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Understanding the potential of emerging digital technologies for improving road safety

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Abstract

Each year, 1.35 million people are killed on the world's roads and another 20-50 million are seriously injured. Morbidity or serious injury from road traffic collisions is estimated to increase to 265 million people between 2015 and 2030. Current road safety management systems rely heavily on manual data collection, visual inspection and subjective expert judgment for their effectiveness, which is costly, time-consuming, and sometimes ineffective due to under-reporting and the poor quality of the data. A range of innovations offers the potential to provide more comprehensive and effective data collection and analysis to improve road safety. However, there has been no systematic analysis of this evidence base. To this end, this paper provides a systematic review of the state of the art. It identifies that digital technologies - Artificial Intelligence (AI), Machine-Learning, Image-Processing, Internet-of-Things (IoT), Smartphone applications, Geographic Information System (GIS), Global Positioning System (GPS), Drones, Social Media, Virtual-reality, Simulator, Radar, Sensor, Big Data – provide useful means for identifying and providing information on road safety factors including road user behaviour, road characteristics and operational environment. Moreover, the results show that digital technologies such as AI, Image processing and IoT have been widely applied to enhance road safety, due to their ability to automatically capture and analyse data while preventing the possibility of human error. However, a key gap in the literature remains their effectiveness in real-world environments. This limits their potential to be utilised by policymakers and practitioners.

Keywords: Safety; Road; Transport; Digital technology; Information

1 **1. Introduction**

2 Road traffic accidents are one of the most critical problems for human life and infrastructure.
3 According to the World Health Organisation (WHO), road traffic injuries cause more than 1.35
4 million deaths per year, with 93% of them occurring in developing countries [1]. Globally, the
5 road traffic death rate ranges from three to almost 36 per 100,000 population. While the rate
6 is less than nine in developed countries, it averages around 20 in the global south, with the
7 African region reporting the highest rate;35.9 [2]. In addition to the human cost, road
8 accidents are also associated with high financial costs, for example, medical spending,
9 productivity losses and property damage that severely burden a country's socio-economic
10 fabric. It is estimated that these costs range from 1% to 5% of countries' GDP, with up to 3%
11 in developing countries and 2.2% to 4.6% in developed countries [3].

12 Recognising the challenge that road safety poses to sustainable development and human
13 rights [4], the UN Sustainable Development Goals (SDGs) aimed to halve the number of road
14 accident-related fatalities and injuries by 2020 (Target 3.6) and provide access to safe,
15 affordable, accessible and sustainable transport systems for all by 2030 (Target 11.2) [5].
16 Despite this, road traffic accidents are on an upward trend [6]. Road traffic injuries are the
17 eighth leading cause of death globally across all age groups, with up to 50 million per year,
18 and are predicted to become the seventh leading cause of death by 2030 [1]. It is therefore
19 unlikely that Target 3.6 will be met by the end of 2020 [7]. Moreover, the targets have not
20 been supported with substantive policy action in many instances [8, 9].

21 The importance of data and evidence for creating an effective road safety policy and effective
22 management systems is well recognised, with poor and incomplete data identified as a key
23 barrier to affect decision-making in this area [10-12]. The development of a raft of different
24 digital and information technologies promise to overcome these problems, generating greater
25 amounts and types of data that can be applied to better understand the diversity of variables
26 that affect road safety. Therefore, if used effectively, such technologies offer the potential to
27 improve existing methods and procedures for data collection, processing and analysis to
28 strengthening policymaking [10, 13]. However, as yet there has been no systematic
29 interrogation of the evidence base produced by these technologies, to understand what this
30 potential is in practice.

31 This study is the first to carry out such a systematic review. It identifies twelve digital
32 technologies that have the potential to support decision making concerning road safety:
33 artificial intelligence, image processing, radars, sensors, geographical information system
34 (GIS), Global Positioning System (GPS), Internet-of-Things (IoT), big data, smartphones,
35 simulators, virtual reality (VR), social media and drones. It explores their ability to provide
36 information on three key road safety factors: road user behaviour (i.e. driver, pedestrian); road
37 characteristics (i.e. road condition), and operational environment (i.e. weather, lighting,
38 accident hotspots, and traffic congestion). This study systematically reviews the applicability
39 of digital technologies in particular, for collecting, monitoring and predicting information
40 associated with a wider range of accident contributing factors, recognising the considerable
41 advances in the field over the past decade.

42 The findings from this study provide a means through which to evaluate the potential
43 utilisation of a range of digital and information technologies for new data collection and

1 understanding in relation to road safety factors, and their potential to support road safety
2 management in practice.

3 The paper is structured as follows, section 2 introduces the current dynamics of the road
4 safety issue and the role of evidence and data in decision making, informing the context for
5 our study. Section 3 explains our method of the systematic review. Section 4 presents our
6 findings, section 5 presents our discussion of the state of the art, it's potential to affect road
7 safety and potential future research directions. In section 6 we conclude.

8 **2. Road Safety and Smart Policy Making**

9 Threats to road safety are caused by multiple contributing factors and not just a single poor
10 decision or action by the road user alone [14]. The existing academic literature has highlighted
11 key factors that affect road safety; namely road infrastructure condition [15, 16], weather [17-
12 21], road user behaviour [22-29], accident hotspots [30, 31] and traffic congestion [15, 32]. A
13 well-maintained and good-conditioned road promise better driving and safety as compared
14 to poor-conditioned roads which increase the probability of accidents. Similarly, the behaviour
15 of the road users (i.e., both drivers and pedestrians) also play an important role in road safety.
16 From a driving behaviour perspective, speed, fatigue, seat belt usage and driving under the
17 influence of alcohol and drugs are found to increase not only the road accident rates but also
18 the severity of a crash [22, 33]. Furthermore, the weather is one key environmental factor that
19 is known to affect road safety as it reduces road friction, impairs visibility and/or makes vehicle
20 handling more difficult. Traffic congestion has been found to have mixed effects on road safety
21 with earlier studies suggesting an inverse relationship between traffic congestion and road
22 accidents as speed is lower in congested situations. However, recent studies, owing to
23 advanced measurement techniques, reveal that congestion could increase road accidents
24 [15].

25 While road accidents cannot be completely prevented, accident rates can be reduced to
26 acceptable societal levels by adopting appropriate traffic engineering countermeasures and
27 management approaches. However, road safety analysts and road asset managers often have
28 to make decisions in circumstances where the data are partial or there is a high level of
29 uncertainty involved in the data. For example, accident databases are often incomplete, due
30 to under-reporting and often with poor quality data, either through omission or misreporting
31 of information [34]. Furthermore, data associated with lighting condition, weather, pedestrian
32 behaviour, and road surface condition at the location of the accident, appears not to be
33 accurately or comprehensively recorded. Accident investigation officers and/or police, due to
34 time restrictions, in addition to lack of experience, are likely to report the minimum permitted
35 contributory factors that may lead to an incident (Personal communication, 2020).
36 Additionally, there is also a concern that the police data on road accident investigations may
37 be systematically biased. Having reliable data to monitor and predict these factors accurately
38 and regularly is therefore critical to formulating and implementing effective road safety policy,
39 but often difficult to achieve [8, 9]. New digital technologies and the data they produce have
40 the potential to plug these gaps, due to their real-time potential and lack of reliance on human
41 input for data collection.

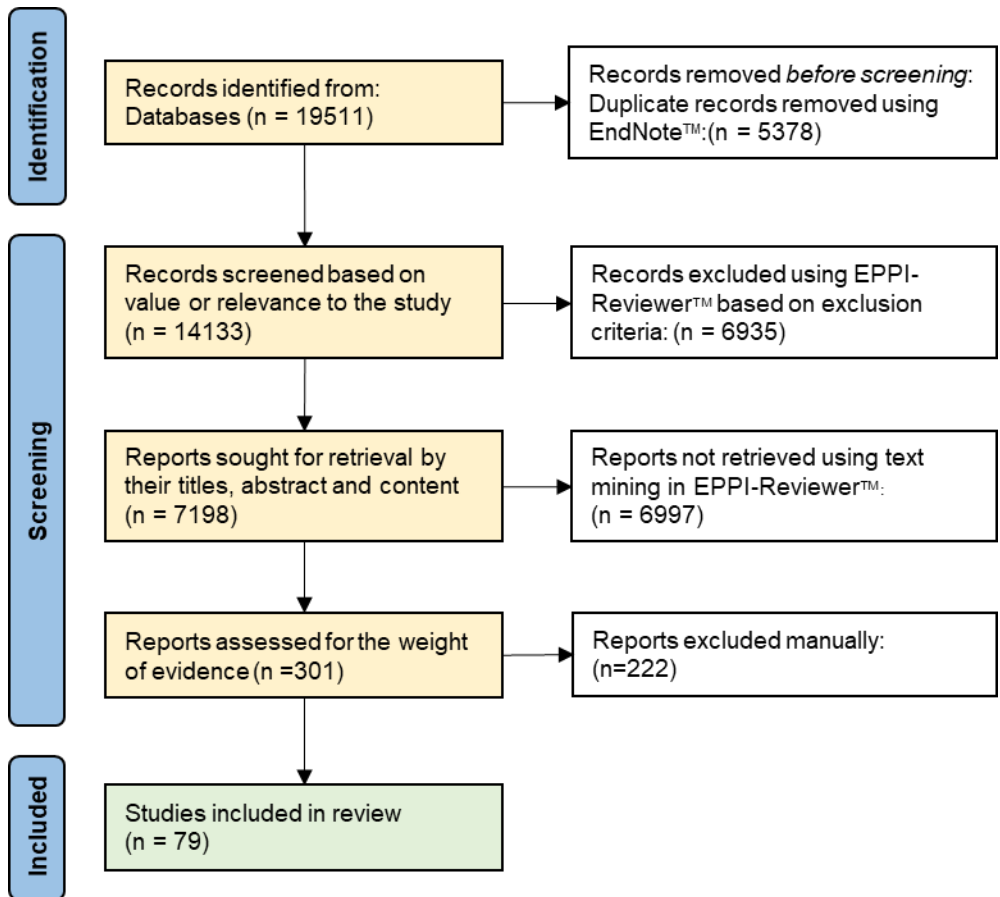
42 Moreover, aside from strengthening the data collection process, they also have the potential
43 to transform the policymaking process itself. Data from new digital technologies and

1 applications can be used to create 'smarter decision-making', in which the more
2 comprehensive and timely data can enable more accurate and efficient interventions [35]; for
3 example about where mitigation measures are required and when [10]. Going one step
4 further though, new digital innovations have the potential to create 'smarter administration',
5 in which data can be shared across traditional policy silos to create a more holistic
6 understanding of road safety dynamics, creating an iterative process of learning, in which
7 issues can be pre-empted and considered to create preventative rather than reactionary
8 policy [35]. However digital technologies and greater data accessibility do not guarantee such
9 results. Evidence is but one factor in decision-making, alongside often unpredictable or
10 intractable political and social factors, that have pervaded the focus on road safety in many
11 countries [36]. However, the role of digital technologies in providing access to new forms of
12 data and the potentially transformative role this could have on decision making increases the
13 pertinence and prescience of exploring the existing quality of the evidence-based to
14 understand the role digital innovations can play for advancing road safety.

15 We are mindful, however, that there exists a hierarchy of evidence within policy circles, in
16 which certain forms of evidence are perceived to be stronger or more robust in the eyes of
17 policymakers than other forms and therefore paid more attention to [37]. For example,
18 Randomised Control Trials tend to be perceived as higher quality than case studies due to the
19 perceived 'scientific' nature of the former over the latter. While this hierarchy is problematic,
20 in particular, because it prioritises qualitative data to the neglect of lived experience, and risks
21 undermining a holistic view, it is also important to bear in mind when trying to affect political
22 agendas [37, 38]. Here then, we have sought to focus on the quality and types of evidence
23 relating to each technology, being cognisant of the above (as will be discussed below). It is to
24 the method for our systematic review of this evidence base, that we now turn.

