Key Artificial Intelligence and Digitalization Solutions Towards Vision Zero in Road Safety

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Abstract The various rapid advances in computer systems and new algorithms have applications in all aspects of transport, and road safety could not be an exception. Artificial Intelligence (AI)-based modelling has become more accessible and approachable, and road safety experts have been acquiring new knowledge on how to enhance road safety in the examined networks using increasingly sophisticated algorithms. Simultaneously, data collection is becoming more affordable, seamless, voluminous and multifaceted, departing from traditional, rare road safety indicators, such as crashes and casualties, to an array of surrogate safety measures with high recording frequency, such as harsh events, Time-To-Collision or a wealth of driver behavior data. The aim of the present chapter is to provide an overview of current progress. Specifically, aspects of AI for (i) modelling road user behavior, (ii) modelling network-level performance and (iii) conducting in-depth crash analysis are discussed. Promising research directions to be explored in the imminent future are presented as well, in the form of high-impact feature engineering, crash and injury causality analyses and ethical AI applications.

Keywords Road safety · Artificial intelligence · Big data · Vision zero · Surrogate safety measures

1 On the Issue of Using AI to Improve Traffic Conditions

Road safety remains an ever-present issue in motorized societies, as a heavy toll of more than 1.19 million deaths occurred annually due to road crashes in recent years, up to 2021 [1]. Specifically in the European area, about 22.800 road traffic

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fatalities were recorded in the 27 EU Member States in 2019, with almost 40% of road fatalities being recorded in urban areas. Vulnerable Road Users (VRUs), which comprise people too young or too old to drive, as well as people with mobility and other physical impairments, account for 70% of road fatalities in urban areas. This seems like an unfair added predicament, as VRUs are forced to conduct their mobility activities while enjoying the least physical protection, contributing to injuries and fatalities disproportionately.

For decades now, highly modernized countries have adopted Vision Zero as their leading strategic approach to reduce crash consequences and to promote road safety. Vision Zero emerged in Sweden during the 1990s and advocates that road crashes are preventable, while humans are imperfect and fallible, which is reflected on their driving behavior [2]. These can be failings which can be mitigated through the adoption of a Safe System Approach, which proposes the creation of forgiving and damage-preventing road environments, adopted by the European Commission and the World Health Organization as the way forward [3]. While significant progress has been made in past decades, in more recent years crash data have shown that crash numbers are plateauing and are quite resilient to further reductions. Therefore, all available tools have to be explored and employed for the creation of a truly Safe System.

In parallel, the rapid technological advancements of the previous decade continue to emerge in the present one at an accelerated rate. The various cities and transport networks are being prepared to receive the circulation of Connected Vehicles (CVs) and Automated Vehicles (AVs), which are expected to roll out in various degrees of automation, aggressiveness profiles and market penetration rates (MPRs) [4]. Meanwhile, the high accessibility and recent publicity of Artificial Intelligence (AI) lead to its rapid adoption, evolution and, ultimately, deployment to solve road safety problems in transport. A vast array of approaches are proposed by academic or industrial researchers, start-ups and even larger technological companies as technically feasible, aided by the rapid data collection venues offered by the Internet of Things (IoT), 5/6G technologies and deeper MPRs of smart devices, as well as advances in processing power.

It is unclear, however, how all these developed approaches will affect in-situ observed road safety levels in the—currently shaping—future mobility societies. Therefore, when the public sector moves to adapt to changes and anticipate new modes and habits of interconnected mobility, they have an unclear picture of real-world effectiveness and the degrees and directions of impacts they should anticipate [5].

At this point, it becomes crucial to define the term Artificial Intelligence. Within the present study, AI is given a wide scope, being defined as any technology (software and supporting hardware) belonging to the family of advanced computing techniques performing tasks traditionally requiring human intelligence and discretion, or newly invented tasks enabled due to the sheer provided computational power and capability. In a transport context, these tasks can include vehicle driving and navigation, traffic management, route optimization, public transport planning and operation, ridesharing, driver recording and monitoring, infrastructure maintenance detection and scheduling, interactions with public and so on. AI is nowadays typically employed in various roles as well, from data collection, transmission, cleaning or pre-processing, processing and storage to analysis and formulation of conclusions.

Similar definitions are given in past literature (indicatively, [6]) with broad applications; nonetheless, fruitful conclusions can also be derived by focusing in a specific sector, such as road safety. Within a more specified road safety context, various forms of AI technologies are being implemented in reactive (diagnostic) and proactive (anticipatory) approaches, e.g. [7], apart from the previous data manipulation tasks. Diagnostic approaches involve causal modelling for road crash occurrence probability, as well as factors contributing to high injury severity. Proactive approaches can constitute analyzing data from Surrogate Safety Measures (SSMs), such as Time-to-Collision (TTC), Post-Encroachment Time (PET) and harsh driving events (harsh accelerations, breakings, cornerings) [8, 9].

Based on all the aforementioned, the present study serves to showcase the more practical dimensions of AI applications used to solve road safety transport problems, departing from the strictly academic AI mathematical formulations and discussing issues related to big data, current challenges and barriers, as well as future developments. After this Introduction (Sect. 1), the structure of the present chapter is as follows: Sect. 2 follows interesting developments in Big Data applications, Sect. 3 showcases examples and conveys data learned from Machine Learning (ML) methodologies in road safety, Sect. 4 discusses AI issues not directly related to data or modelling, such as the handling of vehicular movement and AI strategic applications, Sect. 5 provides promising future research directions in the form of high-impact feature engineering, crash and injury causality analyses and ethical AI applications and finally Sect. 6 summarizes the present chapter and provides the relevant conclusions.

It is critical to mention that the present chapter does not aim to present an exhaustive literature review of all AI-supported road safety studies. Rather, the aim is to provide an overview of all the different pillars of AI and how these different aspects can potentially improve traditional approaches, given the right applications, and how they interact with each other.

