Review of current study methods for VRU safety

Appendix 4 –Systematic literature review: Naturalistic driving studies

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Review of current study methods for VRU safety

Appendix 4 –Systematic literature review: Naturalistic driving studies

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1.3	16-09-08	Corrected draft

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List of Abbreviations

GPS	Global Positioning System
MSF	Motorcycle Safety Foundation
PTW	Powered two wheelers
TRID	Transport Research International Documentation
VRU	Vulnerable road user

1. Introduction

Knowledge about the process leading up to the occurrence of an accident is important in road safety evaluations. In particular, the behaviour of road users and the situational aspects in the seconds before an accident occurs can provide useful information about the chain of events that in the end results in an accident. This information is, however, not available from the official accident records from the police and/or hospital which primarily consist of information gathered after the accident has occurred based on observations and interviews at the accident site, e.g. the location, the date and time, who was involved, weather conditions, road surface conditions, the manoeuvres of the road users, etc.

Naturalistic studies can be used to collect information about road user behaviour. In a naturalistic study, data is collected continuously and unobtrusively from road users while they travel in their own vehicle during their daily trips, as they normally do.

Special equipment is installed in the vehicle to collect data about the road user’s actions, the vehicle and the surrounding environment. For instance, information about speed, acceleration, deceleration, location, position on the road, turning movements, pedal use, weather, road and traffic conditions is collected via sensors. Usually, video cameras are installed to supplement travel information with video recordings of the surroundings as well as the road user. In this way it is possible to see what the road users have seen, e.g. with the use eye tracking, and observe their reactions during the trip and what in-vehicle activities they performed while travelling.

The collection of continuous data in a naturalistic study is particularly interesting from a traffic safety perspective because it makes it possible to collect data from actual safety-critical situations or accidents. Although accidents are rare, and the occurrence of safety-critical events only a bit more frequent, naturalistic studies often involve a large number of road users collecting data over a long period of time, e.g. months or years, which increases the probability of capturing these events. The data collected before, during and after safety-critical events or accidents contains important information about the interplay between the road user, the vehicle and the environment as well as the interaction between road users involved in the situation. By observing and analysing these events, it is possible to increase knowledge about the course of events of an accident or near-accident. This is particularly important for vulnerable road users, since naturalistic riding, cycling or walking studies can potentially be a means to compensate for the large degree of underreporting of accidents, which is higher for vulnerable road users – especially for cyclists – compared to other modes of transport.

1.1. Objective and scope

With the aim of assessing the extent and nature of naturalistic studies involving vulnerable road users, a systematic literature review was carried out. The purpose of this review was to identify studies based on naturalistic data from VRUs (pedestrians, cyclists, moped riders and motorcyclists) to provide an overview of how data was collected and how data has been used. In the literature review, special attention is given to the use of naturalistic studies as a tool for road safety evaluations to gain knowledge on methodological issues for the design of a naturalistic study involving VRUs within the InDeV project. The findings of the reviewed studies will be presented in another future report.

2. Method

2.1. Search strategy

Four databases were used in the search for publications: ScienceDirect, Transport Research International Documentation (TRID), IEEE Xplore and PubMed. In addition to these four databases, six databases were screened to check if they contained references to publications not already included in the review. These databases were: Web of Science, Scopus, Google Scholar, Springerlink, Taylor & Francis and Engineering Village. The screening showed that the found publications of five of the six additional databases were already contained in the first four databases. The last database, Google Scholar, returned a very high number of publications compared to all other databases. The screening revealed, however, that the vast majority of the publications were irrelevant for the scope of the study. This database was therefore discarded from the search.

The systematic literature review aimed at finding papers related to naturalistic studies of vulnerable road users (pedestrians, cyclists, moped riders and motorcyclists). For vulnerable road users, there are strict limitations to the weight and size of equipment that can be used for data collection in a naturalistic study. Furthermore, the need of special equipment may restrict the number of participants in a naturalistic study because the costs related to purchase and installation of equipment are often high. Most new smartphones contains sensors such as accelerometers, gyroscopes, magnetometers and GPS receivers, which can be used for collection of naturalistic data. Since many road users carry a smartphone while travelling, there is a large potential of using smartphones for naturalistic studies as a substitute for special equipment. Therefore, special attention was given to the use of smartphones for data collection.

One purpose of naturalistic studies is to collect data describing road user behaviour before, during and after an accident or a safety-critical situation. For vulnerable road users this is particularly important because their accidents are heavily underreported in the official accident statistics from the police. As accidents and safety-critical events are rare, one challenge is to identify those situations from the huge amount of data collected in a naturalistic study. This challenge is also known from health science, where monitoring and identification of falls, e.g. among elderly people in order to send help, has received great attention. In this review, studies of falls not related to road traffic were covered because they may be relevant also for road safety studies in terms of methodologies used to identify and assess falls in the traffic environment.

The systematic literature review covered the following types of studies:

- Studies collecting naturalistic data from vulnerable road users (pedestrians, cyclists, moped riders, motorcyclists).
- Studies collecting accidents or safety-critical situations via smartphones from vulnerable road users and motorized vehicles.
- Studies collecting falls that have not occurred on roads via smartphones.

To identify relevant studies, the search terms and combinations of keywords in Table 1 were used.

Table 1: Search terms used in the review. Keywords were combined with Boolean ANDs between the first and second keywords and Boolean ORs between variants within each keyword.

First keyword	Second keyword
naturalistic	walking OR pedestrian OR cyclist OR cycling OR riding OR moped OR ptw OR motorcycl* OR “vulnerable road user” OR “unprotected road user”
smartphone OR “mobile phone”	walking OR pedestrian OR cyclist OR cycling OR riding OR moped OR ptw OR motorcycl* OR “vulnerable road user” OR “unprotected road user”
smartphone OR “mobile phone”	fall OR accident OR crash

2.2. Inclusion/exclusion criteria

Only publications in English were included in the review. No time restrictions were applied in the search. Publications describing naturalistic riding/cycling/walking studies, where continuous data were collected from pedestrians, cyclists, moped riders or motorcyclists were included. A naturalistic study has the following characteristics:

- Data are collected continuously
- The road users preferably use their own vehicle
- Special equipment such as various sensors, video cameras, smartphones, etc. is used to collect data
- Data are collected unobtrusively
- No instruction nor intervention is given to the road users, i.e. they travel as they normally do as regards to when, how and where to go

As the number of naturalistic studies satisfying these criteria was expected to be low, this review also includes field studies where continuous data are collected from road users via special equipment although the road users had received instructions prior to the data collection to complete a specific track or route. Studies of the effect of specific treatments (via ‘with or without’ studies) also were excluded.

Publications describing the principles of proposed systems for naturalistic data collection without collecting any naturalistic data with the system – neither in real world, nor in a laboratory setting (e.g. fall simulations on a mattress) – were excluded.

Only studies with naturalistic data collected from vulnerable road users were included. Publications that describe the use of naturalistic data collected from motorized vehicles for assessing the safety of vulnerable road users were excluded.

Publications concerning accidents from motorized vehicles or falls occurring outside public roads (e.g. at home) detected via smartphones were included in the review. Only studies that collected real accidents/falls or collected simulated accidents/falls were included.

2.3. Search results

The search was carried out in February 2016 and resulted in 1592 hits in total from the four databases. After the removal of duplicates from publications that showed up in multiple databases, 1358 hits were left. A preliminary screening was conducted based on the title and abstract. In case of doubt whether a publication should be included or excluded, it passed the preliminary screening and was subject for a further examination. After the first screening, 186 publications remained. A second screening based on an examination of the full texts was conducted. After this screening, 118 publications remained for further analysis. During the analysis, in which the full texts were reviewed, some publications were found to refer to the same studies, e.g. a conference paper followed by the publication of a journal publication describing the same study. Duplicates were excluded to keep only the publication with most information or the largest study size in the event of having multiple publications from the same study in which the methodology and study purpose were the same. In case that the purpose differed in two publications, both were included. Furthermore, some publications were excluded during a thorough review because the criteria for inclusion were not met. Thus, this review includes 80 publications. Figure 1 illustrates the process of selection of publications to be included in the review.