25 **3. Method**

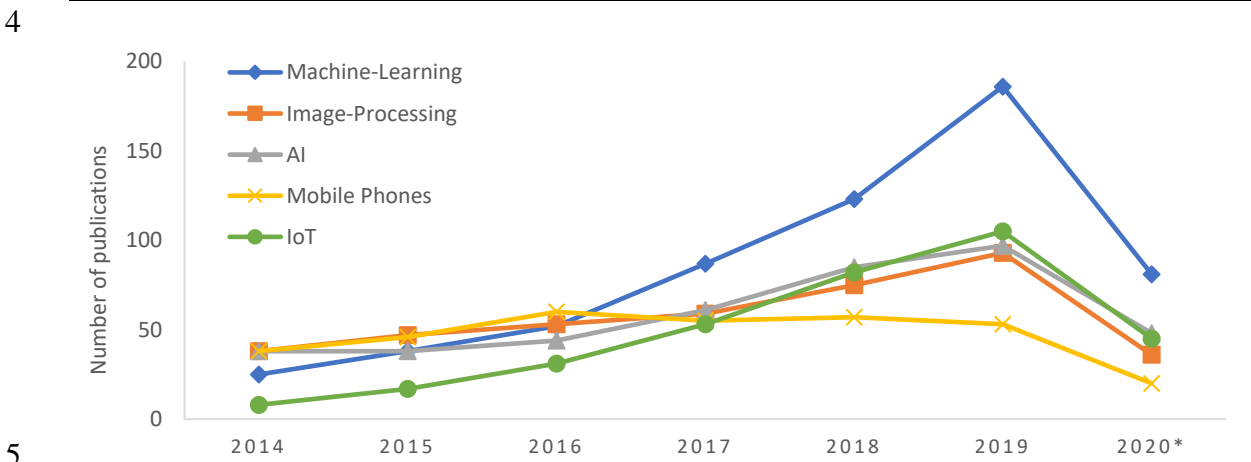
26 A systematic literature review approach was used for this study (see Figure 1 for PRISMA flow
27 diagram). Systematic reviews are used to evaluate the consistency and significance of the
28 scientific findings and whether these could be generalised across various settings [39]. A
29 stepwise review of the applicability of digital technologies for improving road safety in the
30 literature was carried out based on similar procedures adopted in previous studies [40, 41].
31 No limitation on the year of publication was used for the initial search. However, only studies
32 published up to the first quarter of 2020 were included in the search due to when the research
33 was undertaken. The digital technologies considered in this study (and used as the main
34 keywords for conducting the literature search) were selected based on an initial screening of
35 the literature, e.g. [42-44] who studied the application of various digital technologies to the
36 engineering, operations and management of infrastructure and services. The sub-keywords
37 used for the search were identified by considering the key concepts involved in extracting
38 insights and value from all sorts of data (e.g. DIKW model) [45] while applying the digital
39 technologies for informing road safety management (such as data processing, modelling,
40 simulation, forecasting and prediction). The keywords are presented in see Table 1. The search
41 pairs of road safety/accident + contributing factor + main keyword and road safety/accident +
42 contributing factor + main keyword + sub keyword were examined, yielding 19,511 results.
43 Duplicates were eliminated using the EndNote™ reference management software which
44 resulted in a total of 14,133 records.



1
2 Figure 1 PRISMA flow diagram for systematic review

3 Table 1 Keywords used for literature search

Contributing Factors	Keywords	
	Main	Sub
Road condition	Machine-Learning, Image-Processing, Artificial Intelligence, Smartphone, Applications, IoT, GIS, GPS, Drone, Social Media, Virtual-reality, Simulator, Radar, Sensor, Big Data	Modelling, Structural, Functional, Processing, Simulation, Information, Communication, Projection, Prediction
Accident hotspots		
Driver behaviour		
Pedestrian behaviour		
Traffic congestion		
Weather		



5
6 Figure 2 Timeline of research in applying digital technologies in road safety environment (*up to the first quarter of 2020)

1 The EPPI-Reviewer™ software was employed to filter out articles deemed to be of little value
 2 or relevance to this study by using a set of criteria. Articles were removed from the study if
 3 published before 2014, not published in English, lacked a robust and replicable methodology.
 4 For instance, literature review papers and position papers were excluded, not a research study
 5 (e.g., a formal standard or piece of legislation within legal frameworks or regulatory models)
 6 and not validated by either field trial, case studies or simulations (as these are identified as
 7 quantitative research methods with lower potential for researcher bias [46]). Figure 2 shows
 8 that the concentration of studies has intensified over time thus exhibiting a pattern of
 9 increasing interest in the subject area. Artificial intelligence, particularly machine learning, has
 10 been popular amongst road safety researchers, followed by IoT and image-processing. Though
 11 the focus on smartphones (i.e. using GPS and mobile phone-based applications) has received
 12 comparatively less attention recently, it can be argued that research into this technology
 13 matured earlier.

14 Following the initial screening, the remaining 7198 articles were screened by their titles,
 15 abstract and full report using the text mining facility within EPPI-Reviewer™ for the relevance
 16 of the articles to the review (i.e. not a research study, does not propose/test applicability of
 17 technology, not in road safety context). This resulted in 301 articles that were then manually
 18 screened by applying the weight of evidence concept described in Table 2 (see Figure 3 for the
 19 results). Weight of evidence is a concept used in several fields (including law and statistics)
 20 referring to the preponderance of evidence to inform decision making [47]. It is a useful
 21 heuristic for considering the extent to which evidence supports possible answers to a question
 22 [47]. The appropriateness of the literature for the task in hand was ranked against the
 23 hierarchy of validation i.e., field trials and case studies were ranked higher than computer
 24 simulations (see Table 2). For a study to receive an overall rating of high, and therefore be
 25 used in the review stage, it needed to achieve a rating of high in at least one category and
 26 medium in the other two categories. 79 studies were included in the final sample and
 27 reviewed, and summarised in Appendix A.

28 *Table 2 Weight of evidence for the inclusion of literature for the review*

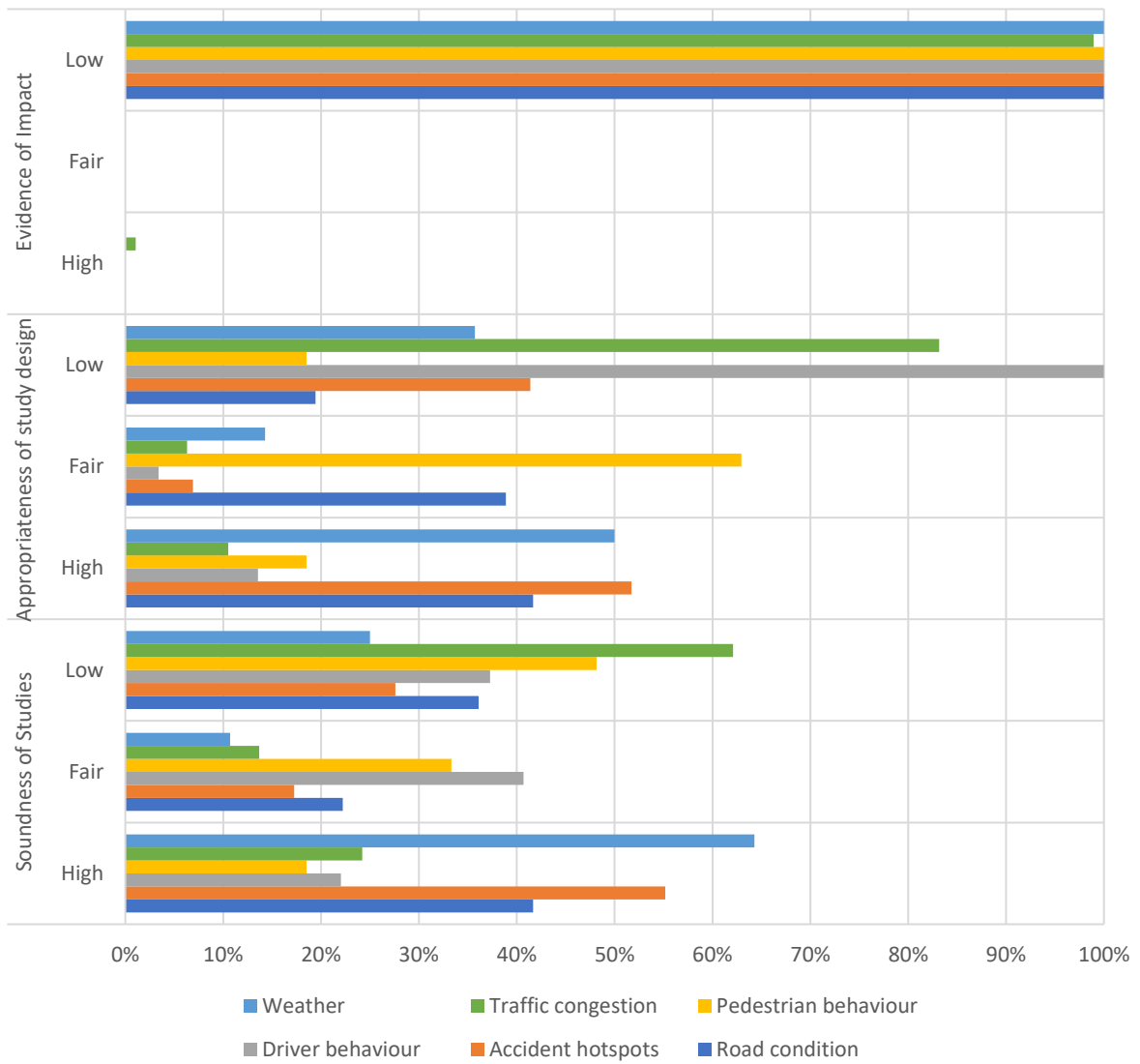
Criteria	Weight of Evidence	
Soundness of studies	High	There were explicit and detailed methods and results for data collection and analysis; the interpretation was soundly based on findings. There was a critical comparison with other similar works.
	Fair	There were satisfactory methods and results sections for data collection and analysis; the interpretation was partially warranted by the findings.
	Low	The methods and results sections were unsatisfactory; there was no interpretation of findings or interpretation was not warranted by the findings
Appropriateness of study design for answering the review question	High	Demonstrating the ability of digital technologies in a road safety environment through a field trial. The field trial had to be collected for at least one year.
	Fair	Demonstrating the ability of digital technologies in a road safety environment through a field trial or case study lasting less than one year
	Low	The results are based on computer simulations only
Evidence of impact	High	Quantitative evidence of road safety performance was provided
	Fair	Qualitative evidence of road safety performance was provided
	Low	No evidence on the road safety performance.

