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TOPICAL REVIEW

Telematics in Insurance: Challenges and Limitations

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ABSTRACT The integration of telematics in the car insurance sector has attracted significant interest due to its potential to disrupt the industry and improve road safety. By capturing actual driving behaviour, telematics offers insurers a data-driven approach to assess risk and price premiums and encourage safer driving practices. A substantial body of literature has explored the applications of telematics in insurance, aiming at enhancing the analysis and understanding of driving behaviour by using more advanced techniques, such as machine learning and deep learning, or introducing new data sources. The results obtained so far are promising. However, few studies have comprehensively addressed the practical challenges and limitations of applying such results in real-world telematics settings. Adopting the perspective of a motor insurance provider, this paper focuses on practical applicability by critically reviewing key contributions in the field. Our aim is to give a high-level overview that not only uncovers the limitations of existing studies but also highlights the potential of using telematics in insurance.

INDEX TERMS Deep learning, insurance, machine learning, telematics, vehicle driving.

I. OVERVIEW

Vehicle telematics refers to data related to vehicle usage and driving behaviour [1]. Applying telematics in insurance enables motor insurance companies to apply a Usage-Based Insurance (UBI) model, which allows for a more personalised and equitable insurance experience [2], [3], while moving away from traditional methods of pricing motor insurance policies that rely mainly on demographic factors. In particular, smartphone sensors or On-Board Diagnostics (OBD) devices (such a device connects to a vehicle's OBD port) can be used to collect, transmit, and analyse real-time driving data, such as speed, acceleration, mileage, and location, to build a clear picture of drivers' habits. Insurance companies can then utilise the insights derived from these results to improve the aspects of risk assessment and provide safer driving assistance. They can use that to price insurance policies and set premiums that align with each policyholder's actual risk profile [3] and influence other decisions, such as policy cancellations or renewal offers.

A substantial body of telematics-related literature focuses on developing models and techniques to gather, analyse, and interpret driving data. For example, [4] have contributed to this field by investigating driving behaviour analysis methodologies in the context of UBI, especially focusing on Manage-how-you-drive (MHYD) insurance models, where drivers are not only charged based on how they drive, but also receive proactive feedback through real-time alerts during their journeys. Meanwhile, [1] has emphasised the methodologies and limitations for analysing driving behaviour using smartphone sensors. More recently, comprehensive reviews by [5] and [6] have covered broader telematics applications, with [5] offering detailed discussions on telematics data modelling techniques and their implications from both behavioural and insurance standpoints.

Many studies report promising results in modelling telematics data for driver risk assessment and in implementing and validating interventions to modify driver behaviour. However,

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while the progress shows theoretical promise for improving telematics insurance and road safety, practical challenges, such as data quality during the data collection phase, the need for diverse demographic data in telematics applications,[1] and issues related to model complexity and interpretability could remain inadequately addressed. Overlooking these aspects could hinder the real-world applicability of their findings.

To highlight these frequently overlooked challenges and limitations, this paper presents the following contributions:

1) We critically review 30 high-quality (SCImago Journal Rank indicator (SJR) [7] > 1) telematics-relevant papers published between March 2021 and August 2024, focusing on the factors that are critical in telematics insurance applications. The search was conducted mainly using Scopus and Web of Science, and filtered using the keywords "telematics", "driving" and "behaviour/behavior".[2] The results were further refined through manual screening and by applying the SJR criteria described earlier.
2) We provide a comprehensive discussion of the aspects that are essential to consider in practical applications, yet have received limited attention in the literature or have only been addressed superficially. The implications of these aspects for practical applications are also discussed.

The remainder of the paper is organised as follows: Section II provides an overview of the fundamentals by discussing how telematics has been used in insurance through UBI models, and introducing telematics variables along with data collection methods. Section III provides an overview of the main topics in telematics applications, including driving behaviour profiling and risk prediction (III-A), the integration of driving risk into pricing schemes (III-B), telematics-based feedback and behavioural interventions (III-C), as well as other emerging areas of interest (III-D). Section IV highlights several aspects that are still insufficiently addressed in the literature, such as challenges related to data quality (IV-A), demographic variability in modelling (IV-B), integration of contextual factors (IV-C), and the interpretability of risk assessment models (IV-D). Finally, a summary of the paper's key points is presented in Section V.

II. FUNDAMENTALS IN TELEMATICS INSURANCE

A. USAGE-BASED INSURANCE

The development of UBI is captured by three key models which have emerged in the telematics insurance sector, i.e. Pay-as-you-drive (PAYD), Pay-how-you-drive (PHYD), and Manage-how-you-drive (MHYD) [3], [4], [8].

PAYD models establish the insurance premium primarily based on the total distance driven [3]. The premise behind it is that the more time or distance drivers spend on the road, the more they are exposed to road risks, thus increasing the probability of accidents. For example, drivers with lower mileage typically present a lower risk and should pay lower premiums, while those with higher mileage represent a higher risk and should be charged more [9]. However, this model assumes a linear relationship between mileage and accidents. In reality, this relationship is far from linear, as the drivers with high mileage may be more experienced or may often drive on safer motorways [8]. This could also be demonstrated by the findings from [10], where a "learning effect" is presented, which implies that more experienced drivers with higher mileage may develop better driving skills over time; thus, increased mileage may actually lead to a decrease in accident risk.

The evolution of the PHYD models [8], [11] is motivated by the neglect of factors such as driving skills and behaviour in the PAYD model. PHYD models are designed based on the idea of "safer driving" [3], which means that the premium can be calculated based on the policyholders' actual driving styles; the safer a driver drives, the lower the premium charged. There are several ways to assess a driver's level of safety, such as analysing their acceleration patterns, braking habits, how they perform manoeuvres, and so on [11]. Research in this area has expanded significantly, as highlighted in [3], [4], [5], [6], [8], and [11].

MHYD models, as the third stage of development in UBI, place greater emphasis on the role of "coaching" or "feedback" in addition to focusing on driver behaviour. MHYD models provide drivers with real-time alerts and suggestions through various monitoring systems, such as driver behaviour and state monitoring, enabling them to adjust and manage their driving accordingly [4]. For example, China Pacific Property Insurance Company aims to minimise losses from commercial vehicle accidents by equipping insured trucks with active safety systems. Technologies such as GPS, Driver Monitoring System (DMS), and Advanced Driver Assistance System (ADAS) are utilised to analyse real-time data on the driver, vehicle, and surrounding conditions [12]. Compared to PAYD and PHYD, challenges remain with MHYD, particularly in driver state monitoring, such as using cameras or wearable devices to detect driver fatigue or distraction in a real-world setting [4]. In addition to technical challenges and higher implementation costs of these approaches, concerns about personal data privacy [1], [4], [5] remain a significant obstacle to large-scale deployment of MHYD. For insurers, robust data governance frameworks must be established before MHYD can be responsibly integrated into relevant products.

Figure 1 presents a taxonomy of UBI methodologies, outlining the relationships between various data collection methods, risk assessment approaches, and derived metrics. The diagram illustrates key behavioural indicators, data processing techniques, and their influence on premium

[1] Demographic factors affect driving behaviour. If modelling is carried out using only a single demographic group, the captured behaviour may be biased (more details will be provided in Subsection IV-B).

[2] The search condition in Scopus is "TITLE-ABS-KEY (driving AND behaviour OR behavior AND telematics) AND PUBYEAR > 2020 AND PUBYEAR < 2025 AND (LIMIT-TO (LANGUAGE, "English"))", and in Web of Science, it is "TS=(telematics AND driving AND (behaviour OR behavior)) AND PY=2021-2024".

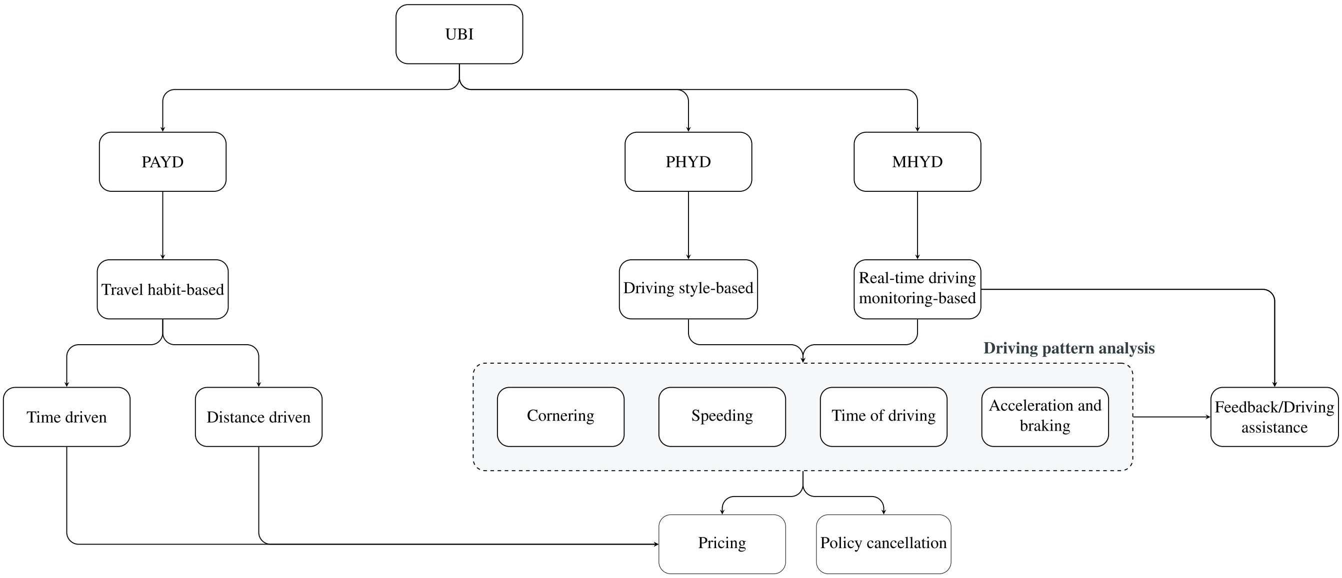

FIGURE 1. Taxonomy of UBI methodologies. The taxonomy categorises UBI into PAYD, PHYD, and MHYD, each with distinct data-driven methodologies.

pricing, policy decisions (e.g., cancellation), and driver feedback mechanisms.

