Research Article

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Advanced Transport Engineering Techniques for Monitoring Driving Habits Through in-Vechile Telematics Systems

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Abstract

Global road traffic fatalities are on the rise, largely due to preventable driving behaviors. In-vehicle telematics has emerged as a technology capable of enhancing driving behavior, widely adopted by insurance companies to monitor their clients' behaviors. This systematic review synthesizes how invehicle telematics has been modeled and analyzed. The review conducted electronic searches on Scopus and Web of Science, selecting studies with a sample size of at least 10 participants, data collected over multiple days, and publication dates from 2010 onwards. Forty-five relevant papers were included, with 27 rated as "good" in quality assessment. The literature showed a split in focus regarding in-vehicle telematics. Some studies explored its utility for insurance purposes, while others investigated its impact on driving behavior. Machine learning analyses were prevalent, particularly in studies focusing on insurance outcomes. Acceleration, braking, and speed were the most frequently analyzed variables. Future research should include demographic information to understand how in-vehicle telematics influences driving behaviors across different demographic groups. Additionally, employing multi-level models would better capture the hierarchical nature of telematics data, which includes individual trip data for each driver

Keywords: Advanced Transport Engineering, In-Vehicle Telematics, Driving Habits Monitoring, Road Traffic Fatalities, Driving Behavior Analysis

1. Introduction

Global road traffic fatalities have been steadily increasing, reaching 1.35 million in 2016 compared to 1.3 million a decade earlier (World Health Organization, 2018). Road traffic injuries rank as the eighth leading cause of death across all age groups (World Health Organization, 2022). In the USA, speeding contributes to 29% of all traffic fatalities (United States Department of Transport, 2021). Figure 1 illustrates that road fatalities per 100,000 inhabitants were highest in the African region in 2021. Low and middle-income countries bear a disproportionate burden, with 93% of all road traffic accidents occurring in these nations (World Health Organization, 2021). Preventable driving behaviors such as speeding, driving under the influence of alcohol, and fatigued driving are significant contributors to road traffic collisions in New South Wales, Australia (NSW Insurance Regulatory Authority, 2019). Young people aged 5 to 29 years are particularly at risk, with 73% of road traffic deaths occurring in young males under 25 years old. Males in this age group are nearly three times more likely to die in road traffic accidents than females (World Health Organization, 2022). This trend is also observed in Australia, where motor vehicle accidents are the leading cause of burden for males. aged 14 to 25 years (Australian Institute of Health and Welfare, 2022) [1]. In-vehicle telematics usage has surged in the past decade due to increased mobile connectivity. Typically, in-vehicle telematics provides data on acceleration, deceleration, turning maneuvers, vehicle speed, and location, which helps in understanding driver behaviors [1-5]. Some countries are making telematics mandatory and most modern vehicles either come equipped with or can be retrofitted with sensors that provide telematics data. The Australian government has advocated for insurance reforms incorporating telematics data to support speed management initiatives. Previous studies have categorized drivers based on telematics data into "safe" and "risky" categories. Traffic signal control (TSC) has emerged as a critical strategy to address these challenges by improving road traffic safety, mitigating urban traffic congestion, and reducing vehicle emissions. Insurers offering pay-as-you-drive (PAYD) or pay-how-you-drive (PHYD) insurance schemes use these classifications to adjust premiums. There is growing interest in how feedback from in-vehicle telematics devices influences driving behavior. Evidence suggests that direct driver feedback and financial incentives for good driving behavior can improve driving habits. For instance, Peer et al. (2020) found that drivers exhibited better behaviors when receiving feedback and incentives promoting safe driving techniques. However, found no significant differences in driving behaviors between groups that received feedback and incentives and those that did not, though the former showed reductions in speeding, harsh braking, and harsh acceleration. This highlights the potential benefits of feedback on driving behavior, despite mixed results. This review aims to analyze how data from in-vehicle telematics devices has been statistically analyzed in previous research, which telematics variables were considered, and the issues telematics has addressed. It also aims to assess the outcomes derived from the use of in-vehicle telematics. In recent years, deployment of machine learning approaches to improve traffic safety is gaining popularity in research world. Have deployed this innovative approach to improve traffic safety in smart city environment, which means communication between vehicles, pedestrians, and the infrastructure. The paper is structured into four sections: methodology, results detailing statistical analyses and telematics variables, discussion of aims for driving behavior and insurance companies, and concluding remarks [6-13].