1 **4. Results**

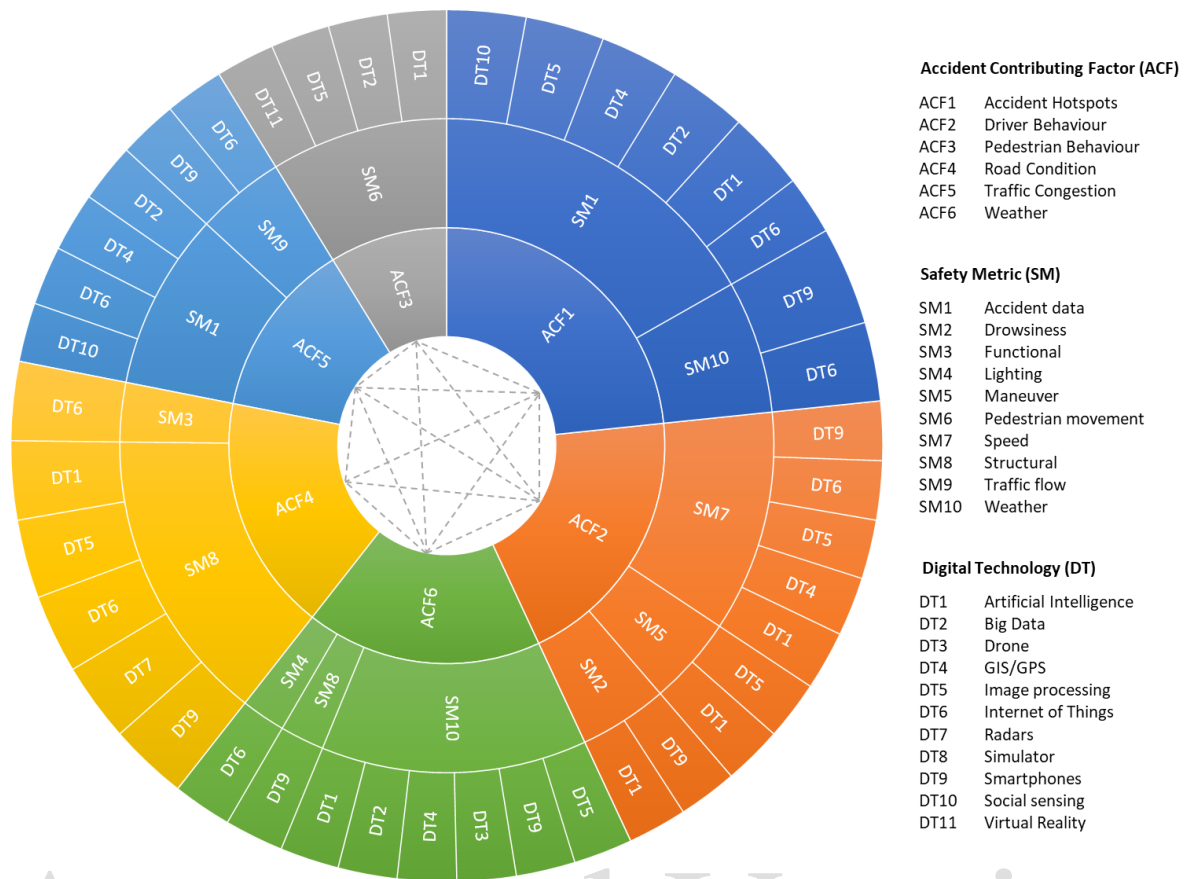
2 The results of our systematic review were found to be very heterogeneous. While most of the
3 literature investigated the applicability of respective digital technologies through case studies
4 and computer simulations, more than half of the studies carried out field trials to validate
5 their proposed approaches. Apart from one study [48], there were no consistent formats or
6 measures for reporting the different outcomes on-road safety performance. This may be due
7 to the varied definitions of road safety performance universally, and the lack of consensus on
8 the measures such as the number of road accidents, casualties and near-misses employed to
9 define road safety. Hence it was not possible to quantify the effects of employed digital
10 technologies for road safety planning, management and enforcement. However, the results of
11 the weight of evidence analysis carried out within this study provide evidence on the
12 adaptability of such technologies for improving road safety (see Figure 3). While there is
13 relatively fair to high-quality ratings for the studies examining the effect of road condition,
14 traffic congestion, accident hotspots and weather on road safety using digital technologies,
15 the ratings for studies focusing on driver and pedestrian behaviour are relatively low to fair.

16 The review also enabled the mapping of the interdependencies between accident
17 contributing factors and the applicability of different digital technologies for collecting,
18 monitoring and predicting information/data associated with relevant safety metrics (see
19 Figure 4). The evidence-based studies judged to be of sound quality are presented in the
20 following sub-sections.

Accepted Version



1
2 Figure 3 Results from the weight of evidence analysis of the reviewed literature



1
2 Figure 4 Mapping the applicability of digital technologies (DT) for collecting, monitoring and predicting information on
3 different safety metrics (SM) associated with accident contributing factors (ACF). The dotted grey line linking the ACFs portray
4 their interdependency

5 **4.1 Road Condition**

6 Regular road inspections and proactive infrastructure asset management are important to
7 ensure road quality and safety. Selected articles for road condition assessment and prediction
8 are listed in Table A.1. Among the 14 listed studies, field trials were adopted by 7 studies to
9 validate the proposed digital technology while case studies were carried out in 6 studies.
10 Amongst the listed studies, artificial intelligence, particularly machine learning, has been the
11 most popular technology (N = 9), while sensing and IoT have two articles each. Different AI
12 techniques such as machine learning [49-54] and deep learning [55-58] were employed to
13 inform the condition of the road surfaces and validated by either field trials or case studies.
14 These technologies have shown promising results for detecting road defects causing
15 accidents, for instance, the study by Acilo, Cruz [55] successfully utilised a deep learning
16 technique for assessing road conditions with an accuracy of over 95%. Ameddah, Das [49]
17 reported an accuracy of over 88% for identifying and classifying road conditions and defects
18 using machine learning to analyse data from accelerometer sensors embedded within
19 smartphones. Bose, Dutta [50] also employed machine learning to analyse data collected from
20 the smartphone-based accelerometer and GPS sensors to recognise driving patterns and
21 detect manoeuvres performed by drivers while trying to avoid road defects (e.g. potholes).
22 This study classified road conditions into 'bumpy', 'filled with potholes' or 'normal' categories
23 and drivers into 'aggressive' or 'calm' categories. Data from accelerometers within
24 smartphones was also employed for measuring road roughness, a key indicator of road
25 condition [59]. Machine learning was also employed by Marcelino, Lurdes Antunes [51] to

1 improve the accuracy of predicting road conditions when fewer data are available. While they
2 reported a link between road defects and road safety, they did not provide any quantitative
3 measure of this relationship. Apart from measuring and predicting road conditions, machine
4 learning was also used to detect drivers' intention to manoeuvre based on road defects [53]
5 with a 90% accuracy. It was also employed to study the impact of road atmospheric conditions
6 on accident prediction for different road surfaces (road conditions) [54].

7 Taha [60] developed an IoT architecture integrated with machine learning for selecting the
8 safest route option, by incorporating the concepts of safe vehicle, driver and road, where road
9 safety is a function of road condition based on the data collected from various sensing
10 systems (including in-vehicle sensors). The developed IoT architecture was reported to enable
11 a safer car journey by incorporating different technologies and their associated data. Marafie,
12 Lin [61] employed IoT to identify hazardous road and weather conditions, and traffic locations.
13 An image processing approach for automatically identifying road attributes including
14 hazardous road defects using video footage was developed by Sanjeevani and Verma [62] and
15 validated using field trials in Australia. Such automated defect detection systems have the
16 potential to replace the current manual systems for road condition and safety assessment as
17 it is faster and can be more accurate. However, it was reported that the image quality has a
18 significant impact on the accuracy of the results, which shows the importance of utilising the
19 right equipment for filming and the potential impacts of natural lighting on the effectiveness
20 of such systems.

21 **4.2 Accident Hotspot**

22 Sixteen studies related to accident hotspots considered within this review are listed in Table
23 A.2. Most of the studies (11 out of 16 articles) have employed more than one validation
24 method, for example, Cuerden and McCarthy [63] and Fan, Liu [64] used both field trial and
25 case study to validate the applicability of their approaches. Automated image processing using
26 machine learning techniques featured in nine studies (approximately 60% of the studies),
27 reporting a shift from traditional and manual traffic monitoring from CCTV images [65]. The
28 application of AI, particularly machine learning, is found to be highly capable of identifying
29 and predicting the accident hotspots, achieving an accuracy of more than 90% [66]. Remote-
30 sensing (radars and sensors) and big data are featured in four studies each. There were three
31 published studies on GIS and one IoT related study.

32 Accident hotspots are locations in which the risk of accidents (i.e. probability and severity) are
33 high. Identifying hotspots and accordingly setting countermeasures for maintaining speed
34 limits in such spots can reportedly result in a 7-8% reduction in accident-related deaths [67].
35 While IoT [63] and big data [68] was used to investigate the severity of accident-related
36 injuries, big data, sensors, social media and GIS [67, 68] were employed to identify the location
37 of the road accidents. Traffic-related content from social media (e.g. tweets) was linked with
38 GIS to identify accident hotspots in New York City [69]; reportedly achieving 8.1% more
39 accuracy than methods employed within the police department's accident report database.
40 Accident hotspots can also be identified and geographically located by using the GPS and
41 motion sensors embedded within smartphones [70]. Traffic flow detection sensors can also
42 be used to predict the potential risk of accidents. E.g. Hammoud [71] proposed a traffic
43 management system with a reported accuracy of up to 84% by employing sensors to inform
44 traffic flow on highways.

1 Machine learning was employed for predicting both the location and severity of traffic
2 accidents [64, 72, 73] and also automatically classifying accident types as drunk driving, fire
3 and skid [66]. Machine learning was also employed successfully by Wang, Liu [74] to map
4 vehicle-pedestrian and vehicle-vehicle collision risks by using data associated with capturing
5 levels of human activity from night-time light density and social media. However, the approach
6 proved unsuccessful for identifying traffic accidents on certain road types such as
7 expressways. In a separate study, however, Kumeda, Zhang [73] developed a machine learning
8 technique that achieved a prediction accuracy of 86% by considering the type of road and
9 vehicle, weather and lighting. Machine learning was also employed by Ma, Ding [75] within a
10 GIS-based data mining approach and successfully tested to identify accident hotspots in Los
11 Angeles, achieving an accuracy of 87%. The study ranked different accident-contributing
12 factors within hotspots and reported that traffic, lighting, driver and pedestrian behaviour
13 were the most influential factors to fatal accidents.

14 However, the major factors for traffic accidents change over space with the weather and
15 spatial conditions impacting rural areas, and road condition and traffic volume in urban areas.
16 Such information on the spatial variation in accident contributing factors can be used to
17 provide specific mitigation strategies to reduce the fatality rate and improve road safety.
18 Electronic crash reporting is key for developing an evidence base of accident hotspots and Hall
19 [68] provides an overview of the data governance approach adopted in the USA.

20 **4.3 Driver Behaviour**

21 Among the thirteen selected studies investigating driving behaviour, six of them employed
22 machine learning and image processing, four used sensors on mobile phones, three on remote
23 sensors, and one article was attributed to IoT (see Table A.3). More than half of the studies
24 validated their proposed approaches using field trials, while four of them failed to validate the
25 developed models and technologies in the real world as it was tested only in a simulated
26 environment [e.g. 76, 77]. Only one study, [78], used all the approaches considered within the
27 weight of evidence, namely field trial, case study and simulation, for validating the
28 applicability of the proposed technology.

29 The growing number of studies employing image processing [77, 79-81] and machine learning
30 [76, 82-87] is not surprising due to the promising application of artificial intelligence techniques
31 such as computer vision (using machine learning or deep learning algorithms) to automate
32 the process of monitoring driver behaviour from images and videos. Machine learning was
33 used to profile driver behaviour [79, 83, 84], predict driver manoeuvres at intersections [87],
34 and evaluate the level of drowsiness [76]. While Das and Khilar [83] and Ferreira, Carvalho [84]
35 employed data from sensors embedded within smartphones (accelerometers and
36 gyroscopes), Puente Guillen [74] recognised driver sleepiness using mobile phone apps.
37 Within different machine learning techniques used for image processing, deep learning
38 reported a better accuracy (over 95%) for monitoring driver behaviour and predicting
39 safe/unsafe driving posture, than convolutional neural networks [85, 86].