B. TELEMATICS VARIABLES AND COLLECTION METHODS

Driving behaviour analysis is a crucial component in both PHYD and MHYD (as shown in Figure 1), which provides valuable insights into drivers' risk profiles. The analysis is typically conducted through several variables monitored by telematics devices or smartphones. Below are some key telematics variables commonly used in driving behaviour analysis:

- Speed: Speed is the most commonly used variable in telematics to monitor driving behaviour, as speed is a critical determinant of driving risk [1], [6], [11]. Studies use various measures to provide more information about a driver's speed, such as the average speed, frequency of speeding, or time spent driving over local speed limits [11].
- Acceleration and Braking: Often measured in events of harsh or sudden changes, the two variables are key indicators of aggressive driving. Multiple studies use thresholds to categorise dangerous acceleration and braking [6].
- Cornering: This variable is measured using lateral acceleration or G-force to assess how sharply and safely a driver handles turns. A sharp or high-speed cornering manoeuvre may result in a loss of vehicle control, posing potential road safety risks. The frequency and severity of these manoeuvres are tracked as "cornering events" to assess driving skills [6], [11].
- Time of Driving and Distance Travelled: These two variables are crucial for understanding risk exposure. Drivers who drive more miles or frequently drive during high-risk periods (such as at night) tend to have an increased risk of accidents [11]. This also captures the PAYD model premise.

The choice of telematics variables highly depends on the data collection methods. Telematics insurance typically adopts two methods: box- and smartphone-based. The telematics box, commonly referred to as a "black box", is an electronic device installed in the car that can record a wide range of information related to the telematics variables mentioned previously, as well as detect vehicle crashes or accidents [4]. However, the main drawbacks of using a black box are its high cost and low customer acceptance, which limit its wide and rapid platform deployment [1]. Smartphone-based solutions, on the other hand, have proven to be a cheaper and more versatile option. A modern smartphone has multiple sensors, including an accelerometer, gyroscope, magnetometer, microphone, cameras, thermometer, etc. Thus, it has the potential to detect not only those key telematics variables but also identify driver distractions [1], [11]. However, the high cost of processing GPS data from smartphones and the challenge of maintaining a stable position for the smartphone in the vehicle pose challenges when implementing this solution [4]. In addition, this method may disadvantage people who do not own modern smartphones, such as elderly drivers or "dumbphone" users, thereby limiting its applicability across the driving population.

III. MAIN TOPICS IN TELEMATICS APPLICATIONS

Building upon the concepts of UBI and usage of driving behaviour variables collected from telematics devices, this section delves into one of its critical applications, namely driving behaviour analysis. More specifically, we evaluate the main contributions of recent studies based on the following factors: (i) telematics data sizes, (ii) data collection methods,

(iii) modelling techniques, (iv) risk measurement types, (v) interpretability, (vi) inclusion of contextual information, (vii) inclusion of demographics information, and (viii) data quality control. These factors are crucial for telematics research and influence the generalisability and scalability of their findings in real-world telematics applications.

Figure 2 provides an overview of the existing research landscape in telematics-based applications that focus on or build upon driver behaviour analysis. It illustrates the distribution of telematics studies categorised by modelling method type, total drivers and total trips (log scale) in their datasets. The four quadrants represent different methodological approaches: Machine Learning, Deep Learning, Data Analysis, and Optimisation. Marker colour denotes the associated risk type (e.g., crash, risky events), and marker shape represents telematics data collection methods. In contrast, marker size indicates whether emphasis was placed on data quality (DQ) in the study. The dashed boxes were intended to categorise studies into three groups, according to the number of insured vehicles (book size) in the relevant dataset. The upper limit of the first group (''Group 1'' or small book size group) was derived from the 75th percentile values (rounded) of the number of drivers and trips in the studies. The upper limit of the second group (''Group 2'' or average book size group) was an estimate of average insured vehicles and trips for small and medium-sized telematics insurance companies in the U.K., according to the statistics in [13] and [14]. We henceforth refer to any book size beyond this limit as a large-scale real-world book size, indicating the potential extent of real-world settings. It can be observed that most of the studies fall into ''Group 1''/small book size, while several are categorised under ''Group 2''/average book size, and no studies fall into the ''Real-world'' group.

It is important to note that: (i) each marker in Figure 2 does not necessarily correspond to a unique study. Several papers adopted multiple modelling approaches (e.g., both Deep Learning (DL) and Machine Learning (ML)). As a result, these studies are represented more than once; (ii) there are 10 papers with missing information on the total number of trips. Therefore, this figure only includes 20 papers. However, this exclusion does not affect the validity of the analysis shown in Figure 2. In addition to Figure 2, Table 1 outlines the relevant papers alongside more detailed key features.

From Figure 2 and Table 1, we made the following observations:

1) Recent studies primarily focus on five topics: driving behaviour profiling and risk prediction, telematics insurance pricing, telematics feedback and behaviour interventions, driver identification, and drivers' stress and interactions with vehicle systems.
2) Studies with driver sample sizes below approximately 3,000 dominate the field, and most studies involve trip numbers around or below 1 million. However, the sample sizes are far below the average number of drivers and trips in real-world telematics data.
3) The majority of studies use hybrid sensors as the primary way of collecting telematics data, with smartphones being more popular in the small group. Only a small number of studies explicitly mentioned data quality problems.
4) Machine learning and deep learning methods are the most popular modelling approaches, with the primary goal of predicting crashes and risky events.
5) Only a small number of studies included demographics and contextual information within their discourse.

To further examine the findings in these studies, we discuss each topic according to the ''Groups'' depicted in Figure 2.

A. DRIVING BEHAVIOUR PROFILING AND RISK PREDICTION

Consistent with the findings from previous review studies [5] and [6], this topic has emerged as a key emphasised area in driving behaviour analysis. In recent studies, 16 out of 30 papers have focused on this topic, highlighting its importance.

1) STUDIES WITH SMALL BOOK SIZE

Most studies (6 out of 8) in this group have utilised smartphones to collect telematics driving data. As mentioned in Section II-B, a smartphone is not only a cost-efficient option but also a versatile tool, particularly for detecting distracted driving behaviour.

Studies [15] and [23] have included distracted behaviour, in the form of phone usage, as an additional risk factor in their driver risk assessment models. More specifically, in [15], the authors proposed a four-dimensional smartphone-based risk assessment framework that analyses speeding, harsh events, and smartphone usage data collected from inertial sensors. To emphasise the flexibility and deployability of the smartphone system, they addressed two challenges associated with smartphones. The first challenge arises from using internal accelerometers to measure three-axis movement when monitoring driver behaviour. To ensure accuracy, the device's orientation must align with a standard reference frame [15]. However, drivers can freely reposition their phones at any time, which could disrupt this alignment. In order to address this problem, they developed a novel self-calibrating system that detects and adjusts smartphone positioning in the vehicle to ensure the reliability of the measurement. The second challenge involved balancing processing power with the smartphone's ability to capture driving distraction behaviour. To address this, the study analysed information content distribution in the frequency domain to find the most appropriate sampling rate for user-to-phone interaction scenarios. The study examined the spectra of the Euclidean norms for acceleration and angular velocity signals under three conditions: when the phone was actively used by the user, when it was rigidly connected to the vehicle, and when it was idle. The findings indicated that user-to-smartphone interactions could be reliably detected

TABLE 1. Summary of papers (all).