2. Methodology

Eligibility Criteria The systematic review focused exclusively on journal articles that utilized in-vehicle telematics data to measure, monitor, or classify driving behavior. Articles were required to employ quantitative statistical analysis to identify driving behavior outcomes and had to be written in English. Grey literature, including abstracts, systematic reviews, conference proceedings, and meta-analyses, was excluded due to its extensive and varied nature in this field. Additionally, only studies with a sample size of at least 10 participants were included. The in-vehicle telematics data used in these studies had to be collected over multiple days, ideally spanning weeks or months, and participants were required to be unsupervised during data collection to reflect real-world driving scenarios accurately [14-17]. Search Strategy A search was conducted online using Scopus and Web of Science, with no country restrictions on publications. This search took place on April 14, 2022, following the PRISMA checklist (Preferred Reporting Items for Systematic Reviews and Meta-analyses). Articles published before 2010 were excluded due to the significant advancements in in-vehicle telematics since then. These advancements are associated with the growing use of the Internet of Things (IoT), which involves connecting physical devices, vehicles, and other devices with electronics, software, sensors, and network connectivity, enabling remote data collection without human intervention. Since 2010, more 'things' can be networked as part of the IoT due to improvements in intelligent sensors, low-energy wireless communication, and sensor network technologies. The search terms “telematics OR OBD2 AND drive AND behavior” were used on the Scopus database, and “Telematics AND driving AND behavior was used on the Web of Science database. Road fatalities records clustered by region is shown in Figure 1 [18-23]. Quality Assurance The quality assessment was conducted using tools developed by the National Health, Lung, and Blood Institute (United States Department of Health and Human Services, 2021). This tool was selected for its versatility in evaluating various study designs. Each article was assessed with a specific checklist: 10 items for observational studies, 12 items for case-control studies, 11 items for pre-post studies, and 14 items for experimental studies. Each article received a score of poor, fair, or good based on the number of “yes” responses required for each study design, as shown in Table 1 [24-28].

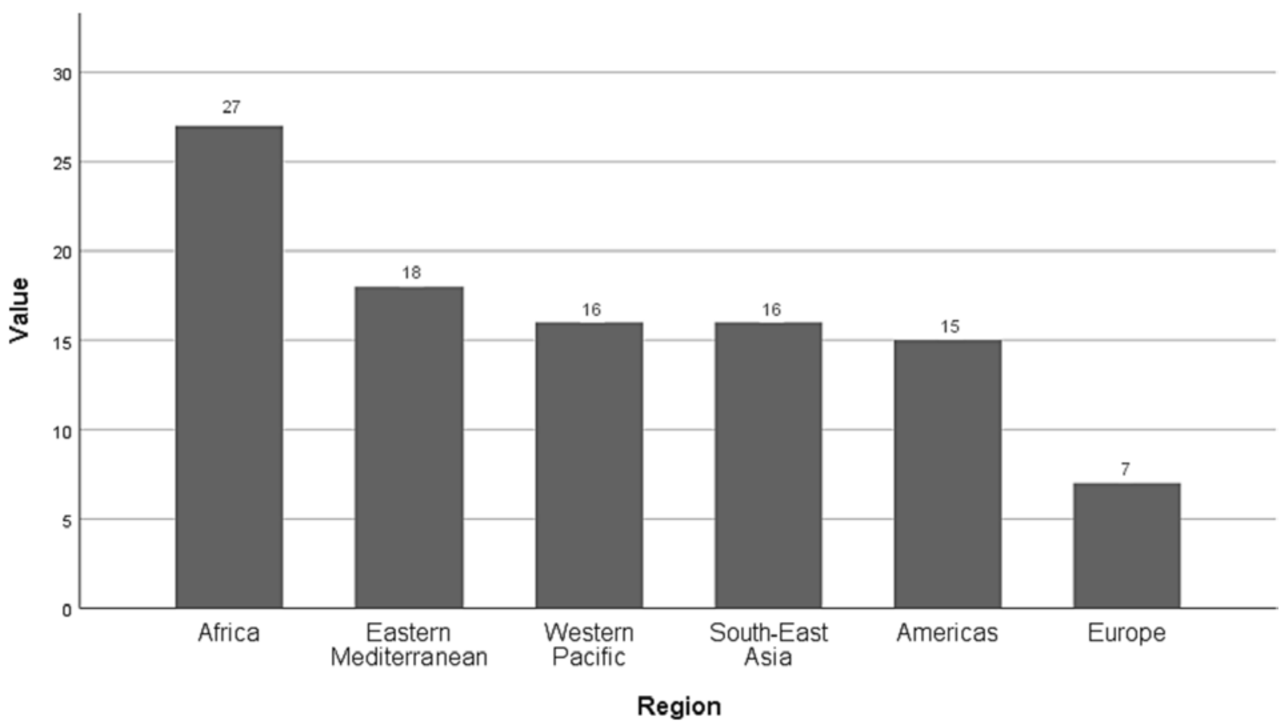

Figure 1: Road Fatalities per 100,000 Population by Region (WHO 2021)