40 Image processing was also used more specifically to study the driver behaviour when
41 approaching urban rail crossings [77] which provided a significant inference. The drivers were
42 found to be over-reliant on the behaviour of surrounding vehicles to alert them to the
43 presence of metro trains. Image processing was also employed to study and predict speeding

1 [81] and outcome/severity of accidents [80]. It was also combined with IoT and AI by and
2 Jabbar, Shinoy [82] to detect driver drowsiness with 82% accuracy. Smartphone-based
3 applications were also utilised for analysing driver behaviour and to inform collision warning
4 systems [88].

5 **4.4 Pedestrian Behaviour**

6 The review identified nine studies investigating pedestrian behaviour using machine learning
7 (N=7), virtual reality (N=3) and image processing (N=2) (see Table A.4). Except for one study
8 [89] that used simulation alone, the majority of the studies carried out a combination of field
9 trials and simulated environments to validate the proposed techniques. While, virtual reality
10 was used within simulators to model pedestrian behaviour [90], image processing and
11 machine learning were often employed together to automate the processing of images and
12 videos collected from CCTV cameras. Raman, Sa [91] combined machine learning and image
13 processing to predict the direction of moving pedestrians with up to 95% accuracy. Yin and
14 Wang [89] applied the same approach with big data for evaluating the walking behaviour while
15 considering features that impair surrounding vision such as the number and size of trees and
16 height of buildings on a street. Image processing was employed to model pedestrian
17 interaction with traffic signals at intersections with different levels of traffic density [92].

18 Machine learning was used to predict pedestrian behaviour at crossings [93] when mixed with
19 cyclists [94] and walking speed respectively [95]. Of particular interest is the approach
20 developed by Neogi and Dauwels [94] that was able to predict the pedestrian stopping 0.9
21 seconds before crossing the road in front of the vehicle. In comparison to the benchmarked
22 system, their approach was able to detect the pedestrian stopping 0.52 seconds before the
23 actual event.

24 Sobhani, Farooq [96], Kalatian, Sobhani [97], Kalatian and Farooq [98] used virtual reality and
25 deep learning techniques to study pedestrian behaviour while crossing the roads and reported
26 that pedestrians are often distracted, particularly when walking with a smartphone. The
27 results from these studies show that an increase in initial walk speed and percentage of time
28 the head was oriented toward smartphones while crossing the road resulted in a higher risk
29 of accidents. While virtual reality is an effective way to simulate user behaviour, Deb, Carruth
30 [90], participants might develop simulation sickness resulting in withdrawing from
31 simulations.

32 **4.5 Weather**

33 Thirteen studies investigated the impact of weather on road safety, amongst which five studies
34 were related to remote sensing, four to machine learning, three on smartphone-based
35 applications, two on GIS, and one each on big data, IoT, smartphone-based sensors and image
36 processing (Table A.5). The weather-related studies involve a wider range of technologies
37 compared to other categories, mainly because of the relatively higher interdependency with
38 other contributing factors. These include weather monitoring [99-102], travelling condition
39 [103], modelling and projection of road condition related to the weather [104, 105], rainfall
40 estimation using CCTV images [106], impacts of weather on the operation of autonomous
41 vehicles [107], driver warning systems [108, 109], public warning systems [110] and enhancing
42 road weather management during extreme weather events [111]. A study of particular
43 interest that has potential for immediate uptake is the approach developed by Lee, Hong [106]

1 employing image processing and machine learning to detect and estimate rainfall from CCTV
2 images in real-time and cluster the regions. With a reported accuracy of 80%, this technique
3 can be employed to identify flood-induced accident hotspots and accordingly alert drivers.
4 Bhat, Claudel [111] used drones, sensors and GIS to manage traffic flow during wildfires, flash
5 floods and other extreme weather events and reported a 21% reduction in accidents. Sensors
6 were also used by Karsisto and Lovén [101] and Liu and Rao [105] to monitor and predict road
7 surface temperature. The latter study predicted the formation of pavement icing.

8 All the studies agreed that extreme weather conditions could threaten road safety by not only
9 impacting the driver behaviour but also worsening the road condition. The considered
10 technologies can enhance road safety through any or a combination of (i) improved weather
11 projection, (ii) predicting the impact of weather conditions on road conditions, (iii) an alert
12 system to effectively communicate such an impact to the road users. However, the extent to
13 which road safety would be improved is not quantitatively evidenced within the reviewed
14 literature.

15 **4.6 Traffic Congestion**

16 Accidents occur when traffic moves and thus it is natural to study the traffic characteristics to
17 understand their impact on accidents. The speed, density, flow and congestion of traffic are
18 linked to each other and understanding of one could provide useful information on the other
19 three. Within the fifteen studies that investigated collecting data on traffic congestion, five
20 used big data and machine learning, four employed sensors, two studies applied IoT, and one
21 utilised GIS (See Table A.6). Greer, Fraser [48] reviewed the benefits, costs, and lessons learnt
22 from the intelligent transportation system (ITS) planning using big data and GIS technologies
23 and reported that sensors, i.e. Electronic Stability Control (ESC), can reduce the risk of fatal
24 accidents by 33%, while traffic congestion alert systems can reduce the risk of accidents
25 involving trucks by 23.8%. It was also reported that a pilot run of an embedded congestion
26 alert system on buses resulted in a decrease of 72% in the number of near-miss events [48].

27 Traffic congestions were also predicted using sensors installed in transport infrastructure and
28 volunteer vehicles. This has informed big data-related research to capture location-specific
29 variability in traffic flows [112, 113]. Big data was also used to inform the variable speed limit
30 (VSL) control strategies for reducing congestion on highways [114]. While machine learning
31 was employed to predict traffic congestions with up to 97% accuracy [115-117] big data
32 collected from the roadside and in-vehicle sensors were used to detect traffic congestions,
33 achieving accuracy greater than 90% [118]. Social sensing has also been employed to estimate
34 the severity of traffic build-up from online content on social media [119]. This content mining
35 model achieves approximately 45% accuracy in predicting traffic congestion. Al Najada and
36 Mahgoub [120] developed a big data mining technique and reported that road user behaviour
37 has a strong impact on traffic flow and safety. The proposed technique was reportedly able to
38 predict the age and gender of the drivers with a 70% accuracy. Studies on traffic flow
39 optimisation using machine learning has also been employed to reduce the probability of
40 traffic congestion by enforcing variable speed limits [121], controlling traffic light waiting
41 times [122] and informing in-vehicle alarm systems and mobile phones [123].

1 5. Discussion

2 **5.1 Findings from reviewed studies**

3 There are several important and timely opportunities concerning future research in digital
4 technologies and road safety. Clear connections between employing digital technologies and
5 their benefits for road safety are identified through this systematic review (see Figure 4). E.g.
6 Artificial intelligence, image processing and IoT have been widely applied to enhance road
7 safety, including better and more accurate information on accident hotspots, user behaviours,
8 traffic congestions, road conditions and weather. Our findings suggest that there are
9 conceivably multiple pathways through which positive impact might arise through
10 information gathering, accident prediction, early warning systems etc. While 56 studies
11 examined within this systematic review focused on the applicability of digital technologies in
12 collecting information and monitoring factors that contribute to road safety, 23 of them
13 concentrated on predicting them. However, given the heterogeneity of the data and findings,
14 it is not possible to conclude the range of impacts offered by the different digital technologies.
15 Furthermore, very few studies even described the efficiency/accuracy of the adopted
16 technology in predicting different accident contributing factors.

17 There is increasing evidence that shows the impact of road condition on driving patterns
18 which provide further evidence on their influence on driving behaviour [53]. For instance
19 Bose, Dutta [50] used digital technologies to investigate the drivers' reactions when using
20 roads of varied conditions. Given the considerable evidence showing that mind-wandering
21 reduces drivers' active attention, it is likely to have negative effects on core driving skills such
22 as speed, vehicle control and lane positioning [124, 125]. The situation will be exacerbated
23 when travelling on a low-quality road (e.g. filled with potholes) or during extreme weather
24 events.

25 The state of knowledge on the engineering aspects of weather-related driving risks is quite
26 advanced. In particular, the physical effects of weather on road surface friction and driver
27 visibility are reasonably well understood and can be predicted with a fair degree of accuracy
28 given detailed information on the storm, road, vehicle, and traffic conditions [101, 110]. While
29 it is unclear from the literature exactly how and to what extent employing digital technologies
30 for weather-warning systems will improve road safety, it may be useful in improving the risk
31 perception and hazard detection of the drivers. For example, the fog or road-icing warning
32 systems notify drivers of the situation and warn them to make appropriate adjustments to
33 their driving (e.g. tyre grip is reduced on icy roads making braking distances longer).

34 There are also salient findings related to employing digital technologies to monitor and predict
35 accident hotspots and traffic congestions, highlighted in the review. There is evidence that
36 traditional technologies such as CCTV are being augmented with advanced technologies such
37 as machine learning, image processing, IoT and sensors to automate the process. However, as
38 a result of relatively low ratings of studies related to driver and pedestrian behaviour, limited
39 conclusions can be drawn regarding the applicability of digital technologies for monitoring or
40 predicting such factors. Except for one on driver [82] and pedestrian behaviour [91]
41 respectively, none of the studies reported the accuracy of the proposed techniques. However,
42 a prominent finding was that machine learning and image processing has the potential to be
43 employed for this purpose, although further research is needed to determine the feasibility,

1 desirability and effectiveness of such techniques, particularly from a data protection
2 perspective.

3 Overall, the studies are moderately weak in identifying exactly what condition factor should
4 be prioritised for monitoring and in what circumstances. This will be disappointing to
5 policymakers and engineers who have to take hard decisions on how to allocate funds and
6 what road safety contributing factors to manage.

7 **5.2 Future research directions**

8 This section outlines the research directions that do not appear to be adequately investigated
9 in the current literature on the applicability of digital technologies for road safety. One
10 significant gap this systematic review identifies is that there is still a very limited understanding
11 of how and if these technologies work in practice and the benefits accrued. A very limited
12 number of studies explored the effectiveness or quantified the impacts of employing such
13 technologies for road safety outside of controlled or simulated environments. This, therefore,
14 limits the extent to which these technologies have the potential to improve road safety
15 interventions and decision making 'on the ground'. This lack of practical application, therefore,
16 casts doubt on grand narratives about the potential for more data-driven and 'smart' systems
17 for improving road safety. While it is exciting to consider the impact of emerging and
18 advanced digital technologies on road safety, caution is warranted in their adoption without
19 sufficient evidence from well-designed studies. More pilots and collaboration with public
20 managers are therefore required to build confidence that investing in these systems will reap
21 the intended rewards and are worth the investment.

22 Accident hotspot detection and prediction is very crucial in informing specific mitigation
23 strategies. An important finding is the revelation of the spatial variation in accident
24 contributing factors between urban and rural areas. Also, many of the studies examined in
25 this paper are based on highways and urban roads and there is a need to investigate the safety
26 effects of these factors in rural areas (particularly in the developing countries) that are
27 dominated by minor roads. Researchers have also shown that hotspots display significant
28 variations throughout the time of day. A reasonable explanation for that would be the
29 variation in the choice of road safety metrics.

30 The real-time analysis could address the issues posed by aggregated analysis. Recent studies
31 have used more real-time and/or high-resolution data because of the advancement in the
32 field of AI, IoT and big data. Moreover, how much data are enough for various aspects of road
33 safety analysis is a question worth further investigation. While insufficient data may lead to
34 inaccurate models and uncertain results, excessive data lead to resource wastage. Therefore,
35 to better leverage data to better inform knowledge and evidence to road safety, research
36 aiming to identify appropriate standards (e.g. information quality levels or DIKW model) and
37 governance of data are warranted.

38 The road user- or human- element contributes to a lot of uncertainty within transport safety
39 policymaking. More than half of all road accident deaths are among vulnerable road users
40 including pedestrians, cyclists and motorcyclists. However, there is limited research that
41 investigates safety for vulnerable road users under the environment of digital technologies.
42 This is a gap that is worth researchers' attention.