2 Big Data, Broad Horizons

2.1 Big Data Sources

Apart from the multiple pillar sources, vast volumes of large databases become available, resulting in big data that open newfound research and operation capabilities. Overall, the rate of accumulation of data by human activity can be characterized as exponential [10]. Big data are a staple of this explosive activity and are known to be characterized by the three v's: (i) volume, (ii) velocity, and (iii) variety.

1. *Volume* denotes the fact that big data includes massive amounts of information points, which often can exceed the capacity of traditional database handling systems.
2. *Velocity* refers to the (high) rate to which data are generated, processed, transmitted and stored, also defining its capacity for real-time or near real-time processing.
3. *Variety* refers to the various formats and structures which big data might assume. These include structured, unstructured or semi-structured databases and file formats such as .json, .xml or .csv types, all requiring unique coding and processing techniques.

Indicative sources of big data can include the following non-exhaustive list:

- Mobile Phone data, including:
  - Cellphone Presence-Based Data (e.g. Google Maps, Here, Waze data)
  - Cellular Network Data (e.g. mobile phone operators, signal triangulation etc.)
  - Cellphone Sensor-Based Telematics Data (e.g. OSeven, ZenDrive, Octo)
  - Private agency sensor data (e.g. INRIX, Waycare)
  - Travel Card data (e.g. Oyster card, Opal card)
  - Public authority sensor or traffic measurement data (e.g. Ministries, Public Transport Authorities, Cities, Regions)
  - Weather data (e.g. OpenWeatherMap, AccuWeather, etc.)
  - Census data (e.g. Eurostat, National Statistics)
  - Digital map data (e.g. OpenStreetMap, Google Maps, etc.)
  - Shared mobility data (e.g. GPS, routing, etc.)
  - Research oriented data (e.g. floating car/instrumented vehicles)
- Vehicular On-Board Diagnostics data (e.g. OEM industry)
- Camera-Based data:
  - On/In-vehicle (internal, dashcam and peripheral)
  - On the road (cities, operators, police)
- Data from Car Sharing Services (e.g. Uber, Lyft, BlaBlaCar)
- Data from Bike Sharing Services (e.g. 8D Technologies, Mobike)
- Data from research project pilots (e.g. SHOW project automated shuttle data)
- Social Media data (e.g. Facebook, Twitter) … and a myriad of similar other sources.

2.2 Big Data Biases

This big data wealth enables differentiations per road user category and focus on niche analyses (e.g. vulnerable road users, professional drivers, freight vehicles etc.). Nonetheless, it is important to not disproportionately rely on big data, as their utility to solve contemporary and future transportation problems is limited by the amount of insightful information that they can provide, as well as the expert knowledge, and also imagination, of the users. There are arguments that big data are overhyped and overstated as to their potential [11].

There are several additional issues regarding the utilization of big data that merit consideration before ambitiously rushing to explore their potential. In particular, the consequences of using data which are not always representative of the whole population should be assessed and properly corrected. Inherent bias toward specific user groups may be present, dependent on an array of factors, such as:

(i) location of the data collection source (e.g. university campuses, hospitals etc.),
(ii) acceptability and trust of technology (e.g. older participants avoiding participation or not having smartphones altogether) and so on,
(iii) influences of a type similar to self-reported data (e.g. applications that can be turned off during poor performances, causing reporting/publication bias).

Self-reported data are known to lack in accuracy and direct observation capabilities [12] while featuring response bias [13]. Response bias may manifest as desirability bias, misunderstanding of the questions and recall error [14].

In addition to the previous, researcher bias can intensely manifest at times through the production of specific desired conclusions that drive the research setup, approach or outcomes. Arguably, this is one of the most critical forms of bias, in the sense that it is deliberate, and should be avoided at all costs. A particular point especially applicable to road safety is the fact that it is easy to wrongly consider a dataset as unbiased if it covers a specific dimension in detail (e.g. covering different road users) while failing completely in another (e.g. not covering exposure). It should also be noted that, in terms of research conduct, there is a high risk for decision makers to be misled by the opportunistic analysis of seemingly low-cost data in absence of qualified data scientists and statisticians working in a transport context.

2.3 Big Data Openness

A critical issue hindering the exploitation of big data pertains to its openness. Stemming from industrial practices, researchers, practitioners and other interested stakeholders find big data encased in 'silos' in the respective companies that they are produced by or sold to. To make matters worse, fragmentation of data ownership for what is often very related (and very pertinent to each other) pieces of information is observed, compounded by a lack of interoperability between datasets and platforms. The high variation within data ownership is driven by the identity of the companies or people generating and collecting the data and reluctance to share data due to privacy, legal liability, IP, competition, or cost related issues. This diversity of data sources typically affects data quality, especially when the same features are measured (e.g. speeding) instead of complementary variables being measured (e.g. speeding being complemented by acceleration data). Finally, the capacity of current computational systems to effectively process big data on traffic and road user behaviour, especially considering real-time responses or low temporal granularities, is typically not developed sufficiently to cover present demands.

On the part of data consumption, different interests in the data of the various road safety stakeholders manifest, creating differing requirements for data access. Specific sensitivities in road safety data need to be taken into consideration effectively, to prevent them being barricaded away by GDPR regulations, as they can be ethically or commercially sensitive. Overall, there is a lack of targeted expertise in machine learning, data mining, and data management with a road safety context among industrial operators that limits the potential that can be displayed by utilizing big data, especially coupled with effective AI technologies.

2.4 Big Data as Surrogate Safety Measures

A specific subset of the aforementioned big data can be utilized as Surrogate Safety Measures (SSMs). SSMs have several demonstrable advantages, such as the fact that they can be collected rapidly compared to crashes, requiring much shorter study and collection periods [9] and the capacity to model hypothetical scenarios, such as the complete change of an intersection's infrastructure layout (e.g. new directions, added lanes, forbiddance of movements, signal timing change) or futuristic scenarios, such as those involving connected and automated vehicles [15]. Alternatively, SSMs can be collected and used in areas with limited or no crash data availability, widening the operational capabilities of road safety practitioners.