2.4. Data extraction

A codebook was made to extract information about each publication during the review. The codebook included, among other things, the following information to be extracted from the publications:

- Road user type (pedestrian, cyclist, moped rider, motorcyclist, motorized vehicle, people outside roads, e.g. elderly falling in their home)
- Equipment used for data collection (smartphone, other portable equipment, equipped vehicle)
- Sensors used (e.g. GPS, accelerometers, gyroscopes, magnetometers, switches, video cameras)

- Purpose of data collection (traffic counts, mileage measurement, trip number estimation, mode classification, travel surveys/tracking, detection of accidents or safety-critical events and other purposes)
- Indicators used for detection (e.g. speed, acceleration, rotation, jerks, sound)
- Study size (e.g. number of participants, duration of data collection, number of accidents/safety-critical events, distance travelled)

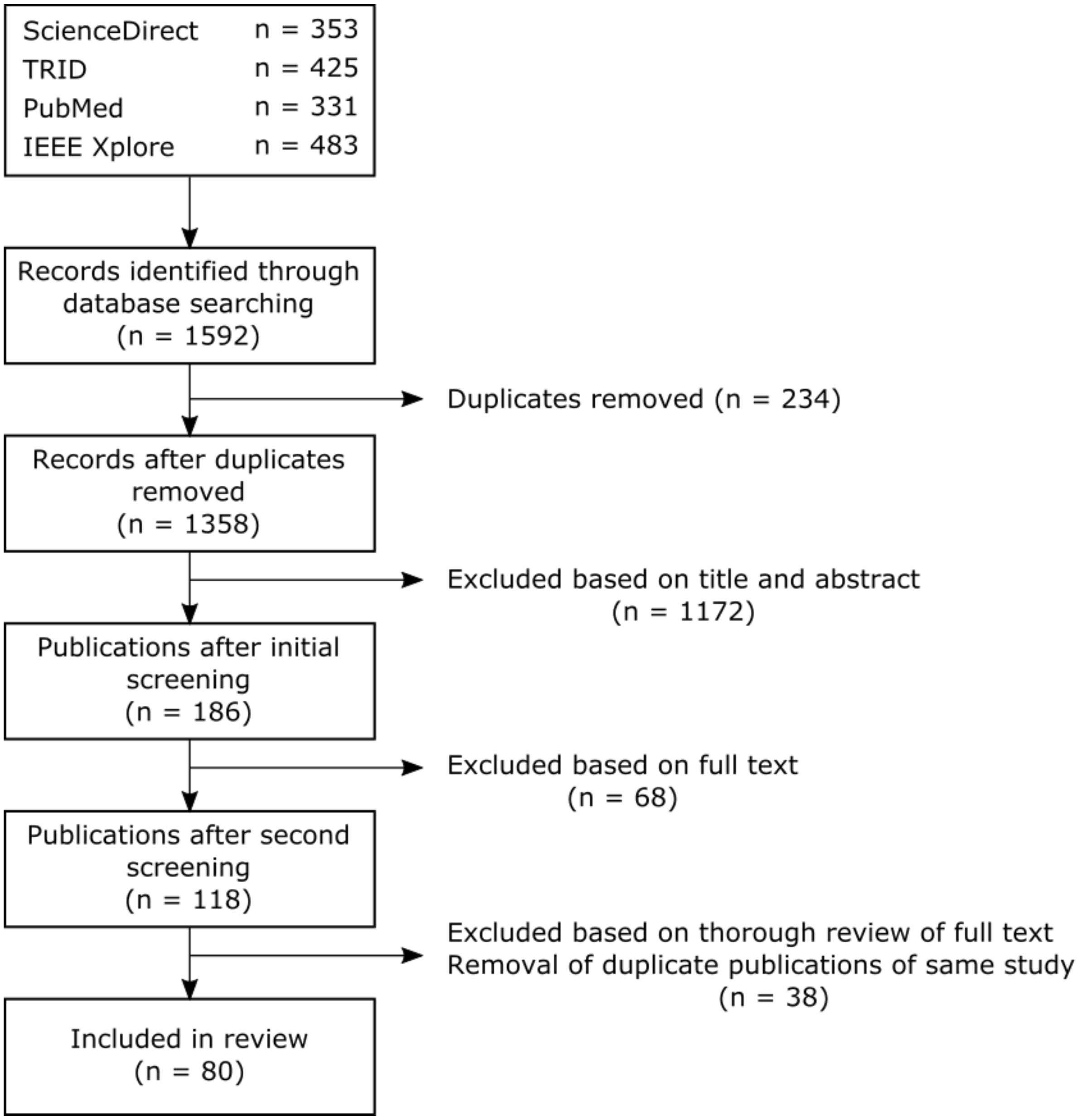

Figure 1: Flow chart of the selection of studies to be included in the review.

3. Characteristics of publications

Of the 80 publications included in this review, 42 described naturalistic studies of vulnerable road users. Thirty eight publications described fall studies that did not occur on roads but e.g. in private homes. In three cases, two publications described the same naturalistic study but had different scopes. Furthermore, two of those pairs based their analyses on the exact same data. Therefore, this review covers 77 different studies when accounting for multiple publications from the same study; 39 naturalistic studies and 38 fall studies not on public roads.

Table 2 shows the distribution of road user types in the 39 naturalistic studies. Most studies have been carried out on cyclists (22) and pedestrians (16). Studies of powered two-wheelers were primarily conducted using scooters or motorcycles; only one study collected naturalistic riding data from mopeds (Saleh, 2015).

Twelve studies included more than one road user type. Of these studies, eleven focused on mode classification. Studies including motorized vehicles are all related to mode classification.

Table 2: Road user types included in studies. Some publications include more than one type of road users.

Pedestrian	Cyclist	Moped rider	Motorcyclist	Motorized vehicles (excl. motorcycles)
16	22	1	8	11

The use of smartphones to collect data is more common than other portable equipment both for naturalistic studies and other fall studies (Table 3). Naturalistic cycling studies usually use portable equipment instead of equipped bicycles. For studies of motorcyclists, the use of special equipment installed on the motorcycle is more common.

Table 3: Equipment used for data collection.

	Pedestrian	Cyclist	Moped rider	Motorcyclist	Motorized vehicles (excl. motorcycles)	Not related to roads
Smartphone	14	10	1	3	10	38
Other portable equipment	3	6	0	1	2	6
Equipped vehicle	-	8	0	4	-	-

Some studies use a combination of different types of equipment, e.g. both smartphones and other kinds of portable equipment. Due to the inclusion/exclusion criteria, no studies of motorized vehicles with equipment installed in the vehicle were included.

4. Naturalistic VRU studies

4.1. Purpose of naturalistic VRU studies

Naturalistic studies of vulnerable road users have been conducted with various purposes, such as traffic counts, mileage measurements, trip number estimation, travel mode classification, travel surveys/tracking, detection of accidents or safety-critical events (

Table 4).

In all studies, besides estimating the distance travelled, the data was used for other purposes,e.g.to calculate the number of trips (Dozza & Werneke, 2014; Dozza *et al.*, 2015; Figliozzi & Blanc, 2015; Gustafsson & Archer, 2013; Hamann *et al.*, 2014; Williams *et al.*, 2015).

Eleven publications measured the mileage travelled during the data collection (Alzantot & Youssef, 2012; Charlton *et al.*, 2011; Dozza & Werneke, 2014; Dozza *et al.*, 2015; Figliozzi & Blanc, 2015; Gustafsson & Archer, 2013; Hamann *et al.*, 2014; Johnson *et al.*, 2014; Schleinitz *et al.*, 2015a; Schleinitz *et al.*, 2015b; Williams *et al.*, 2015).

Strauss *et al*. (2015) estimated the number of cyclists based on GPS data. In combination with the number of injuries, the risk of cyclists was then estimated.

Eleven studies applied naturalistic data for travel mode classification. Data are classified into two to seven different means of transportation. Balagapo *et al*. (2014) distinguish between walking and non-walking to identify transfers between modes on multimodal trips. Two publications distinguished between walking, car and bus (Ansari Lari & Golroo, 2015; Gonzalez *et al.*, 2008), while trains were added as a fourth mode in two publications (Guinness, 2015; Shin *et al.*, 2015). Most studies made a distinction between walking, cycling and driving in a motorized vehicle. Driving was either classified in one group (Long *et al.*, 2009; Reddy *et al.*, 2008), with car and bus trips separated from each other (Jahangiri & Rakha, 2015; Zhang & Poslad, 2013) or with an additional inclusion of subway trains (Wang *et al.*, 2010). An even finer classification was made by Nitsche *et al*. (2014), who distinguished between walking, bicycle, motorcycle, car, bus, electric tramway, metro and train as well as waiting time related to transfers between modes.

Tracking of road users to use for travel surveys were also conducted based on naturalistic data (Alzantot & Youssef, 2012; Ansari Lari & Golroo, 2015; Balagapo *et al.*, 2014; Charlton *et al.*, 2011; Figliozzi & Blanc, 2015; Gustafsson & Archer, 2013; Hamann *et al.*, 2014; Nitsche *et al.*, 2014).

Naturalistic data has been used to investigate how a specific behaviour of a road user is expressed in the data, e.g. patterns when turning to the left or right (Attal *et al.*, 2015) or how cycling can be described via values of acceleration, velocity and rotation (Dozza & Fernandez, 2014; Luo & Ma, 2014). Similarly, the movements of pedestrians have been investigated to detect when crossing an intersection (Bujari *et al.*, 2011) and predict where they will go based on changes in the direction of their movements (Voigtmann *et al.*, 2012).