Citation	Main Topics	Driver Size	Data Collection Methods	Data Quality Emphasised	Methods	Risk Measures	Demographics Information Included	Contextual Information Included
Group 1: small book size								
[15]	Driving behaviour profiling and risk prediction	2	Smartphone	Yes	Predefined Cost Functions	Risky events	-	-
[16]	Driving behaviour profiling and risk prediction	6	Smartphone	-	Transformer Based Model, CNN, GRU CNN-GRU, Transformer-Encoder (T-En), Transformer-Encoder-GRU (T-En-G)	Risky events	-	-
[17]	Drivers' stress and interactions with vehicle systems	16	OBD Device	-	Correlation Analysis	-	-	-
[18]	Driving behaviour profiling and risk prediction	32	Smartphone	Yes	XGBoost, Random Forests, SHAP	Risky events	-	Yes
[19]	Telematics feedback and behaviour interventions	57	Smartphone	-	Generalised Estimating Equations Linear Regression Models	Risky events	Yes	-
[20]	Driver identification	57	Smartphone	-	Statistical Correlation Analysis, Multiple Regression, Deep Learning Algorithms for Driver Identification	-	Yes	-
[21]	Driver identification	95	CAN-bus	-	Siamese Temporal Convolutional Networks	-	-	-
[22]	Telematics feedback and behaviour interventions	174	Smartphone, OBD Device	-	Generalized Estimating Equations	Risky events	-	-
[23]	Driving behaviour profiling and risk prediction	314	Smartphone	Yes	XGBoost, SHAP	Risky events	-	Yes
[24]	Telematics feedback and behaviour interventions	373	GPS, In Vehicle Camera	-	ANOVA, Association Rule Mining	Risky events	-	Yes
[25]	Telematics feedback and behaviour interventions	382	Smartphone	-	Instrumental Variable Regression	Crash	-	-
[26]	Telematics feedback and behaviour interventions	397	GPS, Accelerometer	-	Generalized Linear Mixed Model	Risky events	-	-
[27]	Driving behaviour profiling and risk prediction	398	GPS, OBD, In-vehicle cameras	-	XGBoost, Logistic Regression, SVM Random Forest, Neural Network	Crash	Yes	Yes
[28]	Telematics Insurance Pricing	641	OBD Device	-	Poisson Model	Risky events	-	-
[29]	Telematics feedback and behaviour interventions	696	Smartphone	-	Kmeans, Deep Reinforcement Learning	Risky events	-	-
[30]	Telematics Insurance Pricing	973	Accelerometers, GPS, OBD	Yes	CNN, DNN, Poisson Regression	Claim	Yes	-
[31]	Driving behaviour profiling and risk prediction	1073	OBD, Smartphone	Yes	Poisson Regression, Negative Binominal Regression	Claim	Yes	-
[32]	Telematics feedback and behaviour interventions	1393	OBD Device	-	Neuro Fuzzy	Risky events	-	-
[12]	Driving behaviour profiling and risk prediction	2185	GPS, In-vehicle cameras	-	Poisson Regression, Zero Inflated Poisson Regression	Crash	-	-
[33]	Driving behaviour profiling and risk prediction	2500	Smartphone	-	Self Organising Map, Deep Auto Encoder, K-means Minibatch K Means, Agglomerative Clustering, Spectral Clustering BIRCH Clustering	-	-	-
Group 2: average book size								
[34]	Driving behaviour profiling and risk prediction	3440	Accelerometers, GPS, In-vehicle cameras, Radars	-	Regularized Logistic Regression	Crash	Yes	-
[35]	Driving behaviour profiling and risk prediction	3440	Accelerometers, GPS, In-vehicle cameras, Radars	-	Random Forests	Crash	-	Yes
[36]	Driving behaviour profiling and risk prediction	3542	Accelerometers, GPS, In-vehicle cameras, Radars	-	Decision Tree, SVM, DNN ELM, KNN, Random Forests	Risky events	-	-
[37]	Driving behaviour profiling and risk prediction	4500	Accelerometers, GPS, OBD	Yes	Correlation Analysis	Crash	-	-
[38]	Driving behaviour profiling and risk prediction	6000	-	-	MLP, CNN, LSTM	Crash	-	-
[39]	Driving behaviour profiling and risk prediction	8750	GPS, OBD	-	K Means, Gradient Boosting Classifier, CNN	Crash	Yes	Yes
[40]	Driving behaviour profiling and risk prediction	9585	-	-	Quantile Regression	Risky events	-	-
[41]	Telematics feedback and behaviour interventions	9879	-	-	LR, SVM, DT XGBoost, and bagging classifiers SHAP for interpretability	Crash	-	-
[42]	Driving behaviour profiling and risk prediction	12145	Black box	Yes	Logistic Regression, Random Forests, XGBoost Feed-forward Neural Network, LSTM	Crash	-	Yes
[43]	Telematics Insurance Pricing	25838	OBD Device	-	Generalized Linear Model, Gradient Boosting Machines	Claim	Yes	-

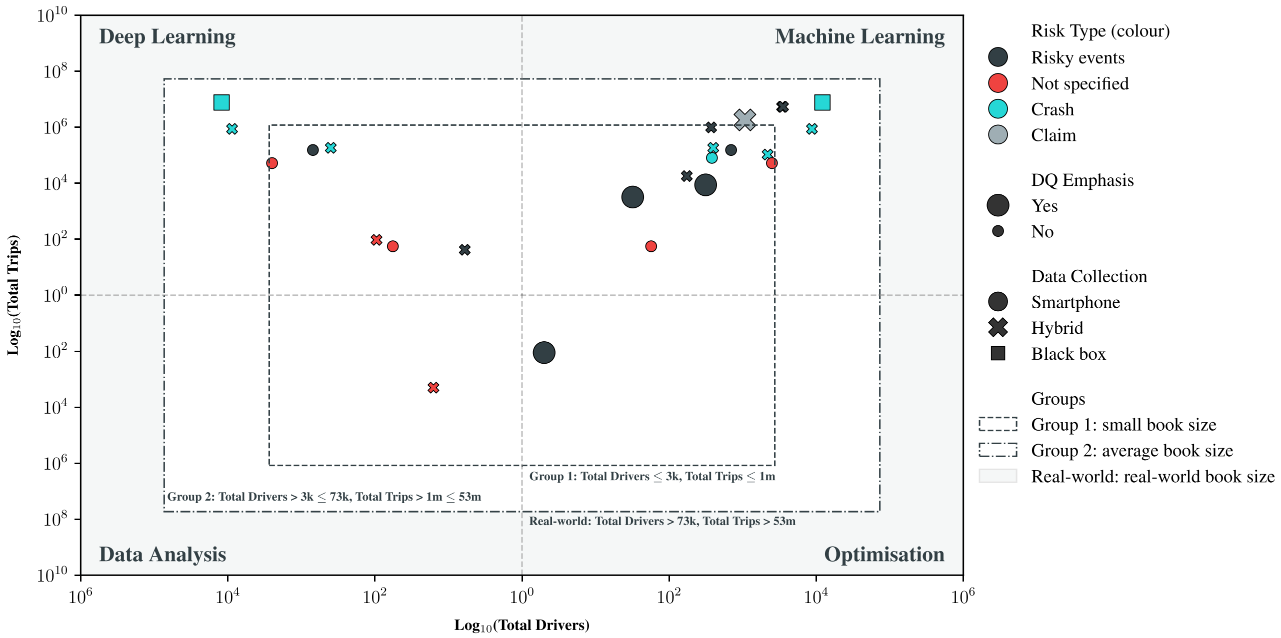

FIGURE 2. Papers specifying trips and driver information (20 papers).

using frequencies around 20 Hz. Accordingly, the sampling rate was set to 40 Hz, adhering to the Nyquist sampling theorem [44]. While [15] focused on general risk assessment using essential driving behaviour and distracted behaviour, the study [23] further included traffic and road geometry data into their framework and investigated the influence on the occurrence of harsh events. They adopted eXtreme Gradient Boosting (XGBoost) and explained the importance of different risk factors through Shapley Addictive Explanations (SHAP). As a result, they revealed that higher traffic occupancy, traffic speed, OpenStreetMap (OSM) segment length and road slope increase the probability of harsh events. Surprisingly, road network characteristics such as speed limits and lane count had a limited impact, and phone usage had a minor influence. Similarly, in [18], XGBoost was proposed to predict frequencies of speeding, harsh acceleration and braking and distracted events, with SHAP being used to rank the importance of 18 contextual features, including road type, weather, and traffic density. However, the results identified speed limit, weather, temperature, and road slope as the most critical predictors for multiple risky events. The findings on speed limits differ from those in [18], but they further support the statement made in [18] that speed limits are more impactful on the severity of harsh events than their occurrence.

Apart from incorporating phone-related distracted behaviour and environmental risk factors, [16] considered driver drowsiness a key risk factor. They analysed fluctuations in accelerations, lateral movements, speed and distance to vehicles ahead (from external sensors) to infer driver drowsiness. They categorised driving behaviour into three classes: drowsy behaviour, normal behaviour, and aggressive behaviour (analysed using speed, acceleration, and gyroscope data). Unlike other studies that commonly employed ML or DL models, this study proposed a more advanced transformer-based framework, which, in their experiments, outperformed existing DL models.