Various big data SSMs can be obtained through an array of methods, such as traffic conflicts, harsh driving events (i.e. harsh braking, harsh acceleration, harsh cornering), spikes in spatial/temporal headways, observations of low PET, TTC or DRAC thresholds, lane encroachments and others.

These big data SSMs can be considered in truly proactive aspects of road safety, providing information on road safety levels before crashes occur. Recent adaptations of the work of Tarko [16] allow for the production of simulated crashes within macroscopic simulation software [17], which broaden the field of potential applications further.

In cases of automated collection, which is both the norm and the entire point of shifting to such SSMs, the analyst should bear in mind that these quantities feature little to no underreporting instances, and, with the correct adaptations to the counting/classifying codes, they can aid with crash reporting and other road closure or disruption events, potentially serving as indicators of transport system resilience as well, as indicated by emerging research topics [18]. This comparative advantage can save a considerable margin of time when considering rapid post-crash interventions, such as first aid, hospital transfers and police interventions.

Regarding naturalistic driving conditions, automated data collection of SSMs is possible through four main venues:

1. Instrumented/floating vehicles with sensors and cameras [19].
2. Unmanned Aerial Vehicles (UAVs—also known as drones) data [20].
3. On-street fixed sensors, possibly including camera video image analysis [20].
4. Smartphone sensors (harsh braking, harsh accelerations, harsh cornering, driving distraction via cellphone use, speeding, poor road surfaces) [21].

Furthermore, a lot of byproducts of these applications and investigations emerge, which lead to a more well-rounded and holistic improvement of road safety. Street imagery, also collected by floating vehicles, supports the assessment of road safety performance (star-rating for roads), such as those conducted by iRAP [22] or more recently proposed by the European Commission with Directive (EU) 2019/1936 [23]. Drones and, with sufficient purpose-oriented adjustments, satellites could potentially complement the available range of data, providing a bird's eye point of view. Drones can start providing image capturing solutions with increased market penetration as their technology improves and becomes more affordable for such uses, especially considering extensions of battery life and charging speed.

Technologies like automatic crash notification (eCall) and event data recorders enable data-driven responses to post-crash problems, which may or may not be classified as big data. Connectivity of vehicles can also provide increased dimensions to these issues, as active safety system activations can also be considered among surrogate safety metrics, for instance for well-established systems such as:

- Anti-lock Braking System [ABS];
- Electronic Stability Control/Program [ESC/ESP];
- Autonomous Emergency braking [AEB].

However, it is critical to note that further research on the validation of big data SSMs is essential, for a variety of reasons: Indicatively, more studies are needed to reveal which metrics not only are correlated with reported crashes but also have predictive capabilities for crashes. Subsequently, a ranking of SSM parameters is needed to determine how appropriately they each can predict the number of fatalities and/or injuries, an approach which might have to be disaggregated to different road/crash/vehicle types.

SSMs can integrate different road user interactions, for instance how pedestrians negotiate crossing decisions with oncoming cars or how motorcycle maneuvers are conducted when bypassing moving buses or trucks. These types of encounters, if appropriately automated, lead to higher dimensionality of available data as the occurrence of an entire situation can be investigated as a pattern. SSMs have a comparative advantage to crashes, as they can be recorded in a more proactive manner, and traffic is not disrupted by SSMs such as harsh brakings or low TTC.

A next step would be then to determine how these metrics can integrate crash participant fragility (proneness to injury), speed, mass and other crash type consequences, such as disruptions or other types of disasters (e.g. secondary road crashes, oil spillages etc.). In all cases, the adoption of SSMs leads to the review of statistical training needs, so that data are not misused/misinterpreted, and the approach of the analysts shifts from strictly a rare-events approach to a hybrid, surrogate-enhanced approach.

2.5 Big Data and Crowdsourcing

In recent years, higher IoT and vehicular connectivity has provided a venue for higher, automated and seamless data collection through crowdsourced trips of CVs. Such datasets can be collected rapidly and can easily reach big data sizes, numbering in the millions of observations. Crowdsourced data can be a conceptual subset of real-time datasets, used either as a substitute or as a control tool to verify prediction robustness [24]. The potential of new SSM investigation is also transferred to crowdsourced data, with new SSMs such as concept of volatility investigated by related research [25]. Crowdsourced data may, however, face redundancies by the reporting of the same effect multiple times by involved people, for which additional data cleaning approaches might be necessary [26], as their absence would skew crash hotspot predictions from multi-counting.

Crowdsourcing can take additional forms apart from road safety or mobility-oriented data. The OpenStreetMap (OSM) initiative is an example of infrastructure-oriented crowdsourcing reaching global scales. OSM serves as a collaborative platform for crafting user-generated street maps. In essence, OSM harnesses Volunteered Geographical Information (VGI) [27]. Originating at University College London in 2004, the OSM endeavor has flourished through exponential crowdsourced contributions, characterized by ongoing refinements and enhancements, resulting in a robust repository of Open Geodata suitable for rigorous research purposes [28]. Embraced by numerous entities, including corporations, projects, and small to medium-sized businesses, OSM has gained widespread recognition and trust (OSM, 2019). Initially focused on England, OSM's coverage has expanded significantly, evolving from capturing 29% of England in 2009, [29] to achieving global coverage with increasing data accuracy [30].

Efforts have also been made to adapt and streamline data collection processes to enhance specific repositories, such as the AiRAP initiative of iRAP, a global charity aiming to evaluate road segments and improve stakeholders through the respective training, while monitoring road safety levels in intervention areas. Through AiRAP, accreditation services were established that will allow data suppliers to seamlessly provide their data to the main iRAP databases. The initiative aims to incorporate data from vision-based analysis, LIDAR, telematics and other AI data sources [31].

3 Machine Learning in Road Safety

The pillar that emerges as more obvious when AI is considered for road safety developments is probably Machine Learning (ML). Apart from a body of research rapidly growing in recent years, even heavily industrial developments, such as object detection algorithms implemented by automated vehicles, rely heavily on ML and its various subdivisions.