Thirteen studies applied naturalistic data from vulnerable road users to identify accidents (Attal *et al.*, 2014; Candefjord *et al.*, 2014; Figliozzi & Blanc, 2015; Watthanawisuth *et al.*, 2012; Williams *et al.*, 2015) or safety-critical events (Dozza & Werneke, 2014; Dozza *et al.*, 2015; Gustafsson & Archer, 2013; Johnson *et al.*, 2014; Saleh, 2015; Sander & Marker, 2015; Schleinitz *et al.*, 2015b; Vlahogianni *et al.*, 2014).

Table 4: Purpose of naturalistic VRU studies

Traffic counts	Mileage measurement	Trip number estimation	Travel mode classification	Travel surveys/ tracking	Detection of accidents or safety-critical events	Other
1	11	6	11	8	13	20

4.2. Sensors

Table 5 indicates the type of sensors used for data collection in the naturalistic studies. GPS receivers and accelerometers were the most frequent used sensors in naturalistic studies of vulnerable road users, whereas video cameras and gyroscopes were used to collect data in approximately 40% of the studies. Switches to measure physical changes such as using the brakes and magnetometers were used less frequently. Some studies used additional sensors to measure speed, measure the proximity to other objects and perform eye tracking.

Table 5: Sensors used for data collection

GPS	Accelerometer	Gyroscope	Magnetometer	Switches	Video	Other
32	26	15	7	7	16	9

4.3. Indicators

Acceleration and speed were often used as indicators to detect road user behaviour for naturalistic data (Table 6). In some studies, rotation was used as an indicator, particularly for the detection of accidents, safety-critical events or other types of safety-related behaviour (Attal *et al.*, 2014; Candefjord *et al.*, 2014; Fang *et al.*, 2014; Saleh, 2015; Tada *et al.*, 2011) and for investigation of patterns associated with a specific behaviour (Attal *et al.*, 2015; Dozza & Fernandez, 2014; Dozza *et al.*, 2014; Voigtmann *et al.*, 2012). The application of jerks for identification of road user behaviour was rare and has only been used in one study (Williams *et al.*, 2015).

Table 6: Indicators used in naturalistic VRU studies

Speed	Acceleration	Jerks	Rotation	Sound	Other
26	30	1	11	0	7

4.4. Number of participants

67% of the naturalistic studies had less than 40 participants (Figure 2). Overall, the number of participants ranges from 1 to 1083 with a median number of 27 participants. The small number of participants indicates that many studies were conducted to test prototypes of systems for collecting and analysing road user behaviour via naturalistic data.

Although showing a general tendency of including few participants, some studies with many participants have been conducted. Five studies collected data from 100-200 participants (Figliozzi & Blanc, 2015; Hsieh *et al.*, 2014a; Langford *et al.*, 2015; Saleh, 2015; Williams *et al.*, 2015), while 2 studies had more than 1000 participants (Charlton *et al.*, 2011; Strauss *et al.*, 2015). The purpose of these studies varied. The largest study (Charlton *et al.*, 2011), which had 1083 participants, collected GPS data from cyclists via an app for iPhone and Android smartphones, *CycleTracks*, to gather information about their route choice. Strauss *et al*. (2015) collected GPS data to estimate the number of cyclists to use for risk estimation when combined with the injury numbers. The other larger studies were primarily conducted with the aim of assessing the safety via the detection of accidents, safety-critical events or other safety-related events.

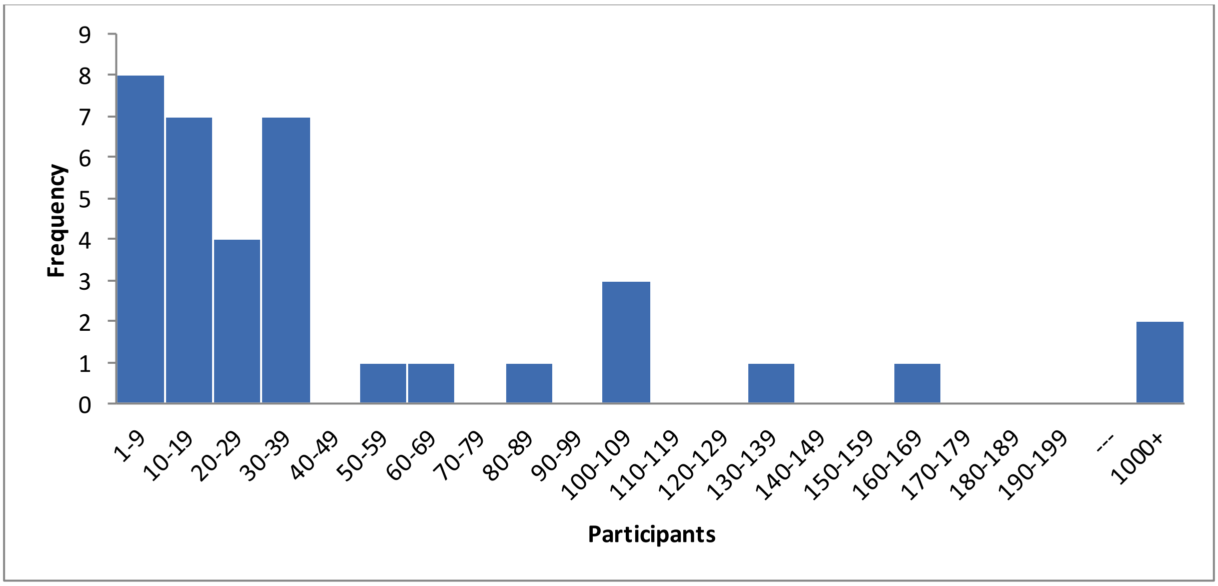

Figure 2: Number of participants in the studies (n = 36) collecting naturalistic data from vulnerable road users

5. Naturalistic VRU studies of road safety

One purpose of naturalistic studies is to assess the safety based on data collected in a naturalistic setting. The recording of data in the emergence of an accident or safety-critical situation provides important information about the road user behaviour prior to the incident. With this information, behavioural characteristics that may have contributed to the occurrence of the event can be studied.

5.1. Accidents and safety-critical events

Thirteen studies identified accidents and safety-critical events from naturalistic data (Annex 1). Five studies identified accidents (Attal *et al.*, 2014; Candefjord *et al.*, 2014; Figliozzi & Blanc, 2015; Watthanawisuth *et al.*, 2012; Williams *et al.*, 2015). Nine studies identified safety-critical events (Dozza & Werneke, 2014; Dozza *et al.*, 2015; Figliozzi & Blanc, 2015; Gustafsson & Archer, 2013; Johnson *et al.*, 2014; Saleh, 2015; Sander & Marker, 2015; Schleinitz *et al.*, 2015b; Vlahogianni *et al.*, 2014).

Naturalistic studies of vulnerable road users have mainly been carried out for cyclists and motorcyclists. The safety of cyclists was assessed in several naturalistic studies. In the *German Naturalistic Cycling Study* (Schleinitz *et al.*, 2015b) 31 cyclists were monitored via speed sensors, video cameras and switches mounted on the bicycle. 77 safety-critical events were identified from the video footage. In a Swedish naturalistic cycling study (Gustafsson & Archer, 2013) 16 cyclists collected naturalistic data from GPS receivers and video cameras. Safety-critical events were self-reported via trip diaries. During the study, the cyclists registered 220 safety-critical events. An Australian cycling study (Johnson *et al.*, 2014) studied the behaviour of 36 cyclists from almost 9000 km of naturalistic cycling data. An analysis of the video footage identified 91 safety-critical events. The *BikeSAFE* project (Dozza & Werneke, 2014) collected naturalistic cycling data from 16 cyclists who had their bicycles equipped with special equipment. From 114 hours of data, which covered a travelled distance of more than 1500 km, 63 safety-critical events were identified partly via kinematic triggers, partly via self-reporting and interviews of the participants. In a similar study of electric bicycles (Dozza *et al.*, 2015), 12 cyclists rode an equipped electric bicycle. Almost 1500 km of travel was covered during the study. Via self-reporting, the participants reported 88 safety-critical events. In a large-scale naturalistic cycling study from Oregon, USA, (Figliozzi & Blanc, 2015), 164 cyclists collected GPS data via a smartphone app, *ORcycle*, for five months. Accidents and safety-critical events were self-reported via the app during the study. In total, 62 incidents were registered.

In the *2-BE-SAFE* project (Vlahogianni *et al.*, 2014), motorcycles were equipped with sensors to collect naturalistic data. Based on indicators such as speed, acceleration and brake activation, data was analysed to identify safety-critical events. The safety of motorcyclists was also assesses in the *MSF100 Motorcyclist Naturalistic Study* (Williams *et al.*, 2015). One hundred participants collected naturalistic riding data for up to two years after having their motorcycle equipped with GPS receivers, accelerometers, gyroscopes, switches and video cameras. In total, about 38,600 trips were recorded. Twenty two accidents occurred during the study.