Instead of analysing driver risk based on the occurrence or frequency of risky events, the study in [31] investigated behaviour patterns in relation to their contribution to insurance claims. They introduced a speed transition matrix to represent speed variations over time, which, in combination with harsh events and driving time-related contextual data, revealed that large speed transitions, nighttime driving, and harsh braking are strong predictors of claim frequency by using Generalised Linear Model (GLM) models.

In [33], the focus shifted from predicting driver risk according to atypical driving behaviour to developing an unsupervised learning framework for extracting driving behaviour patterns from smartphone-based telematics data. The framework features three key components: (i) a self-organising map for reducing data complexity, (ii) a nine-layer deep autoencoder for feature extraction, and (iii) partitive clustering algorithms, such as k-Means Clustering (k-Means), MiniBatch k-Means Clustering (MiniBatch k-Means), Agglomerative Hierarchical Clustering (Agglomerative Clustering), Spectral Clustering Algorithm (Spectral Clustering), and Balanced Iterative Reducing and Clustering using Hierarchies (BIRCH), for grouping driving events into driving behaviours. Compared to supervised methods that commonly have target variables to predict, this unsupervised framework provides more flexibility in discovering different risks and requires less effort in collecting crash and accident data, as well as dealing with the imbalance problems associated with them [23]. They also emphasised learning effects in driving, where severe, harsh events decrease as driving experience increases, suggesting that risk accumulation is non-linear. Furthermore, they discussed data quality challenges in processing large-scale telematics data, which is critical in real-world applications and will be discussed in more detail in Section IV-A.

Apart from using smartphone telematics data, studies [12] and [27] adopted multiple sensors, including GPS, OBD and In-vehicle cameras. The inclusion of cameras not only highlights their potential for integration into MHYD models, but also allows for the detection of a broader range of distracted behaviours by analysing driver facial expressions, such as yawning, eye closing and smoking [12], [27]. To further improve predictive accuracy for crash probability, [27] also included weather and driving time as additional risk factors. By using the best-performing model (XGBoost), they identified that factors such as speeding, sharp turns and distractions significantly influence crash risks. A similar finding on the impact of distractions on crashes was reported in [12], where, to predict crash occurrence, the authors introduced a GLM based risk assessment model specifically designed for commercial truck safety.

2) STUDIES WITH AVERAGE BOOK SIZE

Unlike the predominant use of smartphones as a data collection method in studies with smaller datasets, all studies in this group adopted hybrid telematics devices. In addition, this group primarily focuses on modelling crash-based risk, whereas the small dataset group mainly focuses on risky events-based risk. This difference could be attributed to the fact that studies that adopted larger datasets generally collaborate with insurers or fleet operators, who use professionally graded devices and have access to crash history data, whereas smaller-scale studies lack these advantages.

The work presented in [35] and [36] contributed to driver risk assessment by proposing a driver crash probability prediction framework. In [36] especially, a Random Forest (RF)-based method was proposed to predict crash probability using telematics driving data incorporated with contextual information. However, when using the same RF-based model, the model incorporating contextual information led to worse performance than predictions without contextual information, despite outperforming other machine learning methods such as Support Vector Machine (SVM).

In [42], the authors aimed to improve the accuracy of their accident risk prediction models by incorporating geographical context features, such as weather, points of interest, and land use. They evaluated five popular machine learning classifiers: Logistic Regression (LR), RF, XGBoost, Feed-Forward Neural Networks, and Long Short-Term Memory Networks, for differentiating accident and accident-free drivers. Using the largest dataset among all the studies (12, 145 drivers' worth of data collected from a "black box"), XGBoost achieved the best overall performance with geographical information incorporated (model accuracy improves by up to 8% in Area Under the Curve (AUC)),[3] and LR performed slightly better when the geographical information was absent. LSTMs, however, did not outperform the other methods. This underperformance of LSTMs could be attributed to multiple factors, such as the relatively smaller training dataset and different data aggregation methods. LSTMs used trip-level aggregated features. In contrast, the rest of the models use yearly-aggregated features for each driver, which may have resulted in sparser input data for the LSTMs.

With similar aims of improving driving risk prediction as [39] and [42] includes both geographical information and traffic flow information to refine drivers' risk levels to low-risk and high-risk. This study used a slightly smaller data size of 8, 970 drivers, collected from the OBD port, GPS and accelerometers. Unlike [42], which simply used historical car accident occurrences as risk labels for each driver, [39] employed k-Means to refine these risk labels. Specifically, the authors constructed risk labels by clustering drivers into risk cohorts based on their driving and contextual data. Their past at-fault accidents were then compared with the statistics of the clusters to assign low-risk or high-risk labels. For risk prediction on unseen data, a Gradient Boosting Classifier (GBC) and a Convolutional Neural Network (CNN) were compared, with the CNN demonstrating better performance. Similar results were reported by [38], where the CNN outperformed both the LSTM and Multilayer Perceptron (MLP). However, [38] used accident occurrence as risk labels and represented telematics driving data using a novel traffic entropy matrix. This representation was derived by transforming raw driving data with speed-related variables into abnormality degrees, using a probability-based function inspired by Shannon entropy [45], where higher deviation from typical driving behaviour data corresponds to higher entropy values. This representation was developed not only to improve prediction accuracy, but also to enhance the interpretability of DL models.

The work in [34] improved the traditional predefined threshold-based models by proposing a decision-adjusted driver risk prediction model that optimises the threshold selection for acceleration, deceleration, and lateral movement, in crash risk prediction.

The aforementioned studies all incorporate crash history data, however, such data is often scarce. In order to address the scarcity problem of using crashes as a risk indicator, [37] investigated new metrics for driver risk representation. They performed a correlation analysis between driver behaviour

[3] AUC shows how well a model can tell the difference between two groups in binary classification tasks, with 1 meaning perfect and 0.5 meaning random guessing.

indices, derived from speed, harsh event rates, traffic flow (estimated by total speed counts in different road segments), free flow condition (estimated by the ratio of mean speed in a given road segment and the corresponding speed limit of the segment), and crash frequencies. A strong correlation was found between these indices, and thus new safety metrics, represented by speed corridor maps and hot spots for hard braking and acceleration, were proposed and evaluated. Their findings further support using risky events as an alternative to crash data for risk assessment.

The study in [40] focused on a risk assessment framework for speeding using percentile charts. By using quantile regression models, percentile distributions of speeding behaviour (measured by the number of kilometres driven above speed limits) were estimated based on essential telematics variables and demographic information. They found that the most relevant variables in explaining speeding are total distance driven, the percentage of urban driving, and gender. The simplicity and interpretability of this framework make it a promising candidate for feedback-based MHYD models.

3) SUMMARY OF CONTRIBUTIONS IN DRIVING BEHAVIOUR PROFILING AND RISK PREDICTION

The key contributions in this area focus on improving the accuracy of driver risk assessments, deepening the understanding of contributing risk factors by optimising model selections, and incorporating comprehensive risk factors, such as distracted behaviours and contextual information.

Over half of the studies employ ML and DL methods, with XGBoost consistently demonstrating superior performance across both groups, while CNNs perform better in the group with average book size. The incorporation of distracted and contextual risk factors and essential telematics variables mentioned in Section II-B has gained increasing attention among these studies. Phone-related distracted events are especially prevalent for studies in small book-size groups due to the advantage of using smartphones as data collection methods. Distracted and contextual risk factors (especially weather-related) have been shown to significantly impact driver risk.

However, less attention has been given to data quality, despite GPS sensors being used in every study and smartphones becoming increasingly common for data collection. These two factors often have inherent limitations that can compromise data accuracy. Furthermore, with an increasing number of studies highlighting the critical influence of contextual data on driver risk, greater attention is needed on the quality of such contextual data as well, especially for weather data, which has been demonstrated to be one of the top factors affecting driver risk but suffers from accuracy issues. In addition, as the volume and variety of contextual data expand, their models become increasingly complex, particularly in DL methods, because these models tend to capture intricate patterns between multiple contextual information. Thus, this additional information could further reduce model interpretability without explainable techniques due to the significant increase in internal parameters. However, no studies we have reviewed account for this aspect when applying DL approaches.

Another problem is that most studies (12 out of 16 papers) lack a description of demographic information for their datasets. For those studies that included such information, their data mainly focused on individuals under the age of 40. Predictive models derived from such data may not adequately capture the behaviour and risks associated with older drivers, whose driving patterns may differ significantly due to factors such as more experience, slower reaction times, and different usage of vehicles.

Data quality (reliability), model interpretability, and demographic biases are crucial to ensure practical and equitable applications of telematics-based risk assessment. However, these factors are less apparent when the dataset is small. These limitations raise concerns about the reliability of the relevant results and the feasibility of their real-world applications, highlighting the need for greater awareness and attention. A more detailed discussion on these challenges will be presented in Section IV.

B. DRIVING RISK INTEGRATION WITH PRICING SCHEME

In the context of telematics insurance, the outcome of driving profiling and risk assessment (discussed in Subsection III-A) will ultimately be integrated into insurance pricing models to promote dynamic and personalised premiums. While the studies discussed in III-A have not extended their findings to this integration, three papers have provided details on this process.