In the following section, a brief overview of the various scopes and purposes for which ML is commonly used will be provided, along with examples and outlines of new developments such as Explainable AI. Additional aspects of AI applications in road safety will be outlined subsequently.

3.1 Machine Learning and Its Scopes

The term Machine Learning (ML) denotes a specific aspect of artificial intelligence (AI), focusing on the development of algorithms and statistical models that enable computers to perform tasks without being explicitly programmed for each one. ML algorithms are data-driven, learning from the datasets that they are being provided. Moreover, they are excellent for identifying patterns, making decisions and also forecasting the target quantities in the future based on the data they are supplied, given that specific care is taken to construct them with minimal biases and over-adaptivity to a specific dataset that would hinder generalization, a tendency known as overfitting.

ML algorithms can be categorized in three broad categories:

1. Supervised algorithms, used to read an amount of labeled inputs and then perform classification or regression on a designated target variable based on features drawn from the other inputs.
2. Semi-supervised algorithms, used to read a small amount of labeled inputs to group the outputs of larger unlabeled data in order to improve model performance and generalization capabilities.
3. Unsupervised algorithms, used to read a dataset without specific labels, and then attempt to find any patterns or predominantly emerging groups in these data, for instance with clustering or dimensionality reduction.

In the field of road safety, various forms of ML, deep learning (DL) or similar algorithms have been implemented in research endeavors, with an increasing popularity over the recent years [32]. Some of these ML applications are outlined in the following, including supervised and unsupervised tasks, however it is important to note that the literature is rapidly advancing, constantly forming new connections and opening undiscovered research venues.

It is important to mention that the general good practice steps of ML must be observed. Indicatively, overfitting (and underfitting) must be considered, an issue leading to the algorithm learning too well (or too poorly) from the data and underperforming in new, unseen-before datasets. This problem is typically mitigated by cross-validation (for instance, k-fold cross-validation) Overfitting is also influenced by proper dataset selection and additionally proper feature selection from each specific dataset. When splitting a dataset to train, testing and/or validation subsets, it is important to observe that good distribution of all variables (and especially the target variable) is ensured across all subsets, a process which has been largely automated nowadays (e.g. [33]). Another option is to employ early stopping in the model training process to avoid performance degradation and overlearning from the data, thereby reducing overfitting.

Moreover, scaling techniques are often crucial for the proper function of various ML algorithms (most notably Neural Networks), which becomes critical even before predictive performance can be regarded. Scaling refers to the transformation of input features to the model so that they have comparable ranges (scales). The process ensures quicker computational types, and, more importantly, equal, unskewed contributions of each feature. Some algorithms (especially tree-based algorithms) may not require scaling, but the practitioner ought to verify this based on the individual software package that they are implementing. Scaling is not necessarily used in a blanket manner, as binary or categorical features may not require scaling.

There are various scaling techniques, such as standardization (Z-score normalization), min–max scaling, robust scaling and logarithmic scaling; the latter of which is more meaningful in a road safety context when considering always-positive traits such as the number of crashes/SSMs occurring in an area or time period, temporal metrics such as TTC, or highly varying exposure metrics, such as segment length in different roads of an urban road network.

Another good practice example is that, if the algorithm demands, one-hot encoding must be utilized to convert all data types to numeric values. Further nuances of conducting proper ML analyses will not be analysed here, as they fall beyond the scope of the present chapter. However, practitioners must be vigilant and refer to the respective sources and carefully implement all required steps before extracting results that might be biased, skewed or downright misleading.

Nonetheless, despite the usefulness of ML for analytical tasks, when considering crash occurrence and severity, discovery of causality remains an ever-constant pursuit [34], a common theme in all road safety research. This is an especially pronounced problem in conflict-based studies, as ML does not offer any insights on causality and thus econometric methods have to be implemented [35].

3.2 Classification Tasks

Several core algorithms with numerous variations have been proposed for classification such as various forms of Neural Networks (NNs), Random Forest, Extreme Gradient Boosting (XGBoost), Support Vector Machines (SVM) [36]. Bayesian Networks, Decision Tree and K-Nearest Neighbor algorithms are relevant as well, albeit perhaps less frequently used as first preference. Arguably, some of the most archetypical applications of ML classification in road safety are (i) crash occurrence detection and (ii) injury severity classification and prediction.

For crash occurrence detection, a study was dedicated to the comparison of the performance of several popular algorithms (i.e. k-nearest neighbor, Naive Bayes, Decision Tree, Random Forest, SVM, Artificial NN (ANN), and Deep NN (DNN) [37]) using real-time data from a freeway in Athens, Greece. It was concluded that the DNN had the most promising performance, outperforming other algorithms, and that the Naive Bayes model performed remarkably well given its simplicity. The importance of proper scaling was also echoed in that study.

For injury severity predictions, some of the relevant studies have examined algorithms such as SVM, ANN, KNN, C5.0, CART, and Random Forest, and concluded that Random Forest performs slightly better than the other algorithms [34, 38].

In any case, it is important to note that algorithmic performance is largely data-driven and can change and also be influenced by biases in the data or alterations in data recording schemes. Therefore, there is not a 'one-size-fits all' algorithm, arguably even for not any given task.

The occurrence of secondary crashes (i.e. crashes influenced by the appearance of a primary crash) has been examined as well by utilizing XGBoost, based on data from Florida, USA in a relevant study [39]. The respective model contained a notable feature engineering approach which utilized speed contour data in order to detect speed drops and thus detect the influence of a primary crash in the preceding segments. Moreover, by substituting crashes with conflicts, real-time SSM classification can be conducted, offering a much more dynamic view of the road environment [35, 40].

Classification finds a range of applications in other tasks outlined by road safety studies, such as driver profiling, for instance with ANN and SVM [41], with possible applications as an early warning system. Another example would be the image-recognition based detection of non-pedestrian anomalies in pedestrian walkways such as cars, cyclists, skaters, and similar obstacles, proposed by Pustokhina et al. [42]. The utilized algorithms featured two stages, involving preprocessing to remove noise in the data, followed by mask region convolutional neural networks (Mask-RCNN) augmented by densely connected networks (DenseNet).