The identification of accidents and safety-critical events was performed via self-reporting, manual review of video footage and based on indicators collected via the naturalistic data. In some studies, road users self-reported their incidents immediately via a push-button on the vehicle (Dozza & Werneke, 2014; Dozza *et al.*, 2015) or in a smartphone app

(Figliozzi & Blanc, 2015). Trip diaries (Gustafsson & Archer, 2013) and interviews (Dozza & Werneke, 2014) have also been used to identify incidents from naturalistic VRU studies. Several studies perform a manual review of video footage from naturalistic studies to identify incidents (Johnson *et al.*, 2014; Saleh, 2015; Sander & Marker, 2015; Schleinitz *et al.*, 2015b).

Few studies have been conducted in order to detect incidents automatically based on motion patterns from naturalistic data. Candefjord *et al*. (2014) detected bicycle accidents by analysing the speed, acceleration and rotation patterns from naturalistic data. In the study, six accidents were simulated using a crash test dummy. Attal *et al*. (2014) detected motorcycle accidents in order to trigger the inflation of an airbag jacket for protection of the rider. Falls were detected based on continuous acceleration and rotation data. To collect accidents, a stuntman performed eight simulated accidents of typical single accidents: falls in curves, roundabouts, on slippery roads, leaning off the motorcycle and falling from standstill. Furthermore, a professional rider performed extreme manoeuvres, e.g. extreme braking, and rode on deteriorated roads in order to test the performance under extreme conditions. Similarly, Watthanawisuth *et al*. (2012) collected simulated accidents, extreme riding manoeuvres and normal riding from an equipped motorcycle to identify accidents based on acceleration and speed data. Vlahogianni *et al*. (2014) identified safety-critical events based on speed and acceleration patterns and information from switches on the motorcycle for registration of steering angle, throttle position, brake activation and front wheel speed. Williams et al. (2015) applied a semi-automatic process to identify accidents in naturalistic riding data from motorcycles. Threshold values of acceleration and jerks were used to find potential accidents. These situations were then reviewed manually to identify the actual accidents.

5.2. Other safety-related aspects

Additional 9 studies assessed the safety of vulnerable road users based on other aspects than accidents and safety-critical events (Annex 2).

Five different safety-related aspects were investigated in the studies. Three studies assessed how the participants turned their head or stopped before crossing the road (Dozza *et al.*, 2014; Hsieh *et al.*, 2014a; Tada *et al.*, 2011). In a study of scooter drivers, Hsieh *et al*. (2014a) collected naturalistic riding data from 100 participants via a smartphone mounted on the vehicle. Based on speed and acceleration patterns, they predicted whether the rider stopped or not at intersections so that the rider could be warned in time to prevent red-light running and accidents. Dozza *et al*. (2014) detected if pedestrians crossed the street at the zebra crossing without looking to the sides to check for oncoming vehicles by analysing the acceleration and rotation of the pedestrian. In the study, special equipment was constructed, which the pedestrian had to wear during the data collection. Based on acceleration measurements, it was possible to detect when the pedestrian walked and when he was standing still. In combination with video recordings and GPS-coordinates of zebra crossings, the system was able to detect whether the pedestrian turned his head before crossing the road. Tada *et al*. (2011) mapped head rotation of cyclists to identify locations where the participants turned their head for performing a visual search to look for other road users, e.g. before crossing the road, and where they looked away from the road due to distraction.

In two studies, naturalistic data was collected from cyclists to compare the speed behaviour of cyclists on conventional bicycles and electric bicycles (Langford *et al.*, 2015; Schleinitz *et al.*, 2015a).

Two studies detected obstacles to warn motorcyclists about objects further ahead in order to avoid collisions (Fang *et al.*, 2014) and to warn visually impaired about nearby stairs (Lin *et al.*, 2014) based on naturalistic acceleration data from pedestrians.

In a study of motorcyclists, Smith *et al*. (2013) assessed the occurrence of potential dangerous riding by comparing the stopping distance with the sight distance. Situations, where the stopping distance was higher than the sight distance could potentially lead to accidents if objects were present or unforeseen events were about to happen further ahead.

Lai *et al*. (2015) collected naturalistic data from 34 participants using equipped bicycles to assess their steering behaviour when being passed by an overtaking motorcycle. Based on the wheel angle, swerves of the cyclists were identified and used as an indicator of increased risk of collision.

6. Related studies from other fields

Thirty eight publications reported about studies of detection of falls outside the transport infrastructure. The majority of the studies (35) focused on falls among elderly people. Three purposes were identified in these studies.

Some studies estimate the accuracy of automatic fall detection based on a sample of simulated falls (Allen *et al.*, 2013; Azizul *et al.*, 2014; Dinh & Chew, 2015; Horta *et al.*, 2013; Hsieh *et al.*, 2014b; Lai *et al.*, 2014; Lee & Carlisle, 2011; Ozcan & Velipasalar, 2016; Salgado & Afonso, 2013; Tacconi *et al.*, 2011; Wibisono *et al.*, 2013).

Some studies furthermore distinguish these fall events from activities of daily living, e.g. walking, sitting, standing, lying down and walking on stairs (Abbate *et al.*, 2012; Aguiar *et al.*, 2014; Ando *et al.*, 2015; Cao *et al.*, 2012; Cheffena, 2015; Colon *et al.*, 2014; Dai *et al.*, 2010; De Cillis *et al.*, 2015; Fang *et al.*, 2012; Kaenampornpan *et al.*, 2011; Koshmak *et al.*, 2013; Luque *et al.*, 2014; Mandal *et al.*, 2014; Medrano *et al.*, 2014; Mulcahy & Kurkovsky, 2015; Pierleoni *et al.*, 2015; Rakhman *et al.*, 2014; Shen *et al.*, 2015; Shi *et al.*, 2012; Sie & Lo, 2015; Sukreep *et al.*, 2015; Vermeulen *et al.*, 2015; Vilarinho *et al.*, 2015; Zhao *et al.*, 2010).

Finally, a number of studies also propose to implement functions to notify contact persons about the fall in order to provide immediate help in case of a fall (Abbate *et al.*, 2012; Aguiar *et al.*, 2014; Cao *et al.*, 2012; Fang *et al.*, 2012; Hsieh *et al.*, 2014b; Lee & Carlisle, 2011; Luque *et al.*, 2014; Medrano *et al.*, 2014; Sie & Lo, 2015; Wibisono *et al.*, 2013).

Three studies, which did not detect falls among elderly, were found. Dzeng *et al*. (2014) and Tsai (2014) monitored construction site workers to detect falls and movements that were likely to result in falls. Liu & Koc (2013) use the built-in sensors of the smartphone to detect tractor rollovers and inform contacts about the location and time of the rollover event.

6.1. Sensors

Except for one study (Cheffena, 2015), which detected fall accidents based on audio patterns, all studies used the accelerometer to collect data (Table 7). In about one third of the studies, GPS receivers and gyroscopes were used to supplement accelerometer data. Few studies applied magnetometers to supply accelerometer data with information about the orientation of the smartphone.

Table 7: Sensors used for data collection

GPS	Accelerometer	Gyroscope	Magnetometer	Switches	Video	Other
12	37	13	6	0	1	3

6.2. Indicators

Acceleration was the far most used indicator to detect falls (Table 8). This indicator was used to identify large changes in the acceleration that occurs when a person falls and hits the ground. Fourteen studies supplemented the acceleration by rotation measurements that are used to detect sudden changes in the direction of movement.

Table 8: Indicators used in fall detection studies

Speed	Acceleration	Jerks	Rotation	Sound	Other
0	36	1	14	1	3

6.3. Number of participants

Seventy three per cent of the studies collected data from up to ten participants, while 94% had up to 20 participants (Figure 3). The median number of participants was 5, which reflect that most studies were conducted to test prototypes of algorithms for fall detection based on motion characteristics.