	Observational studies	Case-control studies	Pre-Post studies	Experimental studies
Good	8+	9+	9+	9+
Fair	6–7	7–8	7–8	7–8
Poor	<6	<7	<7	<7

Table 1: Quality Assessment Scoring

Exceptions were made for studies with small sample sizes that recorded telematics data for a short duration; these articles were graded lower than they might have been otherwise. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) flow diagram for this systematic review is shown in Figure 2. Out of 297 records found through combined keyword searches, 45 papers were included in this review. Articles rated "Poor" generally failed to adequately describe their sample or data, making it challenging to understand participant recruitment and measurement methods. They also lacked transparency regarding study limitations. Articles rated "Fair" typically had appropriate sample sizes and study designs but often did not account for confounding factors in their analysis. Articles rated "Good" provided detailed descriptions of their sample, used suitable study designs and analysis to answer their research questions, and clearly articulated their study objectives.

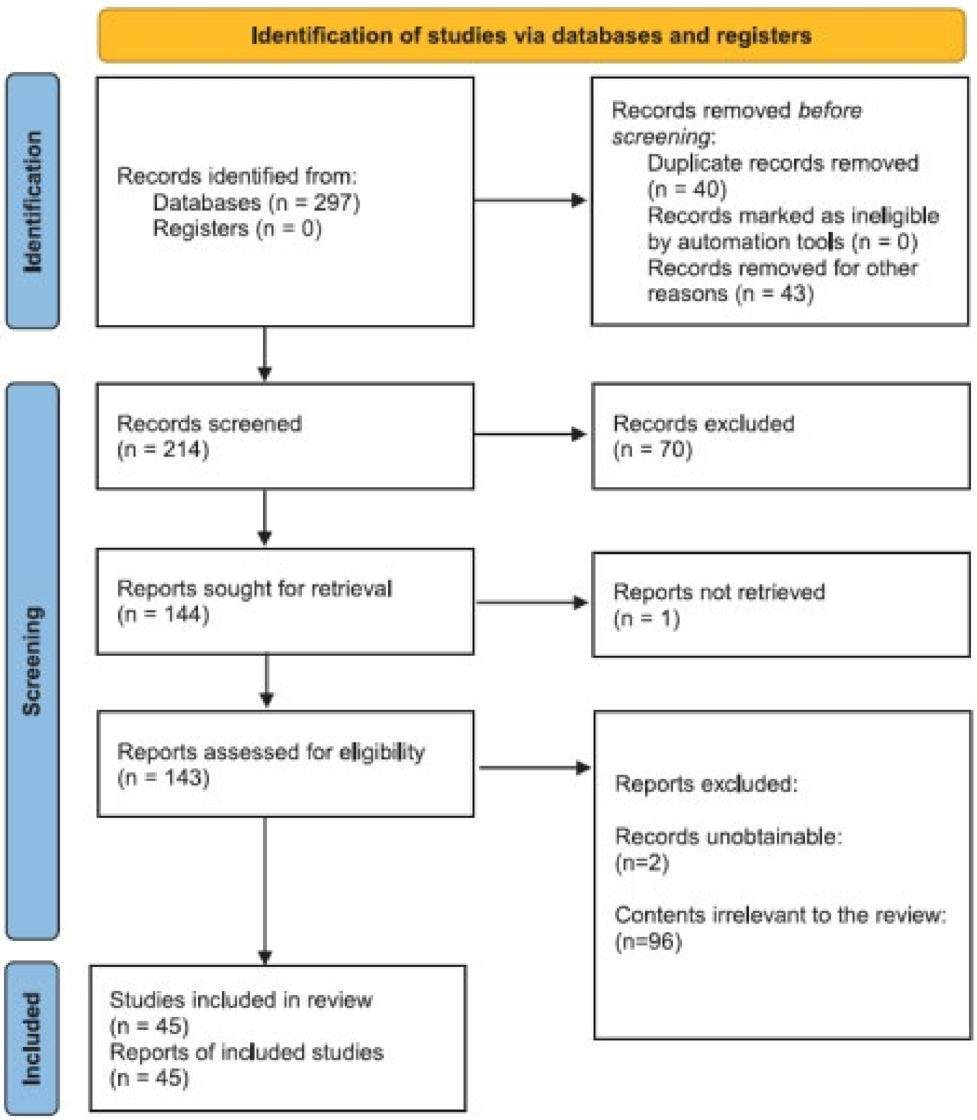

Figure 2: PRISMA Diagram

3. Results

The final count of articles included in the review was 45, and Figure 3 summarizes the distribution of the locations where these studies were conducted.