1) STUDIES WITH SMALL BOOK SIZE

Two studies, [28] and [30], focus on integrating telematics data into insurance pricing schemes. In both studies, Poisson GLMs are used for baseline pricing modelling with predicted claims, but different models are employed for updating the basic price based on telematics data from OBD devices. In [30], telematics data are introduced as a risk factor calculated using speed-acceleration heatmaps with a Deep Neural Network (DNN) and a CNN. It demonstrated that while CNN had a similar predictive performance as DNN, CNN is a better choice due to its lower complexity regarding the number of parameters used in the model. Additionally, the authors used a linear approximation, which explains how specific regions in the speed-acceleration heatmaps contribute to the risk outcomes, to address concerns about the interpretability of the CNN. Their findings highlighted that harsh braking behaviour plays a more significant role than acceleration in predicting risk. Given the positive correlation between harsh braking or acceleration behaviour and claim frequencies, [28] promoted weekly updated premiums by incorporating such information as ‘‘near-miss’’ events into pricing models. Unlike [30], which incorporated a DL model as a factor into the baseline model, [28] is considered to have better interpretability by incorporating these harsh behaviour risk factors directly into the same Poisson GLM as in the baseline model. The use of "near-miss" events as target variables for adjusting insurance prices also dealt with the low-frequency problems of weekly claim data.

2) STUDIES WITH AVERAGE BOOK SIZE

One study that utilised the largest dataset of 25, 838 drivers [43], expanded the use of telematics data in insurance modelling by applying it to both claim frequency and claim severity predictions, though they found that telematics data was less informative in predicting claim severity. Unlike other studies that use Poisson GLMs to predict baseline premiums, this study adopted a Generalised Boosted Model (GBM) and used the Poisson GLM for premium updates based on telematics driving data. Compared with [28], [30], and [43] incorporated a larger range of telematics information, including not only risky events but also driving exposure variables such as mileage, road types, and time of day.

3) SUMMARY OF CONTRIBUTIONS IN DRIVING RISK INTEGRATION WITH PRICING SCHEME

The progressive integration of telematics data with pricing models has shifted premium adjustment from traditional actuarial approaches to ML-driven methodologies. Recent studies [28], [30], and [43] have explored two ways of improving traditional pricing models: by replacing baseline pricing models with more advanced ML models or by improving telematics-based risk representation within the existing baseline models.

Though studies in this area remain limited, existing research has highlighted the critical role of explainability in pricing models, especially for telematics-based risk factors. While several studies have proposed DL based models for representing telematics driving risks, these studies mainly tested on datasets with fewer than a few thousand drivers. As a result, the operational efficiency and the interpretability when applied to large, diverse and noisy real-world driving data remain unknown. Notably, the study with the largest dataset opted for a simpler and more explainable model for telematics-based risk modelling.

C. TELEMATICS FEEDBACK AND BEHAVIOUR INTERVENTIONS

Telematics-based feedback and behavioural interventions, which build on driving behaviour analysis in MHYD models, have become a growing focus in recent studies, as it aligns with the ultimate goal of telematics insurance to reduce claim rates and improve road safety. 7 out of the 30 papers have explored this area.

1) STUDIES WITH SMALL BOOK SIZE

Study [19] focused on the impact of feedback on risky driving behaviour among young drivers aged 17 to 20. The authors investigated the impact of smartphone-based telematics feedback on young drivers' speeding, harsh braking, and harsh acceleration over 11 weeks. These metrics are measured using a score ranging from 0 to 5 based on predefined thresholds. For example, the speeding score is measured by the proportion of time a driver exceeds the posted speed limit, and the harsh braking and acceleration are measured using the g-force thresholds (as mentioned in Section II-B). The overall driving performance score was calculated as the average of these individual scores. Although the study found no significant overall difference between control and intervention groups, drivers in regional areas (compared to metropolitan) and female participants improved some aspects of their driving behaviour.

Using a similar smartphone-based telematics feedback approach, [22] evaluated its impact from a financial incentives perspective. Over a 28-week period, they divided drivers into three groups: one receiving feedback only, another receiving feedback plus financial incentives, and a control group. The feedback group received weekly driving performance assessments (using similar score measurements as in [19]), while the incentivised group lost financial rewards if their driving score dropped below a certain threshold. Although no significant improvements were found in individual scores for speeding or harsh events among different groups, when using an overall score that aggregates all three individual scores, significant improvements were shown in the group receiving feedback with financial incentives. This finding suggests that drivers in the incentive group made small but consistent improvements across all individual behaviours, and providing feedback alone may not be enough to change driver behaviour, but pairing it with financial consequences could be more effective in reducing risky driving behaviours. A similar impact of financial incentives was found in a study [26] across a period of 56 weeks, which evaluated financial incentives on reducing speeding behaviour among taxi drivers. This study further supports the notion that financial incentives, especially penalties, are more effective in influencing driver behaviour. However, the study also found that the speeding behaviour returned to previous levels once the intervention ended, which highlights the necessity of continuous intervention for long-term behavioural change. [32] found a similar decline in improvements among taxi drivers after feedback was discontinued, though with a shorter intervention period (17 weeks). However, interestingly, the improvement effect persisted among bus drivers, which could be attributed to their sense of continued monitoring and/or the larger sample size for bus drivers (over 1, 000) compared to 104 for taxi drivers.

While most studies in this area have demonstrated a positive impact of personalised feedback on driving performance changes, [25] found that immediate feedback (provided directly after journeys) may have negative consequences. They found that immediate feedback could actually worsen driving performance by nearly 14.9% on average. This deterioration was mainly driven by increased speeding, suggesting that some drivers became overconfident after receiving positive feedback. In contrast, drivers who received negative feedback, especially those whose performance scores were just below the financial reward thresholds, were likelier to improve their behaviour.

The findings from [25] highlighted the importance of carefully designing feedback systems. Building on this insight, study [29] developed an enhanced self-aware driving recommendation system using Deep Reinforcement Learning (DRL), which provides driving recommendations according to individual styles and preferences. More specifically, two customised reinforcement learning controllers were developed based on Deep Deterministic Policy Gradient (DDPG) algorithms [46], which were used for generating optimal driving recommendations specific to each driving profile (based on their acceleration, braking, speeding, and mobile phone usage) identified by k-Means clustering. The system's evaluation was performed under a real-time microscopic simulation, and interesting results were found. In particular, it was observed that while the suggestions led to safer and less aggressive driving behaviour for individual drivers, they did not improve overall traffic flows. By following the recommendations, vehicles tended to have increased spacing, which reduced road segment density (the number of vehicles per unit length of road). However, the tendency to have lower average speeds deteriorated road throughput in certain areas.

2) STUDIES WITH AVERAGE BOOK SIZE

One study features the largest driver sample size 9, 879 [41], compared to the rest of the papers (below 1, 393) under this topic. Similar to [29], this study focused mainly on the design of the feedback systems. Unlike [29], which uses clustering for classifying driver behaviour, [41] employed a supervised learning framework due to the availability of historical crash data. Consistent with most of the studies in Subsection III-A, XGBoost was mainly used for classifying accident or accident-free drivers. SHAP values and a Multi-Counterfactual Model (MCM) were used to support the design of feedback and the corresponding mitigation strategies.

3) SUMMARY OF CONTRIBUTIONS IN TELEMATICS FEEDBACK AND BEHAVIOUR INTERVENTIONS

Most studies on this topic fall into the small book-size group, focusing on the impact of personalised feedback or recommendations on driving performance changes, which are measured by performance scores derived from risk events. On the other hand, studies using larger datasets tend to focus on the design of feedback systems.

A key finding in this area is that feedback alone has a limited impact, whereas financial incentives enhance behavioural improvements, though these improvements often fade over time. This suggests the need for continuous intervention for sustained behavioural change. Another finding is that the timing and the actual content of feedback significantly affect its effectiveness. Real-time warnings might effectively prevent risky behaviours, while post-trip feedback might trigger psychological responses that influence driver behaviour differently. This further highlights the challenge of designing effective feedback systems in MHYD insurance models.

However, a key limitation of these studies is whether any changes in driving behaviour are directly attributable to drivers engaging with the feedback. Many studies that deliver feedback through text messages face the challenge of determining whether participants actually read the feedback. This uncertainty makes establishing a causal relationship between the intervention and behavioural changes difficult. However, for feedback provided through smartphone apps, researchers can track whether drivers accessed the feedback page, but this approach does not reveal whether drivers meaningfully engaged with the content or skimmed through it. Apart from this aspect, the long-term effectiveness of a large population is still unknown. The research periods of most studies are shorter than a year with fewer than 1, 393 drivers, during which participants were aware of their involvement in a research project. This awareness raises concerns about long-term adherence, as drivers may eventually lose interest or become disengaged from the system.