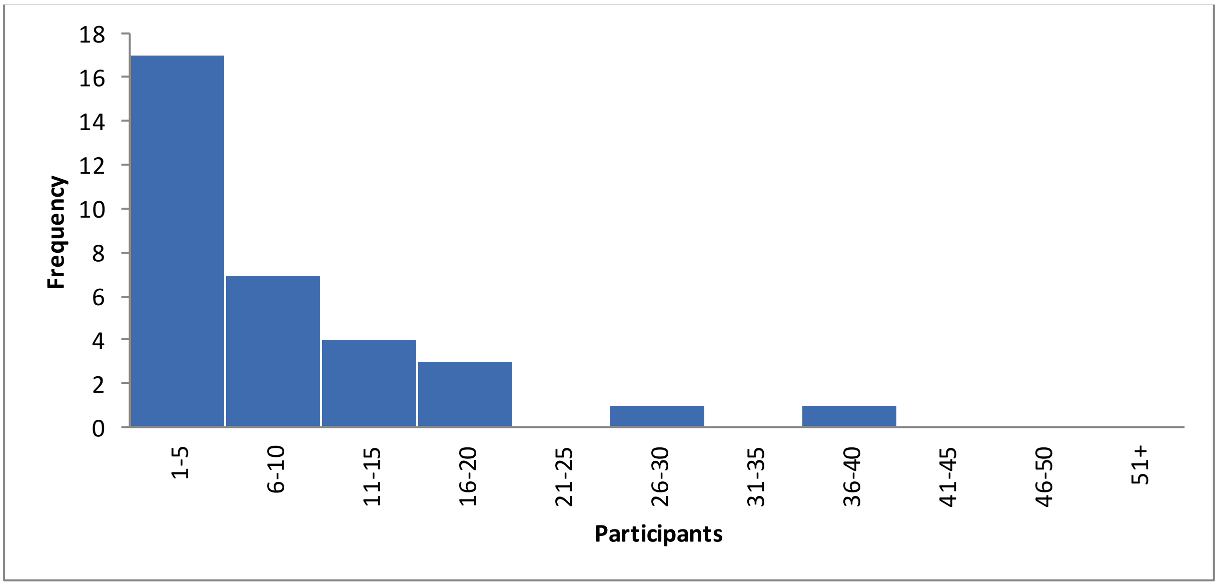

Figure 3: Number of participants in the reviewed studies (n = 33)

6.4. Number of simulated falls

Although the number of participants was small in most studies, many studies were tested on a large number of falls (Figure 4).

Since fall accidents are rare, most studies test the ability to detect falls on simulated falls. Typically, young people simulated different types of falls (forward, backwards, to the left, to the right) by falling onto a mattress. This approach was chosen in order to protect the main target group – elderly people – from having severe injuries during the data collection.

Only few studies detected real falls. For instance, fall data from novice ice-skaters has been used as a representation for real falls as these falls could be collected in short time and occurred naturally while doing ice-skating (Koshmak *et al.*, 2013). In total, 50 falls were recorded from seven participants who performed ice-skated for 15-30 minutes each.

Tsai (2014) monitored 30 students on construction sites for 16 weeks to detect fall accidents. In total, five falls were registered.

The number of simulated and real falls ranged from five (Tsai, 2014) to 1879 (Aguiar *et al.*, 2014), with an average of 250 falls.

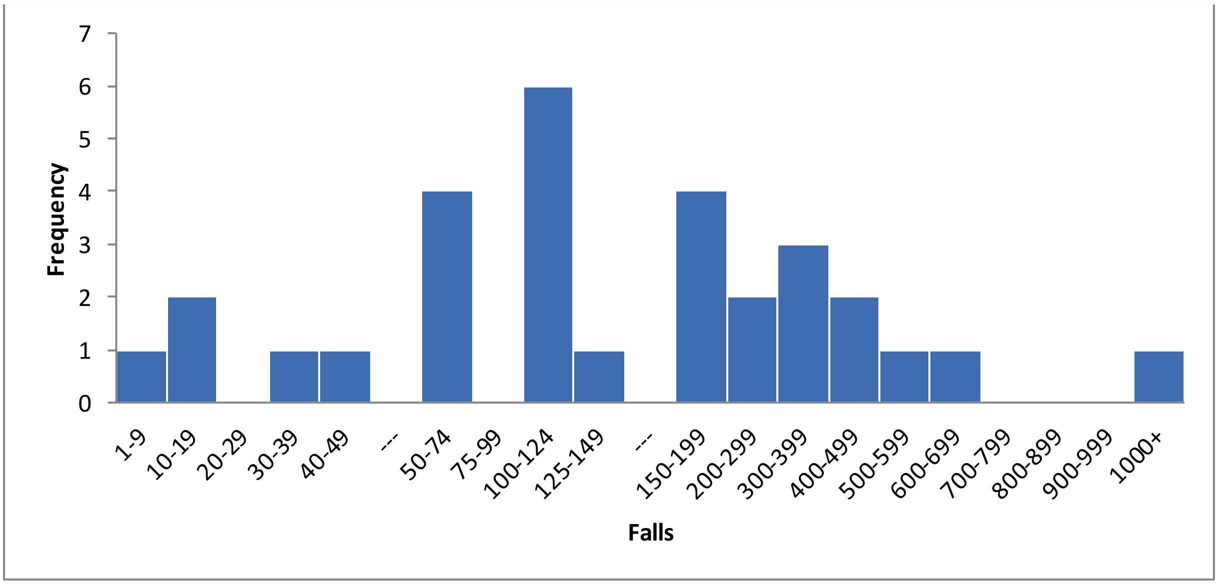

Figure 4: Number of simulated and real falls in the reviewed studies

7. Conclusions

Naturalistic studies of vulnerable road users have mainly been carried out by collecting data from cyclists and pedestrians and to a smaller degree of motorcyclists. To collect data, most studies used the built-in sensors of smartphones, although equipped bicycles or motorcycles were used in some studies. Other types of portable equipment was used to a lesser degree, particularly for cycling studies.

The naturalistic studies were carried out with various purposes: mode classification, travel surveys, measuring the distance and number of trips travelled and conducting traffic counts. Naturalistic data was also used for assessment of the safety based on accidents, safety-critical events or other safety-related aspect such as speed behaviour, head turning and obstacle detection.

Only few studies detect incidents automatically based on indicators collected via special equipment such as accelerometers, gyroscopes, GPS receivers, switches, etc. for assessing the safety by identifying accidents or safety-critical events. Instead, they rely on self-reporting or manual review of video footage.

Despite this, the review indicates that there is a large potential of detecting accidents from naturalistic data. A large number of studies focused on the detection of falls among elderly people. Using smartphone sensors, the movements of the participants were monitored continuously. Most studies used acceleration as indicator of falls. In some cases, the acceleration was supplemented by rotation measurements to indicate that a fall had occurred.

Most studies of using kinematic triggers for detection of falls, accidents and safety-critical events were primarily used for demonstration of prototypes of detection algorithms. Few studies have been tested on real accidents or falls. Instead, simulated falls were used both in studies of vulnerable road users and for studies of falls among elderly people.

8. References

Abbate, S., Avvenuti, M., Bonatesta, F., Cola, G., Corsini, P., & Vecchio, A. (2012). A smartphone-based fall detection system. *Pervasive and Mobile Computing, 8*(6), 883-899. doi:http://dx.doi.org/10.1016/j.pmcj.2012.08.003

Aguiar, B., Rocha, T., Silva, J., & Sousa, I. (2014). Accelerometer-based fall detection for smartphones. *Medical Measurements and Applications (MeMeA), 2014 IEEE International Symposium On,* 1-6. doi:10.1109/MeMeA.2014.6860110

Allen, B., Derveloy, R., Lowry, K., Handley, H., Fell, N., Gasior, W., . . . Sartipi, M. (2013). Evaluation of fall risk for post-stroke patients using bluetooth low-energy wireless sensor. *Global Communications Conference (GLOBECOM), 2013 IEEE,* 2598-2603. doi:10.1109/GLOCOM.2013.6831466

Alzantot, M., & Youssef, M. (2012). UPTIME: Ubiquitous pedestrian tracking using mobile phones. *Wireless Communications and Networking Conference (WCNC), 2012 IEEE,* 3204-3209. doi:10.1109/WCNC.2012.6214359

Ando, B., Baglio, S., Lombardo, C. O., & Marletta, V. (2015). An event polarized paradigm for ADL detection in AAL context. *Instrumentation and Measurement, IEEE Transactions On, 64*(7), 1814-1825. doi:10.1109/TIM.2014.2385144

Ansari Lari, Z., & Golroo, A. (2015). Automated transportation mode detection using smart phone applications via machine learning: Case study mega city of tehran. 15p.

Attal, F., Boubezoul, A., Oukhellou, L., Cheifetz, N., & Espie, S. (2014). The powered two wheelers fall detection using multivariate cumulative SUM (MCUSUM) control charts. pp 1280-1285.

Attal, F., Boubezoul, A., Oukhellou, L., & Espie, S. (2015). Powered two-wheeler riding pattern recognition using a machine-learning framework. *IEEE Transactions on Intelligent Transportation Systems, 16*(1), pp 475-487.

Azizul, W., Imai, S., & Hasegawa, T. (2014). Fall detection using smart phone and ubiquitous pulse wave sensor. *Control, Automation and Systems (ICCAS), 2014 14th International Conference On,* 782-785. doi:10.1109/ICCAS.2014.6987885

Balagapo, J., Sabidong, J., & Caro, J. (2014). Data crowdsourcing and traffic sensitive routing for a mixed mode public transit system. *Information, Intelligence, Systems and Applications, IISA 2014, the 5th International Conference On,* 1-6. doi:10.1109/IISA.2014.6878754

Bujari, A., Licar, B., & Palazzi, C. E. (2011). Road crossing recognition through smartphone's accelerometer. *Wireless Days (WD), 2011 IFIP,* 1-3. doi:10.1109/WD.2011.6098186

Candefjord, S., Sandsjö, L., Andersson, R., Carlborg, N., Szakal, A., Westlund, J., & Sjöqvist, B. A. (2014). Using smartphones to monitor cycling and automatically detect accidents - towards *eCall* functionality for cyclists. *International Cycling Safety Conference 2014,* Göteborg, Sweden.

