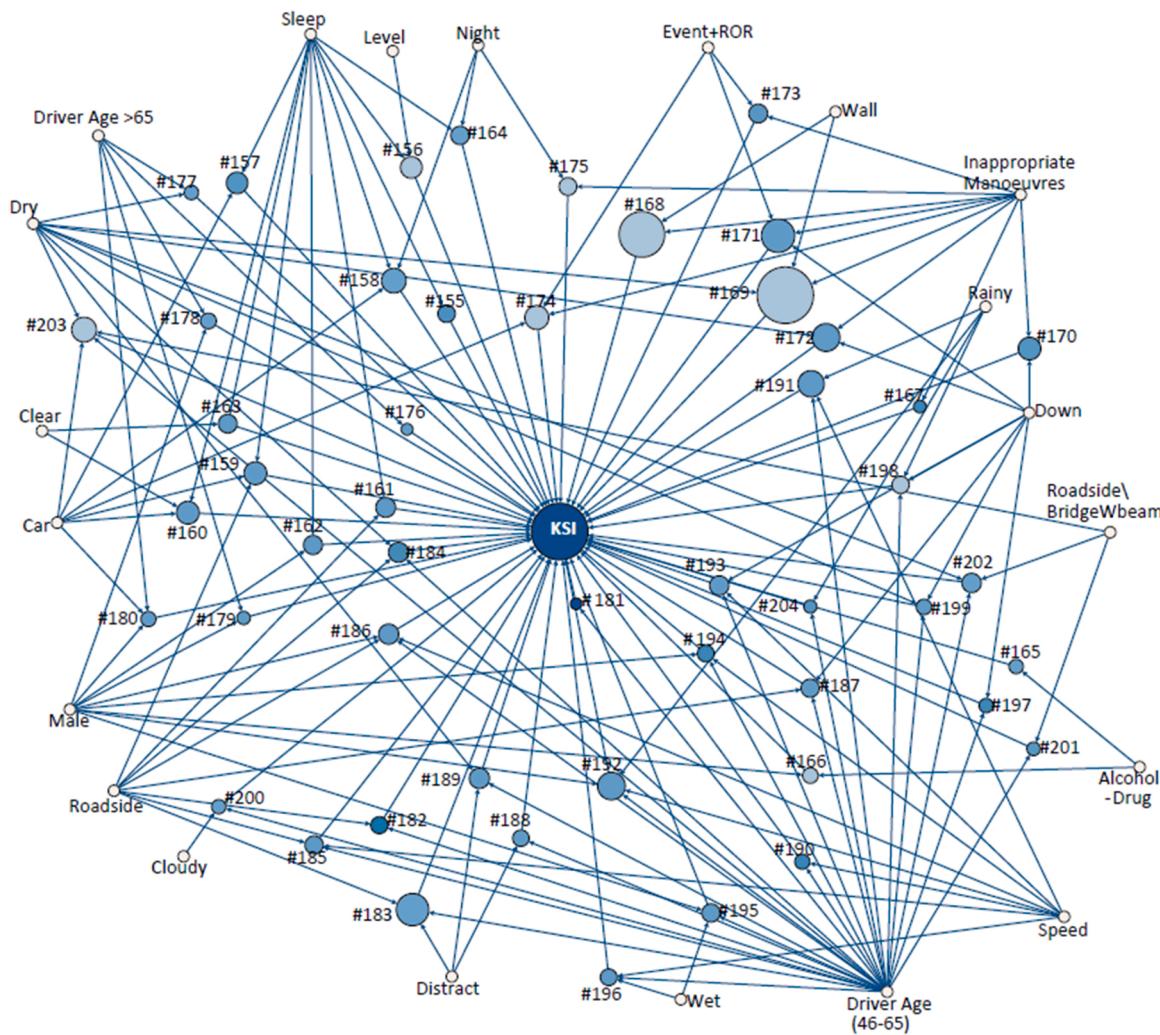
## **6. Discussion and conclusions**

This study identified 94 significant rules with ROR crashes as

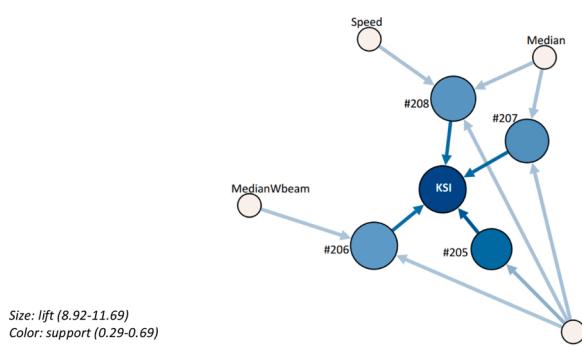
consequent and 129 significant rules with KSI crashes as consequent. These rules represent several combinations of geometric design, roadside, barrier performance, crash dynamic, vehicle, environmental and drivers' characteristics associated with an overrepresentation of ROR and KSI crashes. From the methodological point of view, study results show that the *a priori* algorithm was effective in providing new information which was previously hidden in the data.

As a result of the two-step analysis carried out in this study, we found that some variables showed different effects on the frequency and severity of ROR crashes. As far as geometric design is concerned, small radius curves were associated with an overrepresentation of ROR crashes whilst large radius curves were associated with an overrepresentation of KSI crashes. Unfavourable pavement conditions (wet pavement and slippery pavement) were associated with an overrepresentation of ROR crashes while favourable pavement conditions (dry pavement) were associated with an increase of severe and fatal crashes. Similarly, cloudy weather and rainy