Classification is also very helpful when considering road safety countermeasures, such as real-time fatigue and distraction detection based on driver behavior, and additionally blindspot detection based on smartphone camera vision data based on customized integrated algorithms collectively termed 'CarSafe' [43].

When considering real-time datasets for classification, meaning that they contain uninterrupted temporal periods, it is important to note that the data will almost certainly be imbalanced, i.e. classes will be heavily unequal. A widely accepted definition of data imbalance is when one or more of the classes outclasses the others by a rate of 10–20%, which negatively impacts model performance and hinders learning. Since road crashes are, thankfully, rare events, the respective observational datasets contain very low numbers, and this is a very common issue that researchers have to overcome.

The class imbalance issue is typically mitigated with data resampling methods (involving sampling part of the data and/or generating synthetic data to eliminate class imbalance), cost-sensitive learning and class weight and/or threshold tuning. A famous data imbalance correction technique is the synthetic minority oversampling technique (SMOTE), developed in earlier research [44]. In recent years, SMOTE has been applied successfully for crash occurrence detection, which is an ultimately binary problem via a real-time approach [45]. XGBoost algorithms showed a very high crash detection accuracy and sensitivity using data from Chicago, USA. The authors note that the temporal aggregation of traffic data was selected to maximize performance accuracy but should be reduced in order to predict crashes more rapidly.

Class imbalance can be also noted in crash severity analyses, as fatalities are outclassed by slight/minor and severe/major injuries, and specifically to the slight injuries with a rate of about 10% when aggregate macroscopic data are considered. Multiclass predictions of injury severity have also been achieved aided by SMOTE, with a dramatic difference in accuracies and F1 scores across 6 tree-based algorithms compared to imbalanced training data [46].

Comparable classification problems, even on self-reported data, also benefit from the use of such techniques. For example, cyclist perception scores regarding safety were normalized with the K-means-SMOTE method in recent research [47]. In addition, conflict occurrence predictive tasks can benefit from SMOTE [40].

3.3 Regression Tasks

Another classical application of ML tasks regards regression approaches of various rates and continuous numbers. Notably in road safety, regression is frequently conducted in count-based approaches, with algorithms that use Generalized Linear Models (GLMs) as their basis, typically within Poisson or Negative Binomial frameworks.

Count-based regression has been implemented for modelling crash counts, for instance by applying decision tree regression (DTR) in VRU crashes using data from Florida, USA [48]. In addition to traditional predictor features, spatial features were of nearby traffic analysis zones were incorporated, improving the tree performance. Models were further refined into ensembles by using improvement techniques such as (i) Bagging, (ii) Random Forest overlaying and (iii) Gradient Boosting, with the latter models outperforming all others.

Slightly earlier, crowdsourced data were used to conduct crash count prediction using Random Forest regression trained on crowdsourced data from Waze in Maryland, USA, and the respective heatmaps were also provided. The authors echoed the temporal richness of such data; although six months were collected, even one would have been sufficient for the analysis [49]. Due to the higher data availability provided by SSMs, it is easier to apply count-based approaches to measures such as harsh braking events or traffic conflicts, which yields interesting results especially within a spatial analysis context [50].

Apart from counts, regression can also be performed on crash rates, albeit more rarely. Utilizing crash rates provides the benefit of integrating exposure, by considering relating parameters by which to divide the overall crash counts, like traffic volume, network length or a combination of the two, leading to crashes per vehicle-kilometer, person-kilometer or similar approaches. This process enables more seamless (and fairer) comparison between outcomes and predictions of models in different areas and further enhances research transferability. Modelling of crash rates by demographic characteristics is also possible, shedding light on different relationships that may otherwise be unobserved (e.g. crashes in proximity to homes). Such a study was conducted recently using data from the United Kingdom [51].

Crash modification factors (CMFs) have been used for several decades as a straightforward and intuitive means to calculate the impact of network changes on future expected crash numbers based on past fluctuations. Studies have employed ML regression techniques such as multivariate adaptive regression splines (MARS), which were employed for CMF calculation, outperforming traditional Negative Binomial models [52]. MARS employs non-linear regression techniques to depict complex relationships between features in the analysis.

It should be mentioned that algorithmically, regression tasks are more challenging than classification tasks, which is a reason why the latter are typically a first choice for researchers in the field. Regression tasks, however, have the potential of offering much more meaningful and actionable predictions, especially when their predictive capabilities are proven accurate. Providing evidence for a prediction in the form of: “in the next year, about 23 crashes (with the respective variance) will happen on Main Street” is more palatable compared to a phrasing of “in the next year, Main Street has is in the risk category of 15–25 crashes”, and much more preferable to “Main Street is in the high-risk group”. This approach makes it not only more comprehensive to non-technical authorities and stakeholders to understand, but also makes road safety planning strategies, effectiveness evaluation tools and methodologies such as Cost–Benefit Analyses (CBA) applicable in a more straightforward manner.

3.4 Ranking and Clustering Tasks

Individuals may not be easily defined by a single variable or parameter, or it may not be feasible or intended to do so for a specific approach. In such cases, clustering can be implemented, which is a common form of unsupervised learning used to form groups (clusters) among the data sample.

For instance, it is informative to cluster drivers into different groups based on behavioral traits. Well-known psychological tools can be employed to provide data in such cases, such as the Driver Behavior Questionnaire (DBQ) and the Driver Skill Inventory (DSI) [53, 54]. A well-known, basic form is k-means cluster analysis, which can be used to profile drivers based on DBQ and DSI data [55].

Accordingly, infrastructure such as road segments or entire regions can be clustered, offering insights on which parameters are the most crucial as to how the groups are formulated. In a study for regions of the Netherlands, for instance, it was mentioned that urbanization levels played the most important role when considering a simple clustering approach [56]. Regarding road segments, in a study in Florida, the clustering approach was utilized to mitigate heterogeneity which was present in the data. In other words, clusters served to maximize the within-group similarity and minimize the intra-group similarity [57].