1 Much transport safety research over several decades has been focused on trying to automate
2 the transport system (in terms of vehicle and infrastructure) as far as possible to minimise the
3 damage caused by human decision making (such as pedestrian and driver behaviour). These
4 endeavours can all be further augmented by new technological developments, such as
5 transport applications of big data, connected and automated technologies that can be used
6 to provide a more connected spatial environment, as has been highlighted in this systematic
7 review. For instance, social sensing has emerged as a new sensing paradigm where human
8 sensors collectively report measurements about the physical world (e.g. traffic congestion
9 using mobile crowdsensing and accident hotspot identification using online social media
10 data). This informs and predicts accidents in time, which assists in triggering a quick accident
11 response. Also, interactions among connected and autonomous vehicles (CAV) using
12 advanced sensing, communications and electronic technologies are showing promising results
13 [126, 127]. To realise their advantages, research also needs to focus on its impacts on road
14 user behaviour and the new safety risks raised by CAV.

15 Lastly, the studies do little to tie up the association between employing digital technologies
16 with short- or long-term impacts on road safety. Local long-term impact studies that require
17 repeated surveys and highly qualified researchers are extremely expensive. So simpler
18 methods are needed that can focus on looking at outcomes, but to do this we need to know
19 what the relationship is between policies and the impact on safety, to move forward.
20 Additional factors should be investigated, such as the effect of organisational culture,
21 emergency responses, the reliability of post-accident management systems, and economic
22 influences on road safety.

23 **6. Conclusion**

24 This approach is costly, time-consuming, and sometimes ineffective due to under-reporting
25 and the poor quality of the data, i.e., the omission or misreporting of information. Digital
26 technologies, however, have shown some potential to address the aforementioned issues by
27 automating the process and minimising human involvement and the associated bias. This is
28 the first systematic review conducted in road safety context which exclusively attempts to
29 identify and synthesise, explicitly and transparently, findings from studies on the applicability
30 of digital technologies that are most likely to have a positive, or minimal impact on collecting,
31 monitoring and predicting information associated with different road accident contributing
32 factors.

33 This review provides a thorough synthesis of findings on the impact of employing digital
34 technologies on-road safety performance. However, we have limited data to help us
35 understand the range and scale of impacts for different technologies and what factors
36 contribute to the success or failure of one technology over another. Thus, discussions on the
37 theory and delivery of the different types of digital technologies included in the review need
38 further evidence from primary research 'on the ground' to build a clearer picture of their
39 effectiveness, but also the mechanisms required and involved for their implementation.

40 This study comprehensively reviewed the applicability of digital technologies for monitoring
41 different contributing factors to road safety and hence their application in predicting road
42 accident risks. Several studies show that digital technologies such as AI, Image processing and
43 IoT have been widely applied to monitor and predict road conditions, driver and pedestrian
44 behaviour, accident hotspots, weather and traffic congestion. This is due to the ability of these

1 techniques to automatically capture and analyse data while preventing the possibility of
2 human error. Road safety monitoring and prediction using digital technologies have the potent
3 to include all contributing factors, components, contributors and outcomes if thoroughly
4 applied. Availability of reliable safety data provides the opportunity to contribute to further
5 improvements to the efficiency and effectiveness of road safety strategies.

6 This study indicates that traditional technologies have now been replaced or augmented by
7 advanced digital technologies for analysis and for developing innovative countermeasures to
8 improve road safety. However, the integration of the collected/analysed data to inform road
9 safety policies and strategies need to be explored further. The vision of a perfectly safe road
10 may be utopic, however now it is timely to work on employing appropriate digital technologies
11 to improve the data collection in anticipation of new and advanced road safety analyses that
12 will lead to the development of more successful preventive measures and technologies.

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18 **CReDiT authorship contribution statement**

19 **Mehran Eskandari Torbaghan:** Conceptualisation, Methodology, Investigation, Writing -
20 original draft, Writing - review and editing, Supervision, Funding acquisition. **Manu**
21 **Sasidharan:** Conceptualisation, Methodology, Investigation, Writing - original draft, Writing -
22 review and editing, Visualisation, Supervision, Funding acquisition. **Louise Reardon:**
23 Conceptualisation, Investigation, Writing - original draft, Writing - review and editing, Funding
24 acquisition. **Leila Muchanga:** Investigation, Writing - original draft, Visualisation

25 **Declaration of Competing Interest**

26 The authors declare that there is no conflict of interest

Table A.1: Summary of Road Condition Studies

Authors/Project	Description	Technology/Methodology	Validation			Road safety metrics used	Key Inferences
			Trial	Case Study	Simulation		
Acilo, Cruz [55]	The deep learning method is utilised for assessing road signs integrity/condition. The algorithm was tested using Google images	Machine learning and Deep learning, convolutional neural network		✓		Linked traffic sign assessment but did not quantify the impact of signs condition on road safety	The experiments conducted exhibit test accuracy of 95.70% in the compliance model and 96.20% in the degradation model which shows great potential in developing a streamlined traffic sign assessment platform.
Ameddah, Das [49]	A Cloud-Assisted Real-Time Road Condition Monitoring System for Vehicles. The system can identify road hazards as well as road defects, e.g. pothole	Machine learning and smartphone accelerometer	✓			Identifying road defects as hazards	Experimental results show that it can classify road conditions based on the accelerometer data with 88.67% accuracy
Bose, Dutta [50]/D&RSense	Used Smartphone GPS and accelerometer to detect driving patterns and road anomalies. An experiment was conducted using data gathered on two types of motorbikes, within 35 days.	Machine learning and smartphone accelerometer	✓			Identifying road defects as hazards but without any quantitative approach to measure it	Machine learning algorithm was applied while processing in the cloud to do pattern recognition for classifying roads into bumpy, filled with potholes or normal categories and drivers into aggressive or calm categories.
Jan, Verma [56]	Utilised Convolutional Neural Network (CNN) for identifying road defects. The algorithm was tested on some images	Deep Learning, Machine Learning, CNN, Image processing	✓			Identifying road hazards (e.g. a big tree or electric pole near a road), avoiding which were identified essential for road safety	Was not very successful in identifying some of the objects such as trees. Using LIDAR for addressing this issue was discussed.

Authors/Project	Description	Technology/ Methodology	Validation			Road safety metrics used	Key Inferences
			Trial	Case Study	Simulation		
Kataoka, Gangwar [59]	A smartphone accelerometer was used for managing road safety in India using road roughness and driving behaviour.	Sensing/ Smartphone	✓			Detecting and visualising road roughness and driving behaviour	Data on driving behaviour and road surface roughness were collected and visualised, but their direct attribute on road safety was not measured nor discussed.
Kim, Bong [53]	Vehicle and road surface condition is augmented by using an artificial neural network (ANN) models, which was then fed to a support vector machine (SVM) to detect the driver's intention of lane changing with high accuracy. The system is installed on the vehicle.	Machine Learning/ Artificial Neural Network (ANN),			✓	Identifying the reasons for lane change manoeuvres	The classification accuracy with the augmented information was higher than 90% in any road surface condition.
Marafie, Lin [61]/ ProActive Fintech	A proactive Financial Technology (FinTech) model which uses the IoT to deliver positive InsurTech feedback which was tested in China	IoT 1-year data from three drivers		✓		Identifying hazardous road and weather conditions and traffic locations	Potential for proactive decision making while considering users' data privacy
Marcelino, Lurdes Antunes [51]	Machine learning was used to enhance data collection on road condition and their safety. Data collected from 10 sections of a motorway were used as a case study	Machine Learning	✓			A link has been made between road defects and road safety but without any quantitative approach to measure it	The developed machine learning methods improved the accuracy of pavement condition indicators when fewer data are available
Nemas, Khattry [52]/ TRL	Application of machine learning for driver behaviour,	Machine Learning/	✓			Accident count	Despite showing the application of technology for road condition

Authors/Project	Description	Technology/Methodology	Validation			Road safety metrics used	Key Inferences
			Trial	Case Study	Simulation		
	road condition forecasting and crack detection	Convolutional Neural Network (CNN), Decision trees Case study 1: 20 journeys and 9 drivers. Case study 2: 26645 road sections Case study 3: 5,000 crack images					assessment, inferences were not made directly for road safety
Piryonesi and El-Diraby [57]/FHWA	Application of Machine Learning for data collection	Machine Learning, Decision trees, 942 samples		✓		Crew safety during road condition data collection, traffic flow	The positive Impact of automated data collection on the crew safety and traffic flow was discussed but was not quantified
Sanjeevani and Verma [62]	A novel approach was reported to assess influential attributes of road safety using roadside video data. The study conducted in Australia tested/trained the developed model with 411 images	Image processing	✓			Application of Image processing for identifying road hazards	A positive impact on road safety was reported. It was found that image quality has a huge impact on the accuracy of the result produced from such an approach
Song, Workman [58]/FARSA project	Reported a developed deep convolutional neural network utilised for identifying road defects and attributes, rating the road safety accordingly	Deep convolutional neural network/machine learning		✓		Quantitative and automated road safety assessment	They found that incorporating additional tasks, and using a semi-supervised training approach, significantly reduced overfitting problems, and allowed to optimize more layers of the network, and

Authors/Project	Description	Technology/ Methodology	Validation			Road safety metrics used	Key Inferences
			Trial	Case Study	Simulation		
	The algorithm was tested on a large dataset of real-world images from two US states						resulted in higher accuracy. Claims of cost reduction (not quantified)
Taha [60]	Reported an IoT architecture for assessing road safety in smart cities while incorporating road condition metrics	IoT and machine learning		✓		Safety-Based Route Planning	Identified Collision distribution in time for a case study of New York and classified routes/paths as shortest and safe.
Vasavi [54]	A framework for extracting hidden patterns in accidents to identify the common features between accidents, using Machine Learning Techniques. The framework was tested using the data from national highways in India	Machine Learning		✓		Accident Data	Accidents are observed to be higher during weekends and on cold nights compared to hot and clear conditions. Data on vulnerable road users (elderly) was presented

Table A.2: Summary of Accident Hotspot Studies

Authors/Project	Description	Technology/Methodology	Validation			Road safety metrics used	Key Inferences
			Trial	Case Study	Simulation		
Cuerden and McCarthy [63]	The study provides an in-depth guide on accident data collection and measuring impacts of countermeasures to create an evidence base for policymaking and research. A GIS-based data collection protocol/guideline was introduced for (i) on-scene accident investigators (ii) detailed examination of accident damaged vehicles a few days after the accident and (iii) follow-up data to obtain relevant anonymous injury or post-mortem data from hospitals	IoT	✓	✓		Identifying collision scenarios and severity of accident-related injuries, modelling the impact of road safety measures	The Road Accident In-Depth Studies (RAIDS) evidence base is a key resource to investigate and answer a wide range of accident-related research questions in the UK. As more data is collected and sample sizes increase, it would allow for the improvement of inferences from such evidence bases. The protocols of data collection introduced by RAIDS can be effectively adapted to different countries.
Hall [68]	The study provides an overview of the data governance approach adopted in the US state of Illinois for identifying cost-effective strategies for road safety improvements.	Big Data	✓			Location/GIS-based Fatality/Severity of accidents, the impact of countermeasures for mitigating safety risks	To provide value, data collected must be a shared organisation resource to meet the needs of decision-makers internal and external to the organisation – spatial integration of safety-related data within different agencies is key. Establishing a Data Governance policy and a holistic communication strategy is also recommended

Authors/Project	Description	Technology/Methodology	Validation			Road safety metrics used	Key Inferences
			Trial	Case Study	Simulation		
FHWA [67]	The project introduced a data-driven safety analysis which promoted two strategies: Predictive analysis identifies sites with the most potential for improvement and quantifies the expected safety performance of project alternatives. The systemic analysis uses crash and roadway data to pinpoint roadway features that correlate with specific crash types.	Big Data, GIS		✓	✓	Location/GIS-based Fatality/Severity of accidents, Average speed at routes with black spots, number of accidents and vehicle types, Impact of countermeasures for mitigating safety risks	The value of road safety-related data can be harnessed through advanced software tools to predict the safety impacts of highway projects and countermeasures before implementing them on-field. Identifying black spots and accordingly setting countermeasures for maintaining speed limits in such spots can result in a 7-8% reduction in deaths and a 55% reduction in the number of serious injustices. Routine enforcement of common offences should thus be an integral part of every traffic patrol.
Yuan, Zhou [72]	A Convolutional Long Short-term Memory (ConvLSTM) neural network model was developed to understand the spatial heterogeneity challenge associated with road accidents. Extensive experiments on an 8-year data of the entire state of Iowa showed that the proposed framework makes reasonably accurate predictions	Machine Learning (Artificial Intelligence - Neural Network Model)		✓	✓	Vehicle Crash Data, Rainfall data, GIS and satellite images of road networks, real-time traffic volume data	Artificial and Deep learning techniques are promising solutions to traffic accident predictions. The major factors for traffic accident change over space with the weather and spatial conditions impacting rural areas and in urban areas road condition, traffic volume, and holiday/weekday information are more important
Kumeda, Zhang [73]	Different machine learning techniques were applied to road traffic accident data in	Machine Learning (Fuzzy-FARCHD, Random Forest,		✓	✓	Road Class, road surface, lighting condition, weather,	The fuzzy-FARCHD algorithm is effective to classify the traffic dataset and achieves an accuracy of 85.94%.