weather were associated with an overrepresentation of ROR crashes while clear weather was associated with an increase of KSI crashes. As far as driver gender is concerned, female gender was associated with an overrepresentation of ROR crashes whereas male gender was associated with an overrepresentation of KSI crashes. As far as driver age is concerned, the young age (19–25) was associated with an overrepresentation of ROR crashes while the old middle-age (46–65) and the old age (> 65) were associated with an overrepresentation of KSI crashes.

Study results showed that curve alignment was associated with ROR crashes. This association was even stronger on small radius curves ( $R \leq 400$  m), on curves with large deflection angle ( $> 45$  gon), and on left curves. The combination of curve alignment and difficult environmental conditions, such as rainy weather or cloudy weather, or pavement conditions characterised by low friction, such as slippery pavements and wet pavements, further increased the association with ROR crashes.



**Fig. 8.** Network graph for rules with driver factors as antecedent and KSI crashes as consequent.



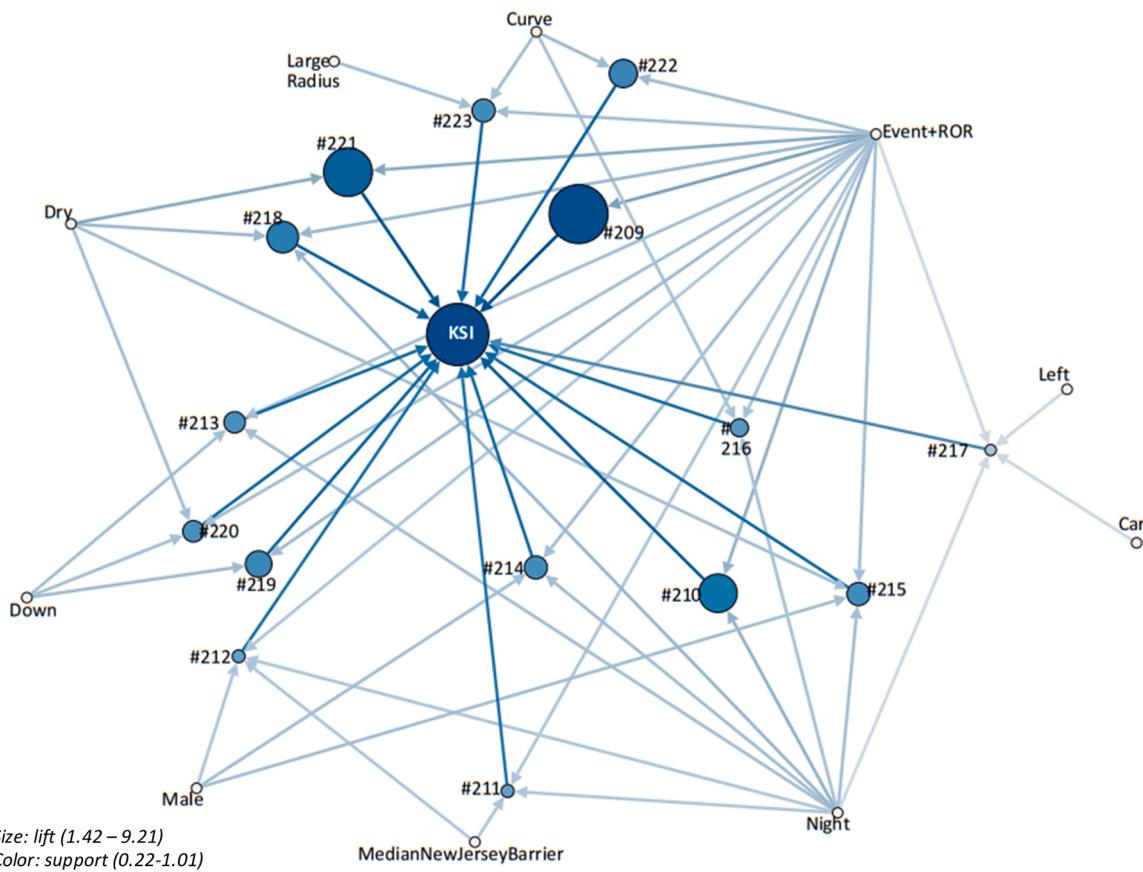
**Fig. 9.** Network graph for rules with vehicle factors as antecedent and KSI crashes as consequent.