D. OTHER TOPICS

There is a unique study [17], which analyses driving behaviour in terms of factors from drivers' stress levels (measured by heart rate and electrodermal activity) by using multiple sensors, including telematics devices, biometric sensors and cameras. They identified that external factors, such as bad weather and high traffic density, contribute to increased stress, while in-vehicle interactions, such as having passengers in the car, generally reduce stress, especially in lower-speed situations. This stress reduction could reduce risky behaviour. Their findings explained how contextual data influences driving by affecting stress levels and highlighted the connection between drivers' emotional states and driving risk. Such insights could benefit insurers in developing MHYD insurance products that account for psychological factors for driver risk assessment. For example, a driver with lower stress levels in high-traffic situations might be considered a lower risk than one with high stress under the same conditions. This additional layer of analysis could potentially contribute to fairer premium rates and improve customer satisfaction, though, at present, the feasibility of deploying such systems on a large scale is still limited by technology costs or customer acceptance of physiological monitoring as part of their driving [4].

While previous studies mainly analyse driving behaviour for assessing risk purposes, studies [20] and [21] focus on using telematics driving data for driver identification. In [21], the authors proposed a DL-based framework to extract driving styles based on 30-second windows of steering data from the OBD port, aiming to support driver identification, verification and imposter detection. Their proposed method, Siamese Temporal Convolutional Network (STCN), was evaluated on 95 drivers and outperformed both traditional ML models and Recurrent Neural Network (RNN)-based models.

Unlike [20], [21] focused on evaluating the reliability of an existing smartphone-based driver identification system in real-world scenarios rather than developing a novel approach. Both studies contribute to UBI models by enhancing fraud prevention, potentially reducing financial losses from claims fraud. However, questions remain on the scalability of the methods proposed in [21]. Beyond the computational cost of STCNs for learning each driver's profile in the database, the proposed framework for imposter detection involves comparing each new input with all the driver profiles in the database. As the data volume increases, the computational burden grows quadratically, due to pairwise comparison, and is also multiplied by the computational load associated with data passing through the DL based models.

IV. ASPECTS OVERLOOKED BY RECENT STUDIES

Although recent studies have advanced the understanding of driver behaviour and risk assessment by incorporating diverse data sources and adopting more advanced modelling techniques, limitations remain in scaling their findings in real-world insurance applications. One key limitation is the usage of relatively small datasets with a limited number of drivers. Compared to large-scale real-world data, this constraint may hinder the identification of critical issues related to data quality and model complexity, especially as the incorporation of contextual data into telematics models becomes increasingly prevalent. In addition, less emphasis has been placed on the demographic representation of training data and the interpretability of modelling techniques. Both of these are crucial in telematics insurance, not only for ensuring model generalisation but also for complying with regulatory requirements.

The following subsections will highlight these key aspects, which have received limited attention in the existing research, but are critical for ensuring the robustness, scalability, and real-world applicability of their results in telematics insurance.

A. THE IMPORTANCE OF DATA QUALITY CONTROL

Data quality can be understood as ensuring that the data gathered can be trusted to accurately assess driver behaviour and determine the associated risk. As highlighted by [8], addressing data quality issues can easily consume more than 90% of the total time required for modelling. This underscores that data quality challenges are ubiquitous in large-scale telematics insurance datasets and that careful consideration of data quality is essential before implementing any machine learning or statistical techniques. Unfortunately, these issues received insufficient attention in recent studies.

1) GPS-RELATED PROBLEMS

Telematics systems rely on either independent GPS sensors or devices integrating GPS to monitor telematics variables, such as speed, location, distance and time. However, GPS data often have inherent limitations [4]. One common issue is the presence of missing GPS records; when this occurs, GPS data will show zero readings [8]. Missing data could result in a lack of information for detecting harsh driving events, such as harsh braking or acceleration, especially for those studies using threshold-based or cost-function-based methods, as these rely highly on continuous data. For example, in [15], GPS speed data was used to estimate longitudinal acceleration. It was also pointed out that the method would not work if the GPS speed data were missing. Such missing data can be problematic in many scenarios. For instance, missing data may make it difficult to identify the start and end of "a trip" [31]. This is crucial for studies that rely purely on smartphone-based telematics, such as in [33], as the recognition of trips mainly depends on change detections in speed and location. In addition, the distance or the time driven in the trip can be overestimated or underestimated because of the incorrect segmentation of the trip duration. This can particularly affect PAYD models. Also, if missing data occurs during a crash, critical evidence will be absent from claim processing, which potentially causes problems for both the drivers and the business. Furthermore, missing GPS data may be a result of drivers manipulating their driving data. For example, a driver may disable the tracking temporarily to hide risky driving behaviour, which could potentially cause financial loss or impact any risk modelling/analysis.

GPS also suffers from inaccuracy problems, such as location data jumps, which make it look like a vehicle suddenly moves a significant distance within a short time. This, in turn, can directly affect speed readings, potentially causing errors in speeding event detection. For example, in [41], the authors considered drivers to have high exposure on the road if they had a higher fraction of driving over "40 km/h". If GPS jumps were not detected, the driver's exposure risk might not have been correctly identified.

Another common problem is GPS drift, where the recorded GPS positions deviate from the road [37]. This problem particularly affects the use of GPS location data to retrieve corresponding geographical information, such as speed limits or road types. The reason is that GPS drift can cause misalignment between the location data and the road segment information, which may result in a driver being matched to the wrong speed limit or road type. Several studies use the comparison of speed limits and driving speed to define "speeding" behaviour, such as [29] and [40], where a speeding measure is calculated based on the distance or time driven at speeds above the corresponding speed limits, and in [19], the authors count the frequency of drivers' speeds exceeding the speed limit. The failure to detect the GPS drift problems could cause drivers to be wrongly flagged as speeding, thus leading to incorrect risk assessment.

Map-matching is a process of aligning raw GPS data with a known digital road network to determine a vehicle's actual path [39], [47]. Figure 3 shows an example of GPS drift. The map-matched route (line markers) accurately follows the intended path, while raw GPS samples (circular markers) show deviations that place points on incorrect roads. This demonstrates how GPS inaccuracies can result in erroneous road attribution and speed estimation without the application of map-matching techniques. Though some studies, like [18] and [37], posit that map-matching can be used to align data points to the correct road segments, the map-matching itself also faces several challenges in real-world implementation.

A significant GPS drift can cause the recorded position to be considerably far from the actual road, leading to a wrong nearby road being chosen or making it difficult to match to any road in the area. To counter this, a visual inspection was conducted in [23] to ensure the correctness of the results of map-matching. This approach may work with a low number of trips (8, 756 in the case of [23]), but it is impractical to implement for millions of trips in large-scale real-world insurance datasets. The map-matching process also becomes particularly challenging when dealing with low-sampled telematics data. For example, infrequent or sparse GPS recordings can lead to significant positioning errors, especially in complex urban environments with a dense road network [39]. Consequently, the map-matching results in [37] may not be reliable due to the 30 second sampling rate used. Similar challenges may also apply to [31], which uses minute-level sampling rates.

2) SMARTPHONE LIMITATIONS

Smartphones, though considered a cheaper and more versatile alternative to box-based devices for collecting telematics data, can have more limitations in terms of data quality when deployed in insurance applications.

GPS problems significantly impact pure smartphone-based telematics, as, unlike some box-based devices, they do not benefit from collecting internal vehicle data, such as vehicle speed via the OBD port, which is less affected by GPS signal loss or inaccuracy problems. In addition, the sheer variety of phone models is, in and of itself, a problem as each different phone can house different quality sensors, all potentially having different sensing and reporting capabilities and standards. Moreover, the state of the phone itself can impact the quality of the collected data. For example, a phone with a low battery may reduce the sampling rate of sensor data or stop using that sensor completely until recharged.

Besides the problems with GPS sensors that smartphones inherit, they also face positioning problems. Generally, when using smartphones to monitor driving behaviour, the phone needs to be placed in a fixed position to ensure accurate measurements of the accelerometer data [1]. More specifically, the internal accelerometers of phones are generally used to measure three-axis movement. To ensure accuracy, the device's orientation must align with a standard reference frame [1]. However, drivers can freely reposition their phones at any time, which can disrupt this alignment. For example, if a smartphone is placed loosely in a cupholder, and the vehicle experiences a sharp cornering event, this behaviour can be recorded incorrectly as a minor turning, as the phone only moves slightly. Conversely, if the phone is in a compartment or on the seat, minor vibrations from the road may incorrectly cause harsh event recordings in the phone, resulting in inaccurate aggressive driving behaviour detection [48].

Among recent studies, 10 studies adopted smartphones in their data collection process. Some of them acknowledged the inherent GPS sensor problems [18], [23], [31], but only one study [15] emphasised the orientation problems of smartphones. Furthermore, this study [15] also introduced an automatic recalibration method that detected when the phone's orientation changed and realigned sensor data to maintain the data reliability.

Some studies use additional methods, such as pairing smartphones with Bluetooth-enabled tags [19] or combining with OBD devices [31], to help mitigate problems of smartphone-only solutions. However, these approaches may ultimately compromise the cost and versatility advantages of smartphones.