Authors/Project	Description	Technology/Methodology	Validation			Road safety metrics used	Key Inferences
			Trial	Case Study	Simulation		
	the UK to extract the hidden patterns (or accident hot spots), predict the severity level of the accidents.	Hierarchical LVQ, RBF Network (Radial Basis Function Network), Multilayer Perceptron, and Naïve Bayes), Big Data				Causality class (driver, passenger or pedestrian), sex and age of causality, vehicle type.	Lighting conditions, road classes and the number of vehicles are the key features while selecting the attributes. The developed classification and prediction model could inform traffic control actions by understanding causal factors and the severity of accidents.
Parathasarathy, Soumya [66]	A hybrid machine learning approach was proposed to predict the type of road accidents (classified as drunk & drive, fire and skid) and the severity of these accidents.	Machine Learning (K-Nearest Neighbour and Support Vector Machines)		✓	✓	Accident data about the severity and cause of the accident.	The proposed approach enhances the accuracy of road accident analysis and prediction of accident type while achieving an accuracy of 92%
Fan, Liu [64]	A novel self-learning machine learning approach was proposed and employed to identify and predict accident blackspots under different weather conditions and morning and evening peak traffic distribution.	Machine Learning (Support Vector Machine, Deep Neural Network)	✓	✓		Accident data, traffic data	The characteristics of traffic accident data varied with time and space and this change pose a challenge to maintaining model performance. The proposed Support Vector Machine approach has the potential of identifying black spots with up to 95% accuracy
Zhang, Lu [69]	A multi-view learning approach is proposed that employs data from social media and remote sensing applications to identify accident hotspots	Big Data, Social Sensing, Remote Sensing	✓	✓		Social Media (traffic-related tweets), accident report database, GIS/Satellite imagery of roads	Results show that the proposed approach outperforms the state-of-the-art baselines in identifying potential accident hotspots in urban areas by 8.1%

Authors/Project	Description	Technology/ Methodology	Validation			Road safety metrics used	Key Inferences
			Trial	Case Study	Simulation		
Ma, Ding [75]	A GIS-based data mining methodology was proposed to analyse the influential factors of fatal traffic accidents for each zones/region in a city.	Machine learning, GIS		✓	✓	Accident data (characteristics of the collision, time and day of the week and location), lighting condition,	Drink-driving, the number of parties involved, rear-end crash, lighting condition, pedestrian involvement, motorcycle involvement, the day of the week and time of the day were found to be the most influential factors of fatal accidents in urban Los Angeles. Driving speed did not rank into the top 15 contributing factors for fatal traffic accidents in urban areas.
Wang, Liu [74]	An approach was proposed to map vehicle-pedestrian and vehicle-vehicle collision risks by road type using data associated with capturing levels of human-activity	Machine learning, Social sensing, Remote sensing		✓	✓	Traffic and pedestrian flow, Road type (arterial or trunk roads)	Night-time light density and point of interest data (social media) can be informed to generate accident hotspots for different road types.
Mamlook, Ali [128]	Prediction models were developed to identify risk factors for road accidents and employed in driving simulators (involving 100 participants)	Machine learning		✓	✓	Weather condition, Driver behaviour (speed and braking)	The prediction model based on Random forest (machine learning technique) reported the highest accuracy. Speed is the most important critical factor to predict injury severity on highways.
Hammoud [71]	An approach to detect incidents or potential accident risks on highways by analysing traffic flows was proposed and tested via simulations	Sensor			✓	Incidence detection rate, false alarm rate, mean-time-to-detect an incidence, traffic flow	A traffic management system that quickly detects incidents on the highways increases the safety of the travellers and decreases overall traffic delay. The proposed technique of analysing traffic flows/bottlenecks on

Authors/Project	Description	Technology/Methodology	Validation			Road safety metrics used	Key Inferences
			Trial	Case Study	Simulation		
							highways has an accuracy of up to 84%.
Mohamed Radzi, Birgin [129]	A model is developed to predict the road crash severity injuries using human, environmental and vehicle contributory factors in Nigeria	Machine learning (Support Vector Machine)		✓		Accident severity	The proposed Support Vector Machine approach has the potential of identifying the severity of accidents with up to 92% accuracy
Pan, Fu [130]	An approach was developed to predict the expected crash frequencies on highways	Machine learning (Deep belief network)	✓	✓			The proposed Deep belief network approach has been proven to be successful in different geographic locations
Aichinger, Nitsche [70]	A novel method is proposed to use low-cost smartphone GPS and motion sensor data to automatically recognise critical car driving situations and near-misses such as emergency braking, evasion manoeuvres or sudden driving speed changes and inform accident hot-spots	GPS, Motion sensor	✓			Driver behaviour	Accident hot spots can be accurately identified and geographically located with smartphones.
Saul, Junghans [65]	An automated video analysis system was proposed to identify black spots for cyclists on roundabouts	Image Processing	✓			Driver behaviour	Spatial and temporal distributions informed that right-turning vehicles in Berlin caused high-risk cyclists in a roundabout.

Table A.3 Summary of Driver Behaviour Studies

Authors/Project	Description	Technology/ Methodology	Validation			Road safety metrics used	Key Inferences
			Trial	Case Study	Simulation		
Bender, Ward [87]	The objective of the study was to develop a method for predicting which manoeuvre a driver will execute at road features such as intersections.	Machine learning,	✓			Generating large-scale maps of driver behaviour	Low-computational cost (actual cost/computational cost was not provided). The method was reported to predict which manoeuvre is being executed at distances from the intersection that could be useful for safety and situational awareness applications onboard the vehicle.
Bifulco, Galante [81]/ DRIVEIN2 Project	A survey was conducted based on the naturalistic (on-the-road) observation of driving behaviour to obtain microscopic data for single vehicles on long road segments and for long periods. Data collection was done using an instrumented vehicle equipped with GPS, radar, and cameras. The behaviour of more than 100 drivers was observed.	Image processing, Sensing	✓			-Calibration of driving behaviour models -Data reduction	Observations show that the speeds are not dispersed across drivers and along the road stretches concerned.
Das and Khilar [83]	Used phone sensors and machine learning to profile driver behaviour. Data was collected using four cars driven for thirteen minutes each.	Machine learning, mobile phones, sensors	✓			Classification of driver behaviour	Accuracy of various machine learning techniques, namely Random Forest, Bagging with Random Forest, Random Subspace with Random Forest, were compared and reported. Random Subspace with Random Forest performed more satisfactorily than the other methods

Ferreira, Carvalho [84]	Investigated driver behaviour profiling using 4 different smartphone sensors and machine learning to identify which system is the most appropriate method.	Mobile phones, Machine learning	✓			Driver behaviour profiling	7 driving event types were detected using data collected from 4 Android smartphone sensors. Results showed that the gyroscope and the accelerometer are the best sensors to detect driving events. Using all sensor axes perform better than using a single one, except for aggressive left turns events
Guerrieri, Mauro [79]	This study investigated both vehicle kinematic parameters (speed and acceleration) and driver behaviour (critical interval and follow-up time) turbo-roundabouts.	Image processing			✓	Speed control and management (but not quantified)	The system claims to achieve continuous measurement of the vehicle kinematic parameters (speed and acceleration) related to entry lanes (both left- and right-turning); Exit lanes; and Inner and outer ring lanes.
Jabbar, Shinoy [82]	A mobile phone app was utilised for collecting and analysing driver behaviour data. The study only validated using simulation with limited images (around 30)	IoT, Mobile Phone Application, Deep Learning, facial image processing			✓	-Driver drowsiness detection -trip data information	A framework for collecting data from individual cars and integrating the data within a cloud network. The platform was tested using two mobile phones. Results showed 82% accuracy in detecting drowsiness detection.
Musicant and Botzer [88]	This study investigated the behaviour of 26 drivers in the initial 2–3 weeks of using a smartphone-based collision warning system, for (1) their responses (speed behaviour) to the received warnings, and (2) the number of warnings	Mobile phone applications	✓			Safer driving behaviours	The collision warning system generated safer behaviours: drivers lowered their speed when warnings were issued and maintained safer headway distance over time. Given the high penetration rate of smartphones, it is suggested that ways to further test and use CWAs be developed.

Riaz, Khadim [131]	An emotion enabled cognitive driver assistance model was reported as an accident prevention scheme while considering different types of driver distractions.	Sensing, artificial human driver emotion			✓	Accident prevention tool	Artificial emotion was utilised in the cognitive agent for human driver inspired collision avoidance. The developed algorithm was not tested with real-world data, the required sensing system was not discussed.
Patil [80]	The study used an existing dataset and a regression model to predict the traffic safety risk for individual drivers. The utilised dataset consisted of 19,600 baseline events	Image processing		✓		-Traffic safety risk -Driving outcome classification	Three driving prediction categories were covered by the algorithm, namely: Crash, Near crash and Baseline
Polders, Brijs [78]/ ElderSafe	Advanced Driver Assistance Systems (ADAS) for considering impacts of intersections on elder drivers. Different studies are reported but limited information on each study is provided.	Sensing/Radar	✓	✓	✓	Elder drivers' safety at intersections	Information provided by all the investigated systems was reported to be effective as a 10% reduction of accepted unsafe time gaps or distance between vehicles was achieved. It was reported that drivers were 5 times more likely to anticipate a traffic light change when the advanced warning sign was displayed compared to the baseline scenario.
Puente Guillen [76]	The research used a machine learning technique, i.e. Neural Networks algorithm, to determine the accuracy of a proposed multiple levels categorisation of sleepiness. The study identified awake, post-awake, pre-sleep and sleep as the multiple levels of sleepiness.	Machine learning			✓	Driver sleepiness recognition	The algorithm achieved high accuracy for differentiating between awake and sleep and between post-awake and pre-sleep. However, when the 4 levels of sleepiness are considered together it was not able to identify them with the highest levels of accuracy