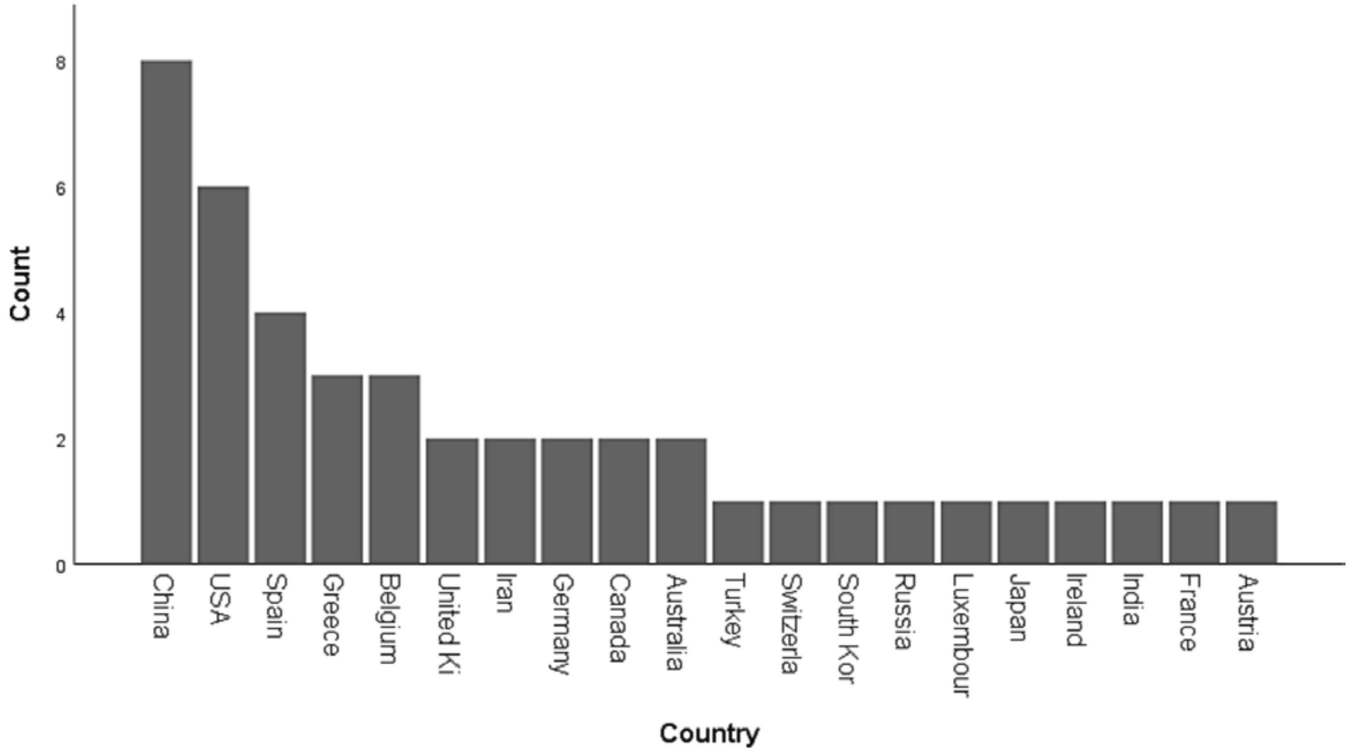

Figure 3: Countries in which the Reviewed Studies are Performed

3.1 Study Design

A division was observed among the articles, with 28 focusing on the insurance implications of in vehicle telematics and 17 concentrating on measuring driving behavior. Out of the 28 insurance-related.

articles, 21 aimed to calculate expected claims frequency or crash risk, while the remaining 7 focused on driver classification and identification. The driving behavior articles were further divided: 10 investigated changes in driving behavior, and 7 explored the factors causing driving behaviors or simply measured them. Given the nature of telematics data, which requires people to drive to generate data, many of the articles in the review used a naturalistic observational design. This design was prevalent because it involved collecting data over many trips spanning several months or years, reflecting participants' unsupervised driving behaviors. The naturalistic observational design was especially feasible for studies that obtained datasets from insurance companies or other organizations, as the data had already been collected before the study began. This design was the most common, with 77.8% of the studies in the review using it. Additionally, 13.3% of the articles employed a control trial design. Control trials were used in studies focusing on changes in driving behavior and examining how incentives or feedback influenced these behaviors. These designs enabled researchers to identify behavioral differences between participants who received interventions and those who did not.