Cao, Y., Yang, Y., & Liu, W. (2012). E-FallD: A fall detection system using android-based smartphone. *Fuzzy Systems and Knowledge Discovery (FSKD), 2012 9th International Conference On,* 1509-1513. doi:10.1109/FSKD.2012.6234271

Charlton, B., Hood, J., Sall, E., & Schwartz, M.,A. (2011). Bicycle route choice data collection using GPS-enabled smartphones. 10p.

Cheffena, M. (2015). Fall detection using smartphone audio features. *IEEE Journal of Biomedical and Health Informatics,* doi:10.1109/JBHI.2015.2425932 [doi]

Colon, L. N. V., DeLaHoz, Y., & Labrador, M. (2014). Human fall detection with smartphones. *Communications (LATINCOM), 2014 IEEE Latin-America Conference On,* 1-7. doi:10.1109/LATINCOM.2014.7041879

Dai, J., Bai, X., Yang, Z., Shen, Z., & Xuan, D. (2010). PerFallD: A pervasive fall detection system using mobile phones. *Pervasive Computing and Communications Workshops (PERCOM Workshops), 2010 8th IEEE International Conference On,* 292-297. doi:10.1109/PERCOMW.2010.5470652

De Cillis, F., De Simio, F., Guidoy, F., Incalzi, R. A., & Setola, R. (2015). Fall-detection solution for mobile platforms using accelerometer and gyroscope data. *Engineering in Medicine and Biology Society (EMBC), 2015 37th Annual International Conference of the IEEE,* 3727-3730. doi:10.1109/EMBC.2015.7319203

Dinh, T. A., & Chew, M. T. (2015). Application of a commodity smartphone for fall detection. *Automation, Robotics and Applications (ICARA), 2015 6th International Conference On,* 495-500. doi:10.1109/ICARA.2015.7081198

Dozza, M., & Fernandez, A. (2014). Understanding bicycle dynamics and cyclist behavior from naturalistic field data (november 2012). *Intelligent Transportation Systems, IEEE Transactions On, 15*(1), 376-384. doi:10.1109/TITS.2013.2279687

Dozza, M., Idegren, M., Andersson, T., & Fernandez, A. (2014). Platform enabling intelligent safety applications for vulnerable road users. *Intelligent Transport Systems, IET, 8*(4), 368-376. doi:10.1049/iet-its.2012.0201

Dozza, M., Bianchi Piccinini, G. F., & Werneke, J. (2015). Using naturalistic data to assess e-cyclist behavior. *Transportation Research Part F: Traffic Psychology and Behaviour,* doi:http://dx.doi.org/10.1016/j.trf.2015.04.003

Dozza, M., & Werneke, J. (2014). Introducing naturalistic cycling data: What factors influence bicyclists’ safety in the real world? *Transportation Research Part F: Traffic Psychology and Behaviour, 24*, 83-91. doi:http://dx.doi.org/10.1016/j.trf.2014.04.001

Dzeng, R., Fang, Y., & Chen, I. (2014). A feasibility study of using smartphone built-in accelerometers to detect fall portents. *Automation in Construction, 38*, 74-86. doi:http://dx.doi.org/10.1016/j.autcon.2013.11.004

Fang, C., Hsu, W., Ma, C., & Chen, S. (2014). A vision-based safety driver assistance system for motorcycles on a smartphone. pp 328-333.

Fang, S., Liang, Y., & Chiu, K. (2012). Developing a mobile phone-based fall detection system on android platform. *Computing, Communications and Applications Conference (ComComAp), 2012,* 143-146. doi:10.1109/ComComAp.2012.6154019

Figliozzi, M., & Blanc, B. (2015). *Evaluating the use of crowdsourcing as a data collection method for bicycle performance measures and identification of facility improvement needs*

Gonzalez, P.,A, Weinstein, J.,S, Barbeau, S.,J, Labrador, M.,A, Winters, P.,L, Georggi, N.,Labib, & Perez, R.,A. (2008). Automating mode detection using neural networks and assisted GPS data collected using GPS-enabled mobile phones. 12p.

Guinness, R. E. (2015). Beyond where to how: A machine learning approach for sensing mobility contexts using smartphone sensors. *Sensors (Basel, Switzerland), 15*(5), 9962-9985. doi:10.3390/s150509962 [doi]

Gustafsson, L., & Archer, J. (2013). A naturalistic study of commuter cyclists in the greater stockholm area. *Accident Analysis & Prevention, 58*, 286-298. doi:http://dx.doi.org/10.1016/j.aap.2012.06.004

Hamann, C.,J, Pooley, M., McGehee, D., & Peek-Asa, C. (2014). A naturalistic study of child and adult bicycling behaviours and risk exposure. 15p.

Horta, E. T., Lopes, I. C., Rodrigues, J. J. P. C., & Proenca, M. L. (2013). A mobile health application for falls detection and biofeedback monitoring. *E-Health Networking, Applications & Services (Healthcom), 2013 IEEE 15th International Conference On,* 36-40. doi:10.1109/HealthCom.2013.6720634

Hsieh, C., Tsai, H., Yang, S., & Lin, S. (2014a). Predict scooter's stopping event using smartphone as the sensing device. *Internet of Things (iThings), 2014 IEEE International Conference on, and Green Computing and Communications (GreenCom), IEEE and Cyber, Physical and Social Computing(CPSCom), IEEE,* 17-23. doi:10.1109/iThings.2014.12

Hsieh, S., Chen, K., Yeh, C., & Chen, C. (2014b). An unfixed-position smartphone-based fall detection scheme. *Systems, Man and Cybernetics (SMC), 2014 IEEE International Conference On,* 2077-2081. doi:10.1109/SMC.2014.6974228

Jahangiri, A., & Rakha, H. A. (2015). Applying machine learning techniques to transportation mode recognition using mobile phone sensor data. *Intelligent Transportation Systems, IEEE Transactions On, 16*(5), 2406-2417. doi:10.1109/TITS.2015.2405759

Johnson, M., Chong, D., Carroll, J., Katz, R., Oxley, J., & Charlton, J. (2014). *Naturalistic cycling study: Identifying risk factors for cyclists in the australian capital territory*

Kaenampornpan, M., Anuchad, T., & Supaluck, P. (2011). Fall detection prototype for thai elderly in mobile computing era. *Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON), 2011 8th International Conference On,* 446-449. doi:10.1109/ECTICON.2011.5947871

Koshmak, G. A., Linden, M., & Loutfi, A. (2013). Evaluation of the android-based fall detection system with physiological data monitoring. *Engineering in Medicine and Biology Society (EMBC), 2013 35th Annual International Conference of the IEEE,* 1164-1168. doi:10.1109/EMBC.2013.6609713

Lai, C., Doong, J., Chuang, K., & Hsu, C. (2015). The likelihoods of bicyclist steering patterns in response to being passed by motorists. *Procedia Manufacturing, 3*, 3339-3344. doi:http://dx.doi.org/10.1016/j.promfg.2015.07.492

Lai, H., Dong, M., Bi, S., Luo, Q., & Tan, J. (2014). Outdoors real-time information analysis system for elderly based on smart phone. *Machine Learning and Cybernetics (ICMLC), 2014 International Conference On, , 1* 285-291. doi:10.1109/ICMLC.2014.7009130

Langford, B. C., Chen, J., & Cherry, C. R. (2015). Risky riding: Naturalistic methods comparing safety behavior from conventional bicycle riders and electric bike riders. *Accident Analysis & Prevention, 82*, 220-226. doi:http://dx.doi.org/10.1016/j.aap.2015.05.016

Lee, R. Y., & Carlisle, A. J. (2011). Detection of falls using accelerometers and mobile phone technology. *Age and Ageing, 40*(6), 690-696. doi:10.1093/ageing/afr050 [doi]

Lin, C., Huang, S., & Hsu, H. (2014). A crowdsourcing approach to promote safe walking for visually impaired people. *Smart Computing (SMARTCOMP), 2014 International Conference On,* 7-12. doi:10.1109/SMARTCOMP.2014.7043832

Liu, B., & Koc, A. B. (2013). SafeDriving: A mobile application for tractor rollover detection and emergency reporting. *Computers and Electronics in Agriculture, 98*, 117-120. doi:http://dx.doi.org/10.1016/j.compag.2013.08.002

Long, X., Yin, B., & Aarts, R. M. (2009). Single-accelerometer-based daily physical activity classification. *Engineering in Medicine and Biology Society, 2009. EMBC 2009. Annual International Conference of the IEEE,* 6107-6110. doi:10.1109/IEMBS.2009.5334925

Luo, D., & Ma, X. (2014). Analysis of cyclist behavior using naturalistic data: Data processing for model development. 17p.