Previous studies found also a considerable effect of friction on ROR crashes (Alhasan et al., 2018; Geedipally et al., 2017; Lyon et al., 2016), since several ROR crashes involve one vehicle that skids off the road due to insufficient skid resistance and friction helps lane-keeping performances when driving at high speeds and when navigating curves. Furthermore, several driver factors, such as sleeping, alcohol or drug use, speeding, distraction, young age, and female gender, were associated to ROR crashes. Interestingly, the combination of driver, environmental and geometric design factors produced the rules with the highest

confidence and lift, i.e. the strongest rules. As an example, the combination of distracted driving (driver's factor), nighttime (environmental factor) and curve alignment (geometric design factor) was associated to ROR crashes.

The a priori algorithm identified several combinations of roadway, environmental and driver-related factors which were associated to severe and fatal crashes. Most important roadway factors were blunt-end terminals, bullnoses, fore slopes, ditches, walls, and W-beam barriers. These results are consistent with previous literature findings (Austroads, 2015; Budzynski et al., 2017; Chalmers University of Technology, 2005; Igbaro et al., 2004; La Torre et al., 2012; Molan and Ksaibati, 2020). It is of great importance to observe that this study carried out on an Italian motorway confirmed the dangerousness of the untreated and unprotected ends of barriers even if the Italian standard (Italian Ministry of Infrastructures and Transports, 2004) does not require the installation of energy-absorption terminals of safety barriers. In favourable environmental conditions, such as clear weather and dry pavement, the association of these factors with KSI crashes was even bigger.

Study results showed that old (> 65) and old middle-aged (46–65) drivers were associated to an increase in crash severity, with the greatest effect for old drivers. This finding is consistent with previous results (Savolainen and Mannering, 2007; Rezapour et al., 2019; Schneider and Savolainen, 2011) and has various potential explanations, such as degradations in driving abilities or reaction time with age, as well as physiological differences that may make older riders more susceptible to injuries. Although older drivers may tend to drive at lower speeds, once



**Fig. 10.** Network graph for rules with crash dynamic factors as antecedent and KSI crashes as consequent.

in a crash they are more vulnerable to severe injury. On the other hand, old middle-aged drivers showed more propensity than older drivers for speeding and are not as resistant as young drivers. As far as gender, male drivers were associated with greater crash severity and this finding could reflect an aggressive driving style and behaviour of males (Montella et al., 2020; Rezapour et al., 2019; Savolainen and Mannering, 2007) due to the high driving self-confidence even in presence of adverse weather conditions, wet pavement or downgrade. As far as behaviour, sleeping, alcohol and drug use, speeding and inappropriate manoeuvres such as sudden braking, tailgating, and sudden lane changing were the main contributory factors of KSI crashes.

In our study, the involvement of PTWs was associated with an impressive increase in crash severity, with a lift value ranging from 8.9 to 11.7. Indeed, motorcycle crashes against safety barriers and roadside objects are widely recognized as a major safety issue. Roadside barriers present a substantial danger to PTW riders, causing serious lower extremity and spinal injuries as well as serious head injuries (ACEM, 2004), and the encroachment in the posts of guardrails gives rise to a high fatality risk of motorcyclists (Gabler, 2007).