When executing clustering, a highly important decision is the selection of the number of clusters. While there are various approaches, such as the Elbow Method, the Silhouette Score (possibly augmented by the Average Silhouette Width) and the examination of Gap Statistics, among others [58] expert knowledge will always play a role in separating groups, and, ultimately, cluster number selection for meaningful formulation of groups is partly an art.

Applications comparable with the aforementioned are conducted and applied in the telematics industry, which has been transforming the insurance landscape in recent years, as new, dynamic ways to measure risk and rank locations and individuals become available through an array of newly developed technologies [59].

Ranking tasks can also be conducted indirectly, by analyzing target road safety variables via regression and/or classification and then ranking segments, regions or individuals by their performance. This can be achieved, for instance, with association rule mining, which can provide instances of simultaneous manifestation of specific attribute characteristics by analyzing the respective dataset [60, 61]. Such approaches are swift in calculation and can also integrate well with large-scale text mining, which is particularly useful when considering the exploitation of social media data for road safety purposes [62].

3.5 Explainable Artificial Intelligence

In recent years, to further enhance algorithmic results, explainable Machine Learning models (often referred to as EXplainable Artificial Intelligence—XAI) have been implemented. XAI contains mechanisms that are model-agnostic. In other words, they are implemented over trained model outputs, and offer insights on how variables influence the final decision of the model, allowing researchers to draw additional levels of interpretation.

A frequent application of XAI is SHapley Additive exPlanation (SHAP) values. Based on coalitional game theory, and specifically on a seminal study of [63], this method quantifies the prediction contribution of each variable by considering it a player in a random game. It is worth mentioning that SHAP values are meaningful both for classification and for regression tasks. This also holds within the road safety domain.

Intuitively, SHAP values have been implemented for multiclass injury severity classification for crashes in relevant research [46, 64]. Remarkably, in the study [64], the highest-ranked features indicated by global SHAP analysis, were used as base to retrain algorithms that were previously tested but not as successful, a process which led to increases in predictive power and overall performance.

As an alternative example, SHAP values have also been implemented during classification of instances of mobile phone distraction [65], denoting non-linear effects for several contributing variables that would not be easily detectable with function-based econometrics models.

On the regression front, counts of different injury severity crashes have been analyzed with SHAP using the output of the XGBoost algorithm [66]. Results were illuminating, as not only the non-linear effect between several built environment variables was examined, due to the flexible tree-based structure of XGBoost, but also the different influence thresholds across which effects can vary were provided by SHAP.

The Local Interpretable Model-agnostic Explanations (LIME) XAI methodology is also comparable and has been successfully interpreted paired with a text-mining approach feeding a Neural Network to identify factors influencing injury severity of heavy vehicle crashes. The authors further increased the scalability of their results by aggregating individual LIME explanations using cross-validation [67].

Lastly, Wen et al. [68] employed an array of XAI model techniques in order to compare their performance and produced a number of fruitful conclusions, including the fact that LIME is often limited to individual prediction-level analysis, and not more aggregate analysis, while SHAP is confined to modelling the interactions of only two factors at a time. The authors also consider Local Sensitivity Analysis (LSA) and Partial Dependence Plots (PDP), which they mention that, while they can adopt a dataset-wide approach, they assume independent distributions of all explanatory features. The use of more sophisticated ML models is also promoted, as they can convey the underlying interrelationships of the various included features more accurately.

4 Artificial Intelligence Beyond Data and Modelling

The broad uses of AI in transport and road safety extend much further than data wrangling and manipulation, and the subsequent modelling. Although arguably most of the contents of this chapter rely on data for automated decision-making, they are conceptually different than the aforementioned processes.

4.1 Vehicle Movements and Trips

Vehicle pathfinding is such a process, featuring high automation possibilities for industrial-scale applications, with the challenge being the maintenance of high road safety levels with manageable incidents, while observing the direction of Vision Zero for the elimination of fatalities. Interdisciplinary cooperation from highly specialized experts is required, as civil and transportation engineers discern and design the optimized the logistic functions of each operational domain, while computer scientists materialize these requirements by optimizing pathfinding algorithms.

Aided by AI, data-driven collision-avoidance functions of pathfinding are in the position to command more complete awareness of surrounding elements, autonomous, highly automated global and local control options, and more diverse transmission options. The latter become crucial in order to handle large volumes of data, especially if these are rapidly generated and/or continuous. It is noted in relevant literature that increased processing power will also be required, not only for the strict processing of data, but for learning and adaptation of user requirements in real-time or near-real-time, while safeguarding user privacy and personal data throughout the process. Hybrid traffic scenarios, with mixed autonomous and human-driven traffic, will pose their own challenges, as the fluidity of human behavior influences predictions adversely [69].

Collision-avoidance pathfinding algorithms can be broadly classified as kinematics-based, which use physics analytics on trajectory data [70] or maneuver-based which use ML classification for specific driving maneuvers, for instance with Dynamic Bayesian Network (DBN) algorithms [71]. Combinations of the previous have been proposed as well.

Special subdomains must also be considered. For instance, Xiang et al. [72] outline how this process can be applied within construction sites using Building Information Models (BIM). Their approach involved multilayer maps, with each layer concerning different domains of information, such as terrain navigational difficulty and the presence of fixed obstacles. Admittedly, the computational time of such approaches have to be considered, as with more layers they can increase radically, even for a more controlled environment such as a construction site.

Routing (also known as route-finding) is a related example, in a more high-level decision-making process using typically more aggregated data from more road segments. Routing began as a static concept, but subsequently the capability of integrating real-time traffic and safety information was explored, leading to dynamic routing algorithms. However, robustness of predictions remains a constant challenge that future endeavors will have to reliably overcome. Moreover, the provision and availability of high resolution, reliable data remains a barrier which prevents the wider application for such algorithms. Task complexity is a critical factor once again, as the algorithms are called to make a conclusive decision within specific time-frames, due to the demands of the transportation processes [73].