3) DATA INCONSISTENCY FROM MULTIPLE SENSORS

The problem of data inconsistency from different sensors refers to a situation where the same values, such as speed and acceleration, are measured by multiple sensors (GPS, accelerometer and OBD port) but produce mismatched results; see [8] for related illustrated results. This inconsistency arises due to the GPS issues or smartphone-related problems mentioned earlier.

For driving behaviour analysis using multiple sensors, it is important to evaluate the data from different sources and identify or infer the most reliable data to ensure accurate driver risk assessment. Although the defects of GPS signals were acknowledged in [30], prompting the study to rely on the speed data from OBD streams, most studies that adopted multiple sensors failed to account for this issue. This lack of attention raises concerns about the validity of the resulting risk assessment models when applied in real-world scenarios, where sensor discrepancies are common and can lead to misinterpretation of driver behaviour.

4) SAMPLING RATE

In telematics, the sampling rate is the frequency at which data points, such as speed, acceleration and GPS location, are collected during a trip. Generally, higher sampling rates in accelerometers enable detecting a wider range of driving behaviours, most importantly, crashes, which occur within milliseconds. Figure 4 compares accelerometer readings at different sampling rates. The 400 Hz sampling captures the high-energy impact event in detail, as highlighted within the (shaded) event window, while the 1Hz sampling misses the transient crash dynamics entirely.

For this reason, using a higher sampling rate is crucial when the objective is to predict crash or accident risk. Otherwise, crash-related features might not be captured or might be inaccurately recorded. In recent studies, nearly half of the studies aimed at predicting crash risk. However, while an extremely high sampling rate may not always be necessary

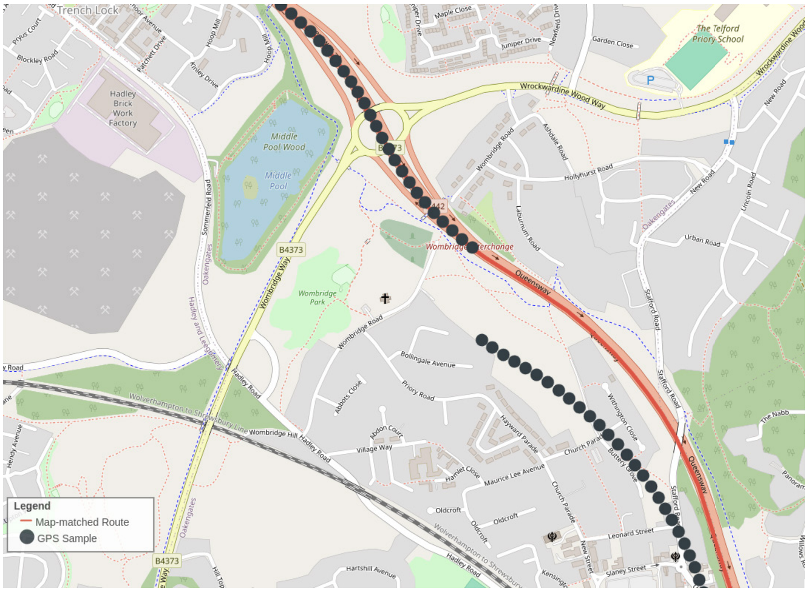

FIGURE 3. An example of map-matching for GPS drift with the map-matched path represented by line markers and the actual recorded path represented by circular markers.

for crash risk prediction (as opposed to crash detection), the low-resolution nature of some of the studies' datasets might limit the accuracy of their results due to a failure to capture the rapid dynamics of vehicles. For example, it can be acceptable to use a combination of a sampling rate of GPS at 1 Hz and accelerometer at 10 Hz, as in studies [34] and [35]. Using a sampling rate at around 0.03 with GPS and the OBD port may have limitations in explaining the correlation between the crash frequencies, harsh events, and speed, as in study [37], since some critical motions contributing to crashes might not be captured. In addition, some studies, namely [12], [25], [41], did not provide information on the sampling rates they adopted, which raises concerns about the reliability and generalisability of their findings, because without details on data resolution, it becomes challenging to assess whether their models effectively capture critical driving dynamics or memorise the data they used.

Overall, a higher sampling rate means that larger volumes of data points are generated, posing challenges in data storage, processing and analysis costs. Determining the right sampling rate that can balance the associated cost and the ability to capture vehicle dynamics is thus an essential task in telematics insurance.

5) IMPACT IN REAL-WORLD SETTINGS

Failing to account for data quality can have significant consequences for both insurance providers and policy-holders. Incorrect risk assessment outcomes due to the above-mentioned problems can lead to unfair premium adjustment in UBI insurance models, where safe drivers might be unfairly penalised by risky behaviours they did not perform. This can put a business's reputation at risk as customers are penalised for errors out of their control or businesses may face legal and regulatory fines for violating insurance regulations and consumer protection laws [49]. Additionally, if the missing or inaccurate data problems were manipulated by certain individuals or caused some risky behaviours to be overlooked by insurers, lower premiums or higher rewards might be offered to high-risk drivers.

B. THE IMPORTANCE OF THE VARIABILITY OF DEMOGRAPHICS IN MODELLING DATA

Telematics insurance can reduce demographic bias by focusing on driving behaviour rather than age or experience. This allows young and older drivers, often charged higher premiums under traditional models, to access fairer rates through usage-based insurance products.

However, even though telematics insurance reduces reliance on static demographic factors, its effectiveness still depends on how well telematics data captures and interprets driving behaviour across diverse populations, as driving behaviour itself is not fully independent of demographic factors. When developing a risk assessment model from driving behavioural data, the ideal model should be able to distinguish genuine risky behaviour, which increases the likelihood of accidents, from demographics-related traits that do not necessarily contribute to accidents. For example, young drivers generally exhibit more aggressive driving behaviour than older drivers [6]. However, the risk level associated with the same degree of aggressiveness can be lower than that of older people due to their faster reaction times.

Thus, it is important for relevant studies to include diverse populations in their dataset to capture natural variations of driving behaviour and provide demographic information to avoid the biased usage of their results in practice. However, in recent studies, only 8 out of 30 papers provided this information. The rest either neglected to provide this

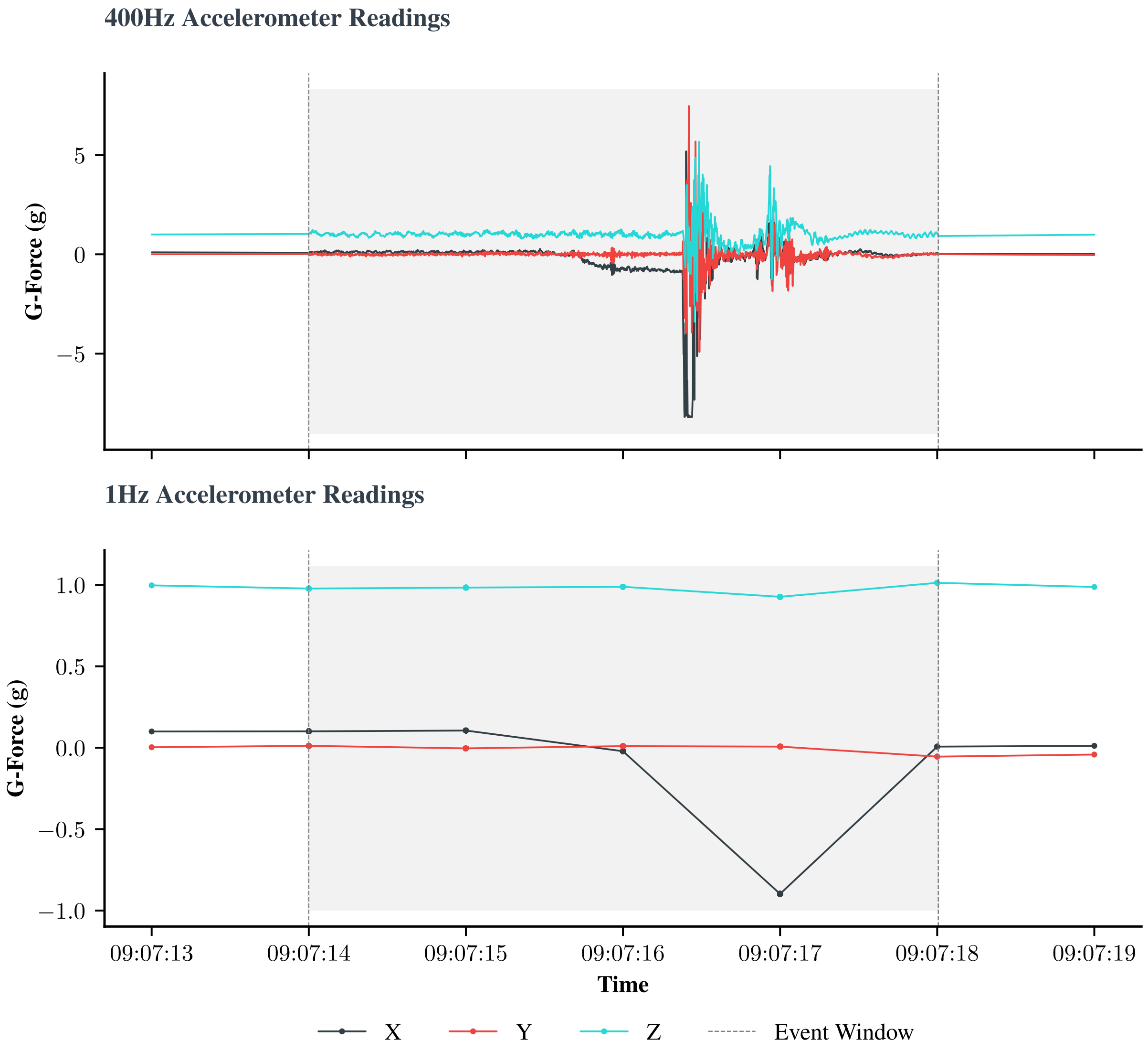

FIGURE 4. Comparison of accelerometer readings at 400 Hz (top) and 1 Hz (bottom) sampling rates.