Furthermore, the study results provided non-trivial and unsuspected relations in the data. As an example, it was found the co-occurrence of an event plus ROR, nighttime and impact against a median New Jersey barrier was associated with KSI crashes.

Several countermeasures may be implemented to solve or mitigate the safety issues identified in our study. It is worthwhile to observe that the study showed a combination of factors contributing to the over-representation of frequency and severity of ROR crashes. Consequently, it is recommended to implement a combination of countermeasures.

To reduce ROR crash frequency, improvement in design consistency and effective nighttime delineation of low radius or large deflection angle curves is recommended. Specifically, because of the potential safety improvement (Cafiso et al., 2007, 2011, 2021; Montella and

Imbriani, 2015), it is recommended to minimize the difference between friction demand and friction supply on horizontal curves, to minimize the operating speed reduction from tangents to horizontal curves, and to avoid low-operating speed curves following long tangents. To reduce slippery pavement and wet pavement crashes, a significant improvement in both pavement skid resistance (e.g., high-friction surface treatments) and pavement unevenness (e.g., full depth reclamation) may be appropriate. In volume 6 of the Guidance for Implementation of the AASHTO Strategic Highway Safety Plan (Neuman et al., 2003), the use of skid-resistant pavements is proposed as a key strategy for reducing run-off-the-road crashes. Research conducted by the FHWA indicates that about 70 % of wet pavement crashes can be prevented by improved pavement friction (FHWA, 2020). Furthermore, because of the potential crash reduction (AASHTO, 2010; Cafiso et al., 2021; Montella and Imbriani, 2015) and the strong association between curve alignment and ROR crashes found in this study, it is recommended to correct superelevation deficiencies as a routine measure when roadways are repaved even if most transportation agencies do not consider the correction of superelevation when designing and planning pavement maintenance treatments.

Based on the strong association between drivers' related factors and ROR crashes, it is recommended to increase safety campaigns addressed towards young drivers with special emphasis on driving under the influence, speeding and the use of mobile phones while driving.

To reduce ROR crash severity, roadside safety features should be improved. First, study results highlighted the need of protection of high embankments, ditches and walls. Then, specific countermeasures to improve blunt-end terminals, bullnoses and safety of PTWs should be carried out. Replacement of blunt-end terminals with energy absorbing terminals that meet the performance standard outlined in EN1317-4 standard or MASH is a priority task. Similarly, bullnoses should be protected with crash cushions. To improve safety of PTW riders, it is

recommended to consider the use of continuous barriers specifically designed with the safety of PTW riders in mind, tested according to the technical specification CEN/TS 17342:2019, with the purpose of retaining and redirecting an impacting rider, preventing direct impact with aggressive elements of the barrier and also preventing a sliding rider from passing between the posts of a barrier and coming into contact with any potential hazard that may be behind the barrier. Furthermore, the replacement of old W-beam barriers with new devices tested according to the standard EN 1317-2:2010 has the potential to reduce crash severity, vehicle rollover, and barrier penetration.

Given that study results showed a significant association of speeding with both ROR frequency and severity, it is also recommended to increase the use of the point-to-point (P2P) speed enforcement system, which is a relatively new approach to traffic law enforcement that involves the calculation of the average speed over a section with very positive effects on both speed and safety (La Torre et al., 2019; Montella et al., 2012b, 2015a, 2015b; Soole et al., 2013).

A potential limitation of this study is the quality of the information related to the use of safety belts and helmets and the absence of information related to pavement skid resistance and unevenness. Moreover, the use of different statistical techniques may provide additional insights of the crash contributory factors and further validation of the association rule analysis.

## Authors' statement

Alfonso Montella: Conceptualization, Methodology, Validation, Writing - Original Draft, Writing - Review & Editing, Supervision.

Filomena Mauriello: Conceptualization, Methodology, Writing - Review & Editing.

Mariano Pernetti: Conceptualization, Writing - Review & Editing, Supervision.

Maria Rella Riccardi: Conceptualization, Methodology, Formal analysis, Validation, Writing - Original Draft, Writing - Review & Editing.

## Declaration of Competing Interest

The authors report no declarations of interest.

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