Luque, R., Casilari, E., Moron, M. J., & Redondo, G. (2014). Comparison and characterization of android-based fall detection systems. *Sensors (Basel, Switzerland), 14*(10), 18543-18574. doi:10.3390/s141018543 [doi]

Mandal, I., Happy, S. L., Behera, D. P., & Routray, A. (2014). A framework for human activity recognition based on accelerometer data. *Confluence the Next Generation Information Technology Summit (Confluence), 2014 5th International Conference -,* 600-603. doi:10.1109/CONFLUENCE.2014.6949248

Medrano, C., Igual, R., Plaza, I., Castro, M., & Fardoun, H. M. (2014). Personalizable smartphone application for detecting falls. *Biomedical and Health Informatics (BHI), 2014 IEEE-EMBS International Conference On,* 169-172. doi:10.1109/BHI.2014.6864331

Mulcahy, M. K., & Kurkovsky, S. (2015). Automatic fall detection using mobile devices. *Information Technology - New Generations (ITNG), 2015 12th International Conference On,* 586-588. doi:10.1109/ITNG.2015.98

Nitsche, P., Widhalm, P., Breuss, S., Brändle, N., & Maurer, P. (2014). Supporting large-scale travel surveys with smartphones – A practical approach. *Transportation Research Part C: Emerging Technologies, 43, Part 2*, 212-221. doi:http://dx.doi.org/10.1016/j.trc.2013.11.005

Ozcan, K., & Velipasalar, S. (2016). Wearable camera- and accelerometer-based fall detection on portable devices. *Computational Intelligence and Security (CIS), 2011 Seventh International Conference on; Embedded Systems Letters, IEEE, 8*(1), 6-9. doi:10.1109/LES.2015.2487241

Pierleoni, P., Pernini, L., Belli, A., Palma, L., Valenti, S., & Paniccia, M. (2015). SVM-based fall detection method for elderly people using android low-cost smartphones. *Sensors Applications Symposium (SAS), 2015 IEEE,* 1-5. doi:10.1109/SAS.2015.7133642

Rakhman, A. Z., Nugroho, L. E., Widyawan, & Kurnianingsih. (2014). Fall detection system using accelerometer and gyroscope based on smartphone. *Information Technology, Computer and Electrical Engineering (ICITACEE), 2014 1st International Conference On,* 99-104. doi:10.1109/ICITACEE.2014.7065722

Reddy, S., Burke, J., Estrin, D., Hansen, M., & Srivastava, M. (2008). Determining transportation mode on mobile phones. *Wearable Computers, 2008. ISWC 2008. 12th IEEE International Symposium On,* 25-28. doi:http://dx.doi.org/10.1109/ISWC.2008.4911579

Saleh, P. (2015). E-bicycles - bicycles or mopeds? overview about the project "SEEKING - SAFE E-BIKING"☐. *6th International Conference on ESAR „Expert Symposium on Accident Research“,* (102) 9p.

Salgado, P., & Afonso, P. (2013). Fall body detection algorithm based on tri-accelerometer sensors. *Computational Intelligence and Informatics (CINTI), 2013 IEEE 14th International Symposium On,* 355-358. doi:10.1109/CINTI.2013.6705221

Sander, J., & Marker, S. (2015). A field test for comparison of e-bikes and conventional bicycles in traffic. 15p.

Schleinitz, K., Petzoldt, T., Franke-Bartholdt, L., Krems, J., & Gehlert, T. (2015a). The german naturalistic cycling study – comparing cycling speed of riders of different e-bikes and conventional bicycles. *Safety Science,* doi:http://dx.doi.org/10.1016/j.ssci.2015.07.027

Schleinitz, K., Petzoldt, T., Franke-Bartholdt, L., Krems, J. F., & Gehlert, T. (2015b). Conflict partners and infrastructure use in safety critical events in cycling – results from a naturalistic cycling study. *Transportation Research Part F: Traffic Psychology and Behaviour, 31*, 99-111. doi:http://dx.doi.org/10.1016/j.trf.2015.04.002

Shen, V. R. L., Lai, H., & Lai, A. (2015). The implementation of a smartphone-based fall detection system using a high-level fuzzy petri net. *Applied Soft Computing, 26*, 390-400. doi:http://dx.doi.org/10.1016/j.asoc.2014.10.028

Shi, Y., Shi, Y., & Wang, X. (2012). Fall detection on mobile phones using features from a five-phase model. *Ubiquitous Intelligence & Computing and 9th International Conference on Autonomic & Trusted Computing (UIC/ATC), 2012 9th International Conference On,* 951-956. doi:10.1109/UIC-ATC.2012.100

Shin, D., Aliaga, D., Tunçer, B., Arisona, S. M., Kim, S., Zünd, D., & Schmitt, G. (2015). Urban sensing: Using smartphones for transportation mode classification. *Computers, Environment and Urban Systems, 53*, 76-86. doi:http://dx.doi.org/10.1016/j.compenvurbsys.2014.07.011

Sie, M., & Lo, S. (2015). The design of a smartphone-based fall detection system. *Networking, Sensing and Control (ICNSC), 2015 IEEE 12th International Conference On,* 456-461. doi:10.1109/ICNSC.2015.7116080

Smith, T., Garets, S., & Cicchino, J. (2013). *The effect of sight distance training on the visual scanning of motorcycle riders: A preliminary look*

Strauss, J., Miranda-Moreno, L. F., & Morency, P. (2015). Mapping cyclist activity and injury risk in a network combining smartphone GPS data and bicycle counts. *Accident; Analysis and Prevention, 83*, 132-142. doi:http://dx.doi.org/10.1016/j.aap.2015.07.014

Sukreep, S., Mongkolnam, P., & Nukoolkit, C. (2015). Monitoring and visualizing the daily activities and in-house locations using smartphone. *Computer Science and Software Engineering (JCSSE), 2015 12th International Joint Conference On,* 291-296. doi:10.1109/JCSSE.2015.7219812

Tacconi, C., Mellone, S., & Chiari, L. (2011). Smartphone-based applications for investigating falls and mobility. *Pervasive Computing Technologies for Healthcare (PervasiveHealth), 2011 5th International Conference On,* 258-261.

Tada, M., Noma, H., & Renge, K. (2011). Measuring cyclists' behavior using wearable sensors for automatic creation of safety behavior map. 14p.

Tsai, M. (2014). Automatically determining accidental falls in field surveying: A case study of integrating accelerometer determination and image recognition. *Safety Science, 66*, 19-26. doi:http://dx.doi.org/10.1016/j.ssci.2014.01.012

Vermeulen, J., Willard, S., Aguiar, B., & De Witte, L. P. (2015). Validity of a smartphone-based fall detection application on different phones worn on a belt or in a trouser pocket. *Assistive Technology : The Official Journal of RESNA, 27*(1), 18-23. doi:10.1080/10400435.2014.949015 [doi]

Vilarinho, T., Farshchian, B., Bajer, D. G., Dahl, O. H., Egge, I., Hegdal, S. S., . . . Weggersen, S. M. (2015). A combined smartphone and smartwatch fall detection system. *Computer and Information Technology; Ubiquitous Computing and Communications; Dependable, Autonomic and Secure Computing; Pervasive Intelligence and Computing (CIT/IUCC/DASC/PICOM), 2015 IEEE International Conference On,* 1443-1448. doi:10.1109/CIT/IUCC/DASC/PICOM.2015.216

Vlahogianni, E. I., Yannis, G., & Golias, J. C. (2014). Detecting powered-two-wheeler incidents from high resolution naturalistic data. *Transportation Research Part F: Traffic Psychology and Behaviour, 22*, 86-95. doi:http://dx.doi.org/10.1016/j.trf.2013.11.002

Voigtmann, C., Sian Lun Lau, & David, K. (2012). Evaluation of a collaborative-based filter technique to proactively detect pedestrians at risk. *Vehicular Technology Conference (VTC Fall), 2012 IEEE,* 1-5. doi:http://dx.doi.org/10.1109/VTCFall.2012.6399117

Wang, S., Chen, C., & Ma, J. (2010). Accelerometer based transportation mode recognition on mobile phones. *Wearable Computing Systems (APWCS), 2010 Asia-Pacific Conference On,* 44-46. doi:http://dx.doi.org/10.1109/APWCS.2010.18

Watthanawisuth, N., Lomas, T., & Tuantranont, A. (2012). Wireless black box using MEMS accelerometer and GPS tracking for accidental monitoring of vehicles. *Biomedical and Health Informatics (BHI), 2012 IEEE-EMBS International Conference On,* 847-850. doi:http://dx.doi.org/10.1109/BHI.2012.6211718

Wibisono, W., Arifin, D. N., Pratomo, B. A., Ahmad, T., & Ijtihadie, R. M. (2013). Falls detection and notification system using tri-axial accelerometer and gyroscope sensors of a smartphone. *Technologies and Applications of Artificial Intelligence (TAAI), 2013 Conference On,* 382-385. doi:10.1109/TAAI.2013.82

Williams, V.,H, McLaughlin, S.,B, Williams, S.,L, & Buche, T. (2015). An exploratory analysis of motorcycle incidents using naturalistic riding data. 12p.