information or failed to account for this factor. Even among the studies that provided demographic information, the age factor is often omitted or underrepresented. For example, in [31], this factor was not considered in their GLM models due to a large percentage of missing data. However, they claimed no significant differences were observed in policyholders' available age data with and without claims. In [40], only drivers between 25 and 35 were considered, which means their results on risky driving can only be applied to a specific population.

While it is understandable that fully accounting for all demographic factors is challenging, it is important to acknowledge and understand their potential impact. The model may introduce bias if derived from a specific or uniform demographic group. For example, if a model is trained only on the driving data of young males, which may feature more aggressive driving behaviour [6], experienced older drivers may, in turn, incorrectly be classified as unsafe due to dissimilar "less aggressive" driving styles. Similarly, if a model is derived using data from urban drivers, who typically drive at lower speeds, it may not accurately predict risk for motorway drivers who generally maintain higher speeds. Ultimately, this lack of demographic diversity in telematics data can be a barrier to achieving fair products in telematics insurance.

C. THE IMPORTANCE OF THE INTEGRATION OF CONTEXTUAL INFORMATION

Contextual data, such as weather, road types and traffic conditions, play important roles in complementing risk factors and improving model accuracy [1], [6], [8]. For instance, [33], the authors defined the behaviour of "driving at normal speed" as driving with speed around 50 km/s and acceleration at $0.3g$. Clearly, this may not be representative across different driving conditions, such as urban driving and motorway driving. Contextual data provides a more complete picture of the driving environment and conditions, which enables more precise prediction of the associated risk.

Several recent studies have contributed to the incorporation of contextual data in driving behaviour analysis from the following aspects: (i) studies in [35], [39], [42] focus on enhancing the risk assessment models with contextual data, and (ii) studies in [18], [23], [24] explored how risky contextual factors influence driving events. These studies have highlighted the value of contextual data in improving risk assessment. Some also discussed several challenges and suggestions in incorporating such data at scale from both data and model perspectives. For example, both [23] and [42] expressed concerns about data availability and reliability for historical contextual data (such as historical regional traffic information or static geographic data, which might be outdated and might fail to capture the actual driving conditions) and suggested the usage of real-time data. From the perspective of model accuracy, [18] highlighted the challenges of the over-fitting problems of RF and XGBoost on data with complex contextual features, and suggested that DL-based methods could be better options.

While these challenges are important to consider during the model development stage, the technological complexities and financial costs of integrating contextual data are also critical for real-world telematics applications. However, these factors have not been adequately discussed in recent studies. From a data processing perspective, incorporating more data from external sources, such as geographical features, weather and traffic occupancy, can introduce additional data quality problems. For example, in [23] and [42], OSM data was used for incorporating geographic data. However, except for the outdated data issues they mentioned, the open platforms like OSM may also contain missing or inaccurate speed limit data. In large-scale telematics data, this could significantly increase the burden of data cleaning, imputation or validation processing. Moreover, one aspect that these studies mentioned is that real-time weather data would be a better choice for dealing with issues of an outdated historical dataset. However, real-time data also presents spatio-temporal issues, as mismatches in both location and time can occur. For example, in [18], real-time weather data was integrated with driving data. However, if the recorded weather conditions' timing and location misalign with the precise driving moments and places, the weather data may not accurately reflect the actual driving conditions. This problem could potentially lead to unfair claim evaluations, such as when a driver files a claim for an accident that occurred during harsh weather, but the data does not indicate the condition.

Additionally, the actual cost of transmission of the real-time data source has not been discussed, which significantly limits the practicality of such data in large-scale deployments. In [23], real-time traffic data were integrated into telematics driving data, which comprised nearly 930, 000 cropped trips collected over 12 days, with an average duration of around 220 seconds. In real-world applications, incorporating traffic flow data from robust sources such as TomTom [50] for such a volume of data could result in an estimated cost of over £4, 000. However, it is important to note that this trip data was derived from 314 drivers, whereas the number of drivers in a real-world setting is typically significantly larger than this, which would substantially increase the associated costs.

In summary, while the benefits of incorporating contextual information into telematics data are well recognised, it is important to consider the trade-off of possible improved model accuracy against the increased processing complexities of data validation and additional costs associated with acquiring such data.

D. INTERPRETABILITY OF RISK ASSESSMENT MODELS

Interpretability of risk assessment models plays a critical role in telematics insurance due to regulatory and compliance transparency requirements [8]. With the growing popularity of ML methods in driving risk assessment [6], the complexity of these models often leads to difficulties for both the insurers and policyholders in understanding how risks and corresponding premiums are calculated. This lack of interpretability can result in insurance companies facing regulatory charges and a decline in customer satisfaction, especially when customers are penalised for risk factors that are not clearly explained.

The incorporation of contextual data is beneficial for improving the interpretability of the risk assessment process, especially when using ML methods coupled with SHAP values, as noted in [18], [23] and [41]. However, there is still insufficient emphasis on interpretability or transparency of driving risk assessment models, especially in studies using novel DL based methods. The work presented in [21] used STCN to learn similarities in steering behaviours among drivers for driver identification and impostor detection. However, this study did not attempt to interpret its models. Though the primary focus was on model performance, from an insurer's perspective, the paper's approach may not be feasible to use unless supplemented with interpretability techniques. Similarly, in [16], the authors aimed at predicting potential drowsy behaviour using advanced transformer-based methods. Although the study demonstrated high accuracy in classifying drivers as aggressive, drowsy, or normal, the explanation of the contributing factors is highly unreadable for humans. In addition, the smaller sample size adopted by these two studies, 95 and 6 drivers respectively, might have prevented them from detecting the data quality problems in their experiments, making their results less robust.

Balanced accuracy of risk assessment and interpretability is crucial in telematics insurance due to the regulatory requirements for transparent and explainable pricing decisions. While advanced models such as DL and transformer-based models are considered effective in improving accuracy by capturing more complex features in driving data, their explainability remains challenging. Several studies have attempted to enhance both accuracy and interpretability by integrating interpretable models, such as regression models, with DL models [30]. However, the complexity involved in explaining DL models, whether through the use of visualisation tools [8], or through the application of SHAP, remains unclear in practical applications, especially given the small-scale datasets used in these studies.

V. CONCLUSION

Telematics plays an increasingly important role in reshaping vehicle insurance. Insurers have integrated telematics into their operations to develop a range of UBI schemes, which assess driver risks based on actual driving behaviour, promote personalised premiums, and encourage safe driving practices.

Significant progress has been made in improving UBI by incorporating more comprehensive risk factors, introducing more advanced methods, and exploring the design and validation of driving behaviour intervention systems. These advancements are driving the transition from PAYD models to more advanced MHYD models.

The key gap in the existing research is the inadequate attention given to the practical challenges in real-world telematics applications during model development. Issues such as data quality problems, demographic diversity, the practical complexities of incorporating complete risk factors, and the need for interpretability in modelling methods all significantly impact the robustness, trustworthiness, and practical applicability of their findings. Failing to address these problems, particularly for data quality and demographic diversity in modelling datasets, can lead to inaccurate risk assessment outcomes, which can result in serious implications for both insurers and drivers.

Through critically reviewing recent literature in terms of these practical challenges, this paper aimed to raise awareness of these largely overlooked aspects and encourage the use of large-scale datasets that better reflect these real-world complexities. While this review focuses on the broader implications of telematics in insurance, it does not present detailed actuarial methodologies, which (though beyond the paper's intended scope) may limit its usage for readers seeking for in-depth methodological explanation. Furthermore, the studies reviewed encompass multiple geographical locations, which should be taken into account when considering their applicability to specific contexts. As telematics insurers, we hope to bridge the gaps between state-of-the-art telematics research and commercial constraints, not only to promote model deployment at scale but also to improve the long-term value of telematics for both insurers and policyholders.

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