4.2 *Strategic Uses of Artificial Intelligence*

In order for noteworthy results to materialize by effectively suppressing crash occurrence and injury severity, strategic planning and concerted efforts are required. Safe, road-worthy AI systems face significant challenges that are only hesitantly tackled by individual designers and need to be decisively addressed:

i. Interfaceability;
ii. Interoperability;
iii. Timelessness;
iv. Scalability.

In that sense, it is critical not to view transport systems as individual, isolated silos, but rather as connected pools that need to be cooperative. Cooperative Intelligent Transport Systems (C-ITS) have been proposed as a way forward. To succeed, C-ITS will have to involve public and private partnership (PPP) and a dedicated vision. As the measures may involve sophisticated components, a main approach is to introduce them more gently and gradually to the public, possibly in dedicated testbeds or study areas [74]. However, this is a process which requires dedication and resilience to outside challenges, such as resistance to change or regulation disobedience.

Notably, a key component of C-ITS is the design and operation of a functional Human–Machine Interface, which must be reasonable, intuitive and function well enough for experienced but also unfamiliar users of the road network. The ideal network should accommodate users that are modestly allocating their attention due to navigation demands or the possible lack of knowledge novice drivers, and have easily comprehensive imagery, with universally understood signs such as the wayfinding signs in airports. While well-trained C-ITS have a positive contribution regarding road safety, evaluating safety benefits from C-ITS inputs alone, without the input of additional sensors, can be a strategic challenge to overcome. Often the obtained data can be low in degrees of freedom (and thus analytic options), but this can be overcome by employing time-series options [75]. The selection and implementation of appropriate sensor recording devices and miscellaneous infrastructure and network is seen as an investment by researchers, but this has to be effectively communicated to stakeholders as well.

The deployment of CAV-oriented technologies, such as Connected-Vehicle-to-Everything (CV2X) technologies can be considered quite fragmented and left to the choices of individual Original Equipment Manufacturer (OEM), with possible cellphone network integration further requiring Mobile Network Operator involvement. This addition forms an even more disjoined overall picture, as the two groups appear to be divided in their prioritization of technological implementations. However, there is a lot of potential in the field, as 5G-supported Dedicated Short Range Communication (DSRC) and CV2X have shown considerable promise in crash prevention [76]. Therefore, it is evident that a more tactical design must be applied within a more hierarchical organization of road crash prevention strategies, which in most likelihood would entail another form of PPP to succeed.

Furthermore, it is imperative to consider the strategic purpose of AI modelling, especially when aiming for sustainable approaches in road safety analysis. Very frequently, the overall strategic vision that research should be shifted towards is not directly addressed by researchers in the field. As AI-based technologies will always require oversight [77], it is critical that this is provided by highly qualified professionals with the necessary expertise. Therefore, a critical need is highlighted to train not only ML engineers or computer scientists, but transport and road safety experts, familiar with the mechanisms and the appropriate context, who would also have a thorough understanding of AI strategic objectives and functions, as well as case-specific ML contextual elements.

The aforementioned tools, and other comparable ones, gradually become available to more road safety researchers, stakeholders and authorities providing estimates on crash risk, injuries and other related topics, without demanding exceedingly technical backgrounds to utilize their results and benefit from them. Undoubtedly, a large number of presented model configurations, including variables, model hyperparameter structures and sequential combinations of ML tasks show very promising performance, albeit on specific datasets. Overall, transferability capabilities are yet uncertain for many of the methods, especially when parameters of uncertainty increase, for instance new areas, transport modes or road user cultures.

5 Future Research Directions for AI-Powered Road Safety

Based on the previous overview, and on the overall state of the relevant literature, a number of future research topics and directions can be gleaned, which all have the potential to benefit from AI-powered techniques. These topics are elaborated in the following sections.

5.1 High-Impact Feature Engineering

It is evident that the new wealth of big data that is presently generated may include several SSMs or other parameters which are all promising in order to shed light in the causes which cause road safety numbers to persist. A high-dimensional problem soon emerges, in which the type and number of variables, the selection of specific algorithms, the areas/individuals and scenarios to investigate, the possible inclusion of connected or automated vehicles, the potential inclusion of real-time components are only some of the components to consider for the study designs of future research. Further to the previous, it is very likely that SSMs have different informative capacities and thus have optimization margins per crash and/or injury category accordingly.

Moreover, researchers must consider the tradeoff between algorithmic accuracy and transferability of their proposed solution. An algorithm may be able to perfectly predict traffic conflict incidents in left turns for powered-two-wheelers based on aggressive behavior. However, its overall applicability and attractiveness as a policy-based mechanism may be limited by its specific demands and approach. On the contrary, a comprehensive system may be very limiting regarding transferability and very costly to maintain, due to data demands. A common rule of thumb states that increased distance hinders transferability and scale ability, and the effects worsen when an approach moves across borders. Therefore, a multiple-criteria based exploration and decision analysis is required to determine the most fruitful SSMs that can be obtained readily or be mined from available big data, and researchers have to prioritize, or create, the ones which are most highly impactful.

Spatial analysis and mapping have also become more accessible in recent years, yielding unique visualization capabilities. Apart from a highly informative resource for stakeholders and authorities, even when only using appropriately extracted descriptive statistics of maps and SSMs, this approach can serve as a validation tool for the spatial distribution of crashes or conflicts as predicted by SSMs, an approach which is not frequently explored. Maps featuring real-time updates, high fidelity, and those that can incorporate flexible data structures, and/or in turn be incorporated in other applications, have competitive advantages over others.