Zhang, Z., & Poslad, S. (2013). Design and test of a hybrid foot force sensing and GPS system for richer user mobility activity recognition. *Sensors (Basel, Switzerland), 13*(11), 14918-14953. doi:http://dx.doi.org/10.3390/s131114918

Zhao, Z., Chen, Y., Liu, J., & Zhao, Z. (2010). Fall detecting and alarming based on mobile phone. *Ubiquitous Intelligence & Computing and 7th International*

Conference on Autonomic & Trusted Computing (UIC/ATC), 2010 7th International Conference On, 494-497. doi:10.1109/UIC-ATC.2010.44

Annex 1: Studies with detection of accidents or safety-critical events

Reference and country	Road user type	Type of event	Equipment	Sensors	Indicators used for detection	Study size	Additional information
(Attal *et al.*, 2014) France	Motorcyclists	Accidents	Equipped vehicle	Accelerometer, gyroscope	Acceleration, rotation	5 participants; 27.5 km; 8 simulated accidents; 10 near-accidents (extreme riding)	Accident simulation with stuntman on a track, near-accidents by professional rider on track
(Candefjord *et al.*, 2014) Sweden	Cyclists	Accidents	Smartphone	GPS, accelerometer, gyroscope	Speed, acceleration, rotation	5.5 hours; 6 simulated accidents	Accident simulation with crash test dummy
(Dozza *et al.*, 2015) Sweden	Cyclists (electric bicycles)	Safety-critical events	Equipped vehicle	GPS, accelerometer, gyroscope, magnetometer, brake force sensors, switches, video cameras, current sensor	Self-reported via push-button	12 participants; 86 hours; 410 trips; 1474 km; 88 safety-critical events	
(Dozza & Werneke, 2014) Sweden	Cyclists	Safety-critical events	Equipped vehicle	GPS, accelerometer, gyroscope, magnetometer, brake force sensors, video cameras	Self-reported via push-button and interviews; Detection via kinematic triggers (indicators unknown)	16 participants; 114 hours; 332 trips; 1549 km; 63 safety-critical events	

Reference and country	Road user type	Type of event	Equipment	Sensors	Indicators used for detection	Study size	Additional information
(Figliozzi & Blanc, 2015) Oregon, USA	Cyclists	Accidents; Safety-critical events	Smartphone	GPS	Self-reported via app	164 participants; 5 months; 1449 trips; 62 events (62 % safety-critical)	
(Gustafsson & Archer, 2013) Sweden	Cyclists	Safety-critical events	Other portable equipment; Equipped vehicle	GPS, video camera	Self-reported via trip diaries	16 participants; > 240 hours; 438 trips; 4910 km; 220 safety-critical events	
(Johnson *et al.*, 2014) Australia	Cyclists	Safety-critical events	Other portable equipment	GPS, video camera	Manual review of video footage	36 participants; 465 hours; 8986 km; 91 potential safety-critical events	
(Saleh, 2015) Austria	Cyclists (electric and conventional bicycles)	Safety-critical events	Smartphone	GPS, accelerometer, gyroscope, magnetometer	Manual review of video footage	137 participants; 57 safety-critical events	Data collected on track

Reference and country	Road user type	Type of event	Equipment	Sensors	Indicators used for detection	Study size	Additional information
(Saleh, 2015) Austria	Cyclists (electric bicycles)	Safety-critical events	Smartphone	GPS, accelerometer, gyroscope, magnetometer	Manual review of video footage	22 participants; 0 safety-critical events	Data collected on predifined track
(Saleh, 2015) Austria	Moped riders (electric and conventional mopeds)	Safety-critical events	Smartphone	GPS, accelerometer, gyroscope, magnetometer	Manual review of video footage	60 participants; 22 safety-critical events	Data collected on track
(Sander & Marker, 2015) Germany	Cyclists (electric and conventional bicycles)	Safety-critical events	Equipped vehicle	GPS, accelerometer, video cameras, sound recording	Manual review of video footage	50 participants; 45 hours; 375 km per bicycle type; 0 safety-critical events; 15 events with strong interaction;	Data collected on a predefined route
(Schleinitz *et al.*, 2015b) Germany	Cyclists	Safety-critical events	Equipped vehicle	Speed sensor, switches, video cameras	Manual review of video footage	31 participants; 372 hours; 1667 trips; 5280 km; 77 safety-critical events	

Reference and country	Road user type	Type of event	Equipment	Sensors	Indicators used for detection	Study size	Additional information
(Vlahogianni *et al.*, 2014) Greece	Motorcyclists	Safety-critical events	Equipped vehicle	GPS, accelerometer, gyroscope, switches, video cameras	Speed, acceleration, steering angle, throttle position, brake activation, front wheel speed	3 participants; 6 weeks; 56 trips (data from one participant)	
(Watthanawisuth *et al.*, 2012) Thailand	Motorcyclists	Accidents	Equipped vehicle	GPS, accelerometer	Speed, acceleration	200 simulated accidents; 50 trials of normal ride; 100 trials of potential accident triggers (bumpy surface, hard braking)	
(Williams *et al.*, 2015) California, Florida, Virginia, Arizona, USA	Motorcyclists	Accidents	Equipped vehicle	GPS, accelerometer, gyroscope, switches, video cameras	Acceleration, jerks Self-reported	100 participants; 2-24 months; ~38,600 trips; 22 accidents	Indicators used to reduce data to potential accidents, which are then reviewed in video footage

Annex 2: Studies of other safety aspects than accidents and safety-critical events

Reference and country	Road user type	Road safety aspect	Equipment	Sensors	Indicators used for detection	Study size	Additional information
(Dozza *et al.*, 2014) Sweden	Pedestrians	Assessing if crossing street at zebra crossing without looking to the sides	Other portable equipment	GPS, accelerometer, gyroscope, magnetometer, video camera, foot force sensor	Acceleration, rotation	3 participants; 8 trips; 32 zebra crossings passed	
(Fang *et al.*, 2014) Taiwan	Motorcyclists	Obstacle detection and safety distance measurement	Smartphone (mounted on vehicle)	GPS, accelerometer, gyroscope, video camera	Speed, acceleration, rotation, video	1 participant; 16 trials	Video analysis applied to detect obstacles on the road. Rotation used to adjust images
(Hsieh *et al.*, 2014a) Taiwan	Scooters	Stopping or not at the intersection	Smartphone (mounted on vehicle)	GPS, accelerometer, gyroscope, magnetometer, video camera, microphone	Speed, acceleration	100 participants; 3 months; 28,273 km; 2095 stop cases, 1810 non-stop cases	

Reference and country	Road user type	Road safety aspect	Equipment	Sensors	Indicators used for detection	Study size	Additional information
(Lai *et al.*, 2015) Taiwan	Cyclists	Steering behaviour when passed by motorcycle	Equipped vehicle	GPS, accelerometer, gyroscope, magnetometer, switches, video camera, distance sensor	Speed, acceleration, proximity, wheel angle	34 participants; 17 hours; 922 passing events	
(Langford *et al.*, 2015) Tennessee, USA	Cyclists (electric and conventional bicycles)	Speed behavior; Driving in the wrong direction	Equipped vehicle	GPS	Speed	100 participants; 2833 check outs from bicycle points	Not all bicycles were equipped
(Lin *et al.*, 2014) Taiwan	Pedestrians	Stair detection for warning of visually impaired	Smartphone	GPS, accelerometer	Acceleration	36 minutes	Data collected from people with normal vision
(Schleinitz *et al.*, 2015a) Germany	Cyclists (electric and conventional bicycles)	Speed behaviour of conventional bikes, pedelecs (up to 25 km/h) and S-pedelecs (up to 45 km/h)	Equipped vehicle	Switches, video cameras, speed sensor	Speed	85 participants; 4 weeks; 4327 trips; 16,873 km	
(Smith *et al.*, 2013) Washington, D.C., USA	Motorcyclists	Ratio between sight distance and stopping distance	Other portable equipment	GPS, eye tracker	Speed, sight direction	29 participants; 30 hours	

Reference and country	Road user type	Road safety aspect	Equipment	Sensors	Indicators used for detection	Study size	Additional information
(Tada *et al.*, 2011) Japan	Cyclists	Register head turning to identify locations with looking around to check for other road users or looking away due to distraction	Other portable equipment; Equipped vehicle	GPS, gyroscope, video camera	Rotation	36 participants; 196 turning head movements	