<p>Yan [85], Yan, Coenen [86]</p>	<p>The studies utilised various technologies to automatically detect driver behaviour and distractions A dataset was prepared using 20 video clips that were recorded at a car park. Ten male drivers and ten female drivers participated in the experiment.</p>	<p>Image processing, Computer vision, Machine learning, Convolutional Neural Network, deep learning</p>	<p>✓</p>			<p>-Monitoring of the driver state -Predicting safe/unsafe driving posture</p>	<p>The automated system was able to identify eight classes of behaviour, including normal driving, responding to a mobile phone call, eating, smoking, and achieved an accuracy of over 89.62%. CNN method was applied which improved the result and achieved over 90% accuracy in identifying driver's behaviour. The deep learning approach was reported to further improve the aforementioned results to an over 95% accuracy.</p>
<p>Young, Lenné [77]</p>	<p>An image processing was used to study the behaviour of drivers on approach to urban rail level crossings. The study was conducted using 8 experienced drivers (4 males, 4 females) and 12 beginner drivers (7 males, 5 females)</p>	<p>Image processing</p>	<p>✓</p>			<p>Driver attention on approaching rail level crossing</p>	<p>-“Level crossings were not a key focus of attention and drivers did not actively scan for trains.” -“Drivers were over-reliant on the behaviour of surrounding vehicles to alert them to the presence of trains.”</p>

Table A.4: Summary of Pedestrian Behaviour Studies

Authors/Project	Description	Technologies/Methodology	Validation			Road safety metrics used	Key Inferences
			Trial	Case Study	Simulation		
Alsaleh and Sayed [93]	The behaviour of mixed cyclist-pedestrian traffic interactions in non-motorised shared spaces was modelled. Video data were collected at two locations of non-motorised shared space, and data were analysed using computer vision algorithms, to obtain several variables that describe elements of road users behaviour including longitudinal and lateral distances, speed and speed differences, interaction angle, and cyclist acceleration and yaw rate.	Machine Learning, Computer Vision	✓		✓	Modelling pedestrian-cyclist interactions	The results show that the Maximum Entropy Inverse Reinforcement Learning (IRL) algorithm outperformed the Feature Matching IRL algorithm, and generally provided reasonable results for modelling such interactions in non-motorized shared spaces, considering the high degrees of freedom in movement and the more-complex road users interactions in such facilities.
Costa, Jacob [95]	A methodology is proposed for pedestrian behaviour elicitation using virtual reality in conjunction with surveys or questionnaires. An experiment was performed with fifteen subjects aged between 16 and 30 years.	Virtual Reality, Machine Learning	✓		✓	Predicting pedestrian behaviour	The resulting model can be used to improve environmental conditions for experiment iterations. The developed algorithm was reported to have difficulties in predicting sudden speed changes (a root means squared error of 0.207)

Authors/Project	Description	Technologies/Methodology	Validation			Road safety metrics used	Key Inferences
			Trial	Case Study	Simulation		
Deb, Carruth [90]	A newly developed pedestrian simulator using virtual reality (VR) technology	Virtual Reality			✓	VR application as a pedestrian simulator	Approximately 11% of the participants experienced simulator sickness and withdrew from the study. Objective measures, including the average walking speed, indicate that participant behaviour in VR matches published real-world norms.
Kathuria and Vedagiri [92]	The research demonstrated the use of advanced trajectory-based data to analyse road user interactions at an un-signalized intersection under heterogeneous traffic complexities. The behaviour-based patterns were categorized based on the SSM like Speed, Time to Collision, and Gap Time profiles of the pedestrian and vehicle interacting on an un-signalized intersection.	Image Processing, Semi-automated system		✓		Pedestrian- vehicle interactions	The proposed severity levels can help to test and evaluate various infrastructure and control improvements for making urban intersections safe for road users.
Neogi and Dauwels [94]	A model was developed to project pedestrian's crossing/not-crossing behaviour in front of the vehicle	Machine Learning		✓		Projecting pedestrian's crossing/not-crossing behaviour in front of the vehicle	While a benchmarking best system predicts pedestrian stopping behaviour with 70% accuracy 0.38 seconds before the actual events, the proposed system achieved such accuracy at least 0.9 seconds on an average before the actual events across datasets.

Authors/Project	Description	Technologies/Methodology	Validation			Road safety metrics used	Key Inferences
			Trial	Case Study	Simulation		
Sobhani, Farooq [96], Kalatian, Sobhani [97], Kalatian and Farooq [98]	An Immersive Head-Mounted Virtual Reality (IHMR) device was used to evaluate pedestrian crossing behaviour under 3 scenarios: Pedestrians are not distracted, pedestrians are distracted with a handheld device, and a safety measure is implemented on the road for distracted pedestrians with a handheld device. The proposed safety measure aimed to alert the distracted pedestrian by flashing LED lights on the crosswalk when a pedestrian initiated crossing.	Virtual Reality, Deep learning (2020 study)	✓		✓	VR application for developing a pedestrian alert system	Distracted pedestrian performed more dangerous crossings compared to when they were not distracted. The proposed safety treatment did not prove to improve the safety of distracted pedestrians, which might be because this countermeasure added to the distraction of the pedestrians. However, it did improve the crossing success rate meaning pedestrians were able to decide to cross with the presence of these lights.
Raman, Sa [91]	A framework was proposed for predicting the direction of a moving pedestrian as perceived in a 2-D coordinate of CCTV cameras which is used for pedestrian monitoring in traffic control systems.	Machine learning, Image Processing		✓		Automated Pedestrian monitoring in a traffic control system	The experiments results showed accuracy indices for pedestrian direction projection as 94.58%, 90.87%, and 95.83%, for three different datasets. The method can estimate the direction of human motion through his gait patterns.
Yin and Wang [89]	Application of Big data and Machine learning on Google street view images for evaluating walkability and street features	Big data, Machine learning, Image Processing			✓	Google Street View imagery for walking behaviour analysis	The developed algorithm was reported successful in recognising the sky. The number and size of trees along streets and the heights of buildings both have impacts on the visual enclosure.

Table A.5: Summary of Weather Studies

Authors/Project	Description	Technology/ Methodology	Validation			Road safety metrics used	Key Inferences
			Trial	Case Study	Simulation		
Allal, Senouci [99]	The study provides a new strategy to optimise the exploitation of solar energy system in emerging countries to power Small Cell Base Stations (SBS) based on a Markov Decision Process (MDP) to make decisions according to weather conditions evolution and battery level.	GIS, Cellular Networks, Mobile Phone	✓	✓		Weather monitoring	The MDP proves its ability to optimise the use of solar energy without impacting the base station availability: 30 rewards over a month were offered compared to 18 rewards by a traditional approach in case of unstable weather conditions.
FHWA [103]	This report shows a Road Condition Reporting app developed to share information between maintenance vehicles and its Traffic Management Centre (TMC). The intent is to make it easier for the staff to report road and atmospheric conditions, variable speed limit suggestions, traffic incidents, and road hazards. In addition to providing real-time information on travel conditions, it allows motorists to submit photos.	Integrated Mobile Observation, Crowdsourcing, Mobile Applications	✓	✓		Travelling condition	The incorporation of additional data and existing software tools in this newly developed app resulted in: Crowdsourced data at no cost and fewer labour costs to improve corridor performance in the region. As a result of an accident, a 37-mile road closure detour, improved from 4 hours to a cut driving time of 64 minutes when adopting INDOT. The DeIDOT weekly basis reports of each district, to inform plans for repair of potholes or other issues.

Authors/Project	Description	Technology/ Methodology	Validation			Road safety metrics used	Key Inferences
			Trial	Case Study	Simulation		
Spielman, Gertman [104]	This study presents a review of applicable technologies to address severe weather and road conditions through the application of advanced modelling methods for improving the Idaho National Laboratories (INL) driver safety and dispatch planning.	Machine Learning, Big data	✓	✓		Driver Safety Dispatch Planning Microclimate prediction for hazardous weather conditions on the highway	Predictive ML analytics has been suggested in the US to be implemented in other parts of the country where severe weather is an ongoing concern. Even though only tested in small areas (i.e. less than one kilometre), ML has been recommended to be adopted to predicting black ice conditions that pose considerable to the INL fleet and private vehicles. In conjunction with this work, INL is developing information presentation strategies for motor coaches and INL dispatch.
Kodali and Sahu [100]	The study proposes a low-cost weather monitoring system to retrieve the weather condition of any location from a database and show the output on a sensor (OLED) display.	IoT, Cloud Solutions Microcontrollers Sensors				Climatic Condition	This study was tested in India (Warangal City). The OLED sensor has proven to reduce the cost to a greater extent when compared with a classical sensor (e.g. DHT).
Lee, Hong [106]	The study adopts an algorithm for selecting the number and size of selected regions to be optimised for rainfall estimation through CCTV images followed by generating data patterns. Additionally, the algorithm clearly distinguishes the selected regions by clustering the pattern data	Cellular networks, CCTV, Image Processing, Deep Learning		✓		Road hazard, Accident hotspots	The conducted experiment using the real image proved the clustered learning model generated in the same region to have more than 80% accuracy. This proposed method has proven that it can be applied to any environment where several CCTVs are installed, and images can be collected and stored in real-time.

Authors/Project	Description	Technology/ Methodology	Validation			Road safety metrics used	Key Inferences
			Trial	Case Study	Simulation		
	graphs and estimating the amount of rainfall.						
Zang, Ding [107]	This study investigates the applicability of state-of-the-art sensors in one of the most critical issues in the development of autonomous vehicles and driver assistance systems: their poor performance under adverse weather conditions, such as rain, snow, fog, and hail.	GPS, camera, Lidar Sensor			✓	Radar Crosscheck (RCS) areas	The simulation results of this study show the detection range of mm-wave radar reduced by up to 45% under severe rainfall conditions. Moreover, for a close-range target with a small RCS area, the backscatter effect plays a more significant role, causing additional performance degradation.
Scholliers, Jutila [108]	This paper describes how a fog vision sensor has been developed and deployed for warning drivers about adverse road weather conditions. A hardware-in-the-loop driving simulator has been utilised to test the transmission of vehicle data.	Cellular, Networks, Sensors, QoS, Geotagged, Priority System, V2V	✓		✓	Warnings to driver	This approach was conducted in Finland in real-life scenarios involving a central server and communication with the National Traffic Information System (TIS). The results show delays of less than 2 seconds for transmission between vehicles and of less than 4 seconds when messages are routed via the Traffic Information Server, which is within the limits set by relevant specifications.
Bhat, Claudel [111]	This project focused on enhancing road weather management during wildfires, flash floods, and other extreme weather through data collection, sharing, and public dissemination technologies.	ITS, Drones, GIS, Sensors	✓				21% reduction in crashes, reduction in the severity of incidents, improved corridor reliability; reduced speed due to weather-related advisories; reduced average speed and minimised crash risk

Authors/Project	Description	Technology/ Methodology	Validation			Road safety metrics used	Key Inferences
			Trial	Case Study	Simulation		
Karsisto and Lovén [101]	This study verifies Road surface temperature forecasts assimilating mobile observations. In addition to using measured values directly, different statistical corrections were applied to the mobile observations before using them in the road weather model. The results are compared to a control run without surface temperature measurements and to a control run that utilised interpolated values from surrounding road weather stations.	Mobile Sensors, ITS, Simulator	✓	✓	✓	Road condition Road Weather Station (RWS)Points	In comparison with traditionally based observations, the mobile observations improved the accuracy of the road surface temperature forecasts when compared to the forecast scenario in which there would not be road weather stations in the area. Adding statistical correction to the measurements increased the accuracy further during the winter period. However, there was no clear improvement for the winter period when the results were compared to the forecast scenario.
Kangas, Heikinheimo [110]	To strengthen warnings of hazardous traffic conditions to the general public, services towards a more efficient estimation of rapid road surface varying conditions at a national scale, a simulation model (RoadSurf) has been developed.	Smartphone Application, Simulator	✓	✓	✓	Pedestrian Safety, Road condition	Since 2000, RoadSurf has proven to be versatile and also has proven to be very robust and reliable. It included models for Pedestrian sidewalk conditions; Road maintenance guidance; road condition alert; road station-based forecasting
Tomás, Pla-Castells [109]	An autonomous system to forecast weather conditions in a short time and to give users the information obtained.	ITS, Autonomous systems	✓				Increase in the system timeliness (time to detect the incident) and the service provider because no operator is required to warn end-users.