5.2 Crash and Injury Causality

A promising research direction refers to the causality of crash occurrence and injury severity with the appropriate contributing factors, which can be variables from the classic road safety pillars of (i) driver, (ii) vehicle and (iii) road infrastructure or highly complex features such as parameters describing the interactions of road users (e.g. motorcycle maneuver trajectories, harsh deceleration profiles in angular conflicts, and so on). Causality, in other words the direct relationship between presence of a set of factors and the manifestation of a road crash or high injury phenomenon, can be enhanced by AI due to the different combinations of parameters to potentially investigate, and the highly non-linear interactions of many involved quantities.

As an example, AI-supported agent-based simulation has been shown to yield interesting results in causal discovery and counterfactual reasoning for crash generation [78]. In another approach, using data from urban interstates in Texas, a recent study combined Granger causality analysis with the most popular ML algorithms (DT, RF, XGBoost and DNN) and identified an array of crash contributing factors, however they note that the heavily imbalanced nature of their data leads to biases [79]. Therefore, high amounts of precise efforts are required from future research to train and, most importantly, validate causal ML algorithms from existing in-depth datasets in order to train reliable AI tools. Undoubtedly, as a judicial event, each crash must be investigated individually. However, crash and injury mitigation efforts will highly benefit from determining causal factors with high accuracy.

Crash (or even traffic conflict) causality and its investigations will become increasingly relevant in the future, as the advent of CAVs may partially remove responsibility from drivers, or, depending on the legal context, add additional responsibility layers to OEMs. Some approaches have been proposed for the rapid and automated collection of data relaying the causing factors of incidents as detected by CAVs. This objective is mainly assisted by assessing the performance of autonomous driving systems (ADSs). One such venue is the analysis of feature extraction based on the messages that the various systems exchange with each other, after removal of the necessary noise data [80].

However, in line with the rest of CAV developments, it is crucial to underline that a centralized system must be eventually established. Otherwise, the technical disputes regarding causation, and thus fault, in each crash will be overwhelming, especially given that OEM equipment and also algorithms will be directly in competition with each other. As a consequence, the research for the optimal high-level mechanisms is still ongoing, as is the search for the best performing features to be engineered. Both pillars will have to be not only representative of the safety profile of the circulating CAVs, but also manageable regarding their volume and able to be analyzed in real-time conditions as decisions will need to be taken instantaneously. Once again, interdisciplinary knowledge of highly specialized computer science applied in the road safety domain will be required.

Lastly, it should be mentioned that, due to the frequently high data demands of ML methods, there is presently very little research conducted on the effectiveness of road safety interventions and countermeasures. It is becoming gradually more feasible, however, to install sensors and establish data collection schemes in order to obtain the necessary data. Therefore, the completely unexplored field of generating AI dynamic feedback loops on the various impacts of road safety measures on selected SSMs, and, in the longer term, crashes and casualties, should emerge soon, and would be a valuable research direction.

5.3 Ethics in Artificial Intelligence

It is widely recognized that AI technologies should adhere to ethical design values such as explainability, inclusiveness, fairness and justice [81]. However, the definition and management of issues related to ethics and fairness, which are inherently human-oriented concepts, in AI algorithms is a complex, challenging matter.

The previous sections outline the value of added data and new technologies in AI research. There are huge discrepancies globally, however, in terms of technological readiness and overall degrees of industrialization. Even within a region, there are often deprived areas that lack the funds or development to keep up with their peers. Therefore, prioritizing the already relatively safer heavily developed countries or areas, introduces a new set of attention biases to countering the issue of crashes and casualties, which transcends borders to the degree it has been termed as a constant 'global pandemic'. Care should be taken by research to include, and ideally prioritize, the most deprived regions globally. In order to achieve that, new, transferable and actionable research results are needed, which the developing world is presently lacking.

Therefore, it stands to reason that ethics and value-oriented engineering are elevated as a new dimension, integrated and considered to be equally worth to financial, temporal, bias removal or similar constraints. Thus, the quantification of ethical constraints has to be further investigated in future research. Emphasis should be placed on collaborations across countries for the integration of all road realities and road safety and traffic cultures, which comprise elements influencing adherence to laws and regulations, aggressiveness and overall road user performance.

Conversely, relevant data have to be made available from users without violating their privacy, and by granting them actual and perceived freedom of movement. Research efforts have to cultivate a relationship of trust with the road users, and to successfully transmit the message that AI methods demand data but offer higher road safety potential improvements in turn. Absence of monitoring and accountability in administrative authorities frequently seriously limits cooperation of the public due to mistrust and stagnates improvements in road safety performance. To counter these worries, acceptance and public trust ought to be increased by establishing monitoring and reporting processes.

6 Conclusions

Artificial Intelligence (AI) serves as a catalyst for unlocking immense road safety potential for further advancements. AI has led to the creation of large-scale, rapidly generated big datasets with ease and seamlessness. Quickly developing Machine Learning (ML) algorithms have disclosed new, complex interrelationships latent in within road safety analyses, and have in parallel enabled a vast array of new options for road safety modelling, shedding further light on non-linear effects governing road user interactions. Meanwhile the addition of Explainable Artificial Intelligence (XAI) has provided higher interpretability of ML models by outlining how each individual parameter influences model outcome.

The increased methodological and computational complexities render the training of specialized road safety-oriented professionals with in-depth computer science knowledge, who will be able to understand the mechanisms of the transport network, to create AI that is fair and bias-free, to navigate the rising challenges of big data and to successfully communicate the benefits of AI to the broader society. Moreover, funding must also be available to road safety multi-disciplinary professionals to conduct post-intervention assessments and validate road safety countermeasure effectiveness and verify or re-calibrate the outputs of risk prediction tools.

Apart from professional training, it is critical to foster higher degrees of knowledge exchange across all various subfields. For instance, data fusion knowledge and feature engineering lessons learned from telematics-based AI can provide for the advent of CAVs and Connected, Cooperative and Automated Mobility (CCAM).

Furthermore, there is a need to balance carefully between accurate road user recording and concerns of the public against to privacy disruptions, observing standing legislations such as GDPR and AI-based control without human oversight. To assuage these worries, multilevel and more frequent dialogue channels must be established between industrial and technical data holders and policymakers for standardization and openness of data.

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