Authors/Project	Description	Technology/ Methodology	Validation			Road safety metrics used	Key Inferences
			Trial	Case Study	Simulation		
Raveena and Berlin [102]	The system uses a set of algorithms and rules to determine dangerous weather situation on roads, which provides a more accurate prediction of weather on the road network.	Mobile Sensors, Safety Measures, MANETS	✓			Road Type, Road Condition	This paper discussed broadcasting historical weather report to the vehicle on urban roads using traffic, road condition and weather information. The used system proved that can predict an unexpected increase or decrease rainfall, flood, road damage intensity and events of climatic changes can be prevented.
Liu and Rao [105]	In this paper, the parameters of pavement are collected by sensors, and support vector classification (SVC) is used to judge whether the pavement will freeze at a certain time in future.	SVC				Pavement icing warning, Traffic Accidents	In this study, the SVC method was adopted to predict the pavement icing warning. The results show that the model can predict the pavement icing warning more accurately. This research demonstrated that it can reduce the damage caused by road icing. And that can reduce the occurrence of traffic accidents and improve traffic management in a range of a full country.

Table A.6: Summary of Traffic Congestion studies

Authors/Project	Description	Technology/ Methodology	Validation			Road safety metrics used	Key Inferences
			Trial	Case Study	Simulation		
Greer, Fraser [48]	The study presents information on the benefits, costs, and lessons learnt regarding ITS planning, deployment, and operations obtained from almost twenty years of evaluation data. The update report from 2018 includes 10 new or revised factsheets relative to the 2017 Update Report.	GIS, Big Data, ITS	✓	✓	✓	Fatal accidents, Near-miss events	Electronic Stability Control (ESC) systems can reduce the risk of fatal crashes by 33 %. Forward collision warning systems have the potential to prevent 23.8 % of crashes involving large trucks. In a pilot test, bus drivers using in-vehicle collision avoidance warning systems were involved in 72 % fewer near-miss events than a control group where the warning feature was turned off.
Celesti, Galletta [123]	This paper investigates an alternative solution for addressing traffic congestion considering mobile traffic sensors directly installed in private and/or public transport infrastructure and volunteer vehicles.	IoT, Alert messages for rescue	✓			Risk of Accidents, Response time	Obtained response times prove that the solution can be adopted in a real road traffic environment. In this scenario, a fast-real time processing of big traffic data is fundamental to prevent accidents.
Shi and Abdel-Aty [112]	This study aspires to improve the system performance of urban expressways by reducing congestion and crash risk. In particular, Microwave Vehicle Detection System (MVDS) deployed on an expressway network in Orlando was utilised to	Big data, Sensor	✓	✓	✓	Crash Risk Congestion Index	This detection system archives spot speed, volume, lane occupancy and volume by vehicle type per lane on a minute basis. Congestion detection and real-time safety analysis were developed for three expressways based on the data. Traditional congestion measures cannot capture the variability of congestion. Real-

	<p>achieve the objectives. The system consisting of 275 detectors covers 75 miles of the expressway network, with an average spacing of less than 1 mile.</p>						<p>time Big Data is, therefore, more desirable to identify the congestion pattern in Spatio-temporal dimensions. The congestion index was introduced to measure congestion intensity and visualised via a filled contour plot. It was found that congestion on urban expressways is highly time and location-specific. Recurrent congestion at different hours of the day is observed for specific locations. Faced with the large traffic demand during peak hours, the traffic authorities could not always expand the system capacity as a solution.</p>
<p>Anass, Yassine [113]</p>	<p>Applies the Kerner three-phase traffic theory to realise a synchronised system by establishing an ITS that will provide automatic management of traffic lights while establishing a communication mode based on the concept of the Internet of Things for various traffic lights controllers to enable them to collaborate. To resolve the traffic jam issues, so the reduction of CO₂ emissions and also the mobility metrics like the travel time.</p>	<p>IoT, VANETS</p>			<p>✓</p>	<p>Road Condition</p>	<p>The results of V2V and IoT outperform with better mobility and emission metrics than standard communications. Furthermore, the suggested model marks acceptable benefits in terms of service quality and optimisation provisioning in vehicular networks.</p>

Cárdenas-Benítez, Aquino-Santos [118]	A traffic congestion detection system that combines inter-vehicular communications, fixed roadside infrastructure and infrastructure-to-infrastructure connectivity and big data. This system permits drivers to identify traffic congestion and change their routes, accordingly, thus reducing the total emissions of CO ₂ and decreasing travel time. It monitors, processes and stores large amounts of data, which can detect traffic congestion in a precise way using a series of algorithms that reduces localised vehicular emission by rerouting vehicles.	Big Data, Connected vehicles			✓	Vehicular emissions	Overall, by detecting traffic congestion and changing the routes, the average arrival time to the destination is 70% shorter. The algorithm's accuracy in detecting traffic congestion with 10.1% of the vehicles equipped with On-Board Units (OBU) is 93.7% in 64 programmed traffic congestions; traffic congestion of 50% of the vehicles with an OBU in place, increases to 98.4% in 64 programmed traffic congestions. CO ₂ greenhouse gas emissions are reduced by 50% on average, by detecting and conveniently modifying the route.
Wallace, Ban [132]	The purpose of the survey was to assess the current state of the practice for DOTs in using social media for traffic operations.	Survey		✓		Traffic operations	From the survey, It was found that only 12% of the sample had full-time staff entirely responsible for social media, 45.5% had staff dedicated to social media during certain times of the day such as the peaks, and nearly 42% had no dedicated social media staff, rather existing staff responded to social media issues.
Georgiou, Abbadi [119]	This is a novel traffic-congestion estimation model, that utilises the volume of messages and complaints in	Social Media, Big data, Sensors, Data Mining	✓	✓		Human assistance Time	Social sensors offer a fast and low-cost way to understand the physical world through online content on social media. Mining the correct

	online social media, based on when they happen. An experimental evaluation proposes a model to estimate, with higher accuracy, traffic jam severity and compare results with several baselines.						correlation between the crowd's reaction and an event's magnitude can be very critical and improves our understanding of what is happening and how much it affects our lives. The model achieves at least a 38% improvement of absolute error and more than 45% improvement of relative error when compared with a baseline that assumes a linear correlation between traffic and social volume.
Walraven, Spaan [121]	This study shows a traffic flow optimisation problem formulated as a Markov Decision Process. Q-learning is used to learn policies dictating the maximum allowed driving speed limits in a highway, such that traffic congestion is reduced.	Q Learning, Markov decision process			✓	Speed limit, Traffic flow	The proposed method to reduce traffic congestion is primarily focused on speed control, which aims to reduce the speed along the highway such that traffic congestion is reduced. Even though speed control has shown to be able to reduce congestion, it should be noted that speed control is not always sufficient to achieve effective congestion reduction. Traffic flow on highways can be characterised using speed, density and flow. This means that for a fixed and controlled maximum speed, there can be a large variety of flow values, which consequently influence the density and occurrence of traffic congestion.
El Hatri and Boumhidi [122]	This is a multi-objective traffic light control system that is based on an Intelligent Multi-	ITS, Q-Learning,			✓	Waiting time, Flow rate	The microscopic traffic simulator SUMO was chosen to apply a signal control model to real traffic system

	Objective Particle Swarm Optimisation (MOPSO) method. It manages traffic congestion by taking the average junction waiting time and the flow rate of vehicles on the congested road as two objectives.	Traffic light control					management. It offers the opportunity to interact with the traffic control interface (TraCI) used to dynamically control the execution of road simulation. The behaviour of the vehicles involved in a SUMO simulation depends on both road directions and speed. The speed of each vehicle depends on its distance to the vehicle in front of it, with a predefined maximum speed typical of urban areas.
Al Najada and Mahgoub [120]	This paper uses H2O and WEKA mining tools. It applies feature selection techniques to find the most important predictors. Also, it tackles class imbalance by employing bagging and using different quality measures.	Big Data, VANET ITS, Data mining		✓		Human Mobility, Traffic Crashes	This analysis showed that human behaviour has a strong impact on traffic flow and safety decisions. The results revealed that the driver's attributes such as age and sex could be predicted correctly up to 70% by providing other attributes for an accident or casualty.
Li, Liu [114]	The key objective of this study is to incorporate the reinforcement learning technique in variable speed limit (VSL) control strategies to reduce system travel time at freeway bottlenecks.	Machine Learning			✓	Travel time, Highway bottlenecks, Speed limits	Overall, the QL-based VSL control strategy outperformed the feedback control strategy in reducing system travel time. In a simulation environment, the proposed VSL control strategy reduced the system travel time by 49.34% in the stable demand scenario and 21.84% in the fluctuating demand scenario. The maxi change rate of the speed limit was set to be 10 mph per 1 min. More specifically, the QL-based and the feedback-based VSL reduced the total

							travel time by 43.25% and 16.24% in the stable demand scenario, and by 14.46% and 6.91% in the fluctuating demand scenario.
Elfar, Talebpour [116]	This paper explores the use of three machine learning techniques: logistic regression, random forests, and neural networks, for short-term traffic congestion prediction using vehicle trajectories available through connected vehicles technology.	Machine Learning V2V, V2I			✓	Vehicle trajectories	Results show that the accuracy of the models built in this study to predict the congested traffic state can reach 97%.
Bae, Choi [117]	This study investigates predicting long-term traffic flow rates and the corresponding truck percentages. With the use of these predicted values, stereotypical patterns of traffic volume-to-capacity ratios were created for typical urban night-time closures. Third-order curve-fitting models to achieve potential work zone travel time delays in heavily trafficked large urban cores were then developed and validated.	Machine Learning	✓	✓	✓	Construction work zones, Travel time delay	The findings showed relevant results to improve mobility at CWZs by informed travellers having advanced knowledge about the potential traffic effect. Through high-resolution traffic sensor data with multi contextual characteristics, the proposed approach to learning how travellers react to CWZs and transportation management decisions and modelling the effect of CWZs, Promising areas for this study could be its potential for automation leading the mandated mobility effect assessments of highway CWZs to become quicker and more reliable.
Zhang, Onieva [133]	This paper develops a Hierarchical Fuzzy Rule-Based System (HFRBS) optimised by	Machine Learning			✓	Traffic Congestion	To test the performance of this to the prediction of traffic congestion with real traffic data collected from PeMS,

	Genetic Algorithms (GAs) to develop a more accurate and robust traffic congestion prediction system employing a large number of input variables.						as well as benchmark datasets from KEEL have been used. The obtained results have demonstrated the simplicity of the fuzzy rules of the obtained models, and the effectiveness of GHFRBS for predicting traffic congestion with time horizons of 5, 15 and 30 min. Because of its serial hierarchical structure and its automatic ranking and selection of the input variables, the adopted technique may explore a new research topic in the field of data mining, in obtaining a better understanding of the usefulness of the available datasets.
Ata, Khan [115]	A prediction of congestion is operationalised by using the algorithm of backpropagation to train the neural network. The proposed system aims to provide a solution that will increase the comfort level of travellers to make intelligent and better transportation decision, and the neural network is a plausible approach to find traffic situations.	Machine Learning			✓	Comfort level of traveller, Travelling route decision	The Proposed MSR2C-ABPNN with Fitting & time series model system gives high regression fit values of 0.96 and 0.98 respectively compared to traditional methods.

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