Statistical Approaches One of the key objectives of this review is to understand how telematics data was analyzed. Table 2 provides a list of the analysis techniques and their frequencies. The division between insurance studies and behavioral studies was also reflected in the analysis techniques used. Insurance-focused studies relied more heavily on machine learning techniques such as neural networks and random forests. These techniques were particularly useful for articles focused on creating models for driver identification and classification. Machine learning was employed in half of the studies included in the review (22 studies used some form of machine learning), while regression techniques were used in 30 studies. Among the machine learning techniques observed were neural networks, random forests, support vector machines (SVM), and the adaptive boosting algorithm. These techniques were used to create models with the highest predictive power for crash risk and to classify drivers into subgroups based on their driving styles.

Telematic Variables A wide range of telematics variables were used, with speeding, acceleration, and braking being the most popular. Table 3 provides a list of these variables and their frequencies. Speed variables varied across studies; some measured speed using average velocity, while others used the time spent above the local speed limit or the number of occasions where the participant was speeding as their measure. Multiple studies employed thresholds to determine instances of acceleration and braking.

Analysis techniques observed.

Analysis techniques used	No. of articles
ANOVA	3
Cluster analysis	1
Correlations	1
Error Corrections Model (ECM)	1
General Estimating Equation (GEE)	2
Generalised Linear Model (GLM)	3
Linear Regression	2
Logistic regression	9
Machine learning	22
OLS Regression	2
Parametric regression	1
Poisson regression	6
Principal component analysis (PCA)	1
Regression	8
T-tests	1
Deep deterministic off-policy algorithm	1
Difference-in-difference model	1
Fourier analysis	1
Non-parametric test	3
Quantile regression	2
Multivariate normal model	1
Negative binomial regression	1

Table 2: Analysis Techniques

Analysis techniques observed Some studies used thresholds to determine whether instances of acceleration and braking were dangerous or risky. For example used thresholds ranging from 0.3 g to 0.7 g for longitudinal acceleration, latitudinal acceleration, and braking, considering events equaling or exceeding these thresholds as "high G-force events." The frequency of turning/cornering events was analyzed in some articles, while others measured the severity of cornering events using values of lateral acceleration (measured in g's or m/s²). Used several cornering variables in their study, including average speed and standard deviations of turns, frequency of turns per 100 km, and the proportion of left and right turns. Driving Behavior Feedbacks The study aimed to determine whether driving behavior changes based on whether participants received feedback, feedback and incentives, or neither (control group). Although no significant differences were found between the groups, both intervention groups (feedback and feedback with incentives) showed reductions in harsh braking and harsh acceleration compared to the control group. Conducted a similar study without a control group and found improvements in driving behavior for both groups receiving feedback, with greater improvements in those receiving monetary incentives and more frequent feedback. A randomized control trial by examined whether feedback from in-vehicle telematics would reduce risky driving behaviors. The treatment group, which received weekly feedback, showed a significant reduction in risky driving behaviors, whereas the control group showed no significant changes. Conducted a field experiment using “personal best,” “personal average,” and “last score” nudges to provide feedback to three different treatment groups. The groups receiving “personal best” and “personal average” nudges demonstrated improved driving performance compared to the control group, which received no feedback. Another study by investigated the impact of “safe driving coaching” on driving behavior. Significant reductions in harsh braking and harsh cornering were observed when coaching was provided. This study was conducted across two companies using heavy goods vehicles; one company provided feedback while the other did not.

Classification and Identification The classification of dangerous and safe drivers is beneficial for insurance companies to adjust premiums according to the risk of accidents. Machine learning techniques were the primary methods for classifying and identifying these driver groups in most reviewed studies. Used support vector machines to classify 809 insured drivers as safe or risky based on the frequencies of accelerations above 2.4 m/s², decelerations exceeding 1.4 m/s², and left acceleration exceeding 1.1 m/s².

Classified individual trips using a deep deterministic off-policy algorithm. Aggressive trips were characterized by higher levels of acceleration and deceleration, and a higher frequency of harsh events per minute. Used cluster analysis and machine learning to classify heavy goods vehicle drivers into eight unique driving profiles. Only 317 drivers out of 21,193 were left unclassified after two stages of analysis. Tested classification models across three datasets using various machine learning techniques. Worked on group ensemble performance for classification tasks and studied the effect of training formation of the ensemble under time and resource constraint on resulting network of classifiers. Gated recurrent unit (GRU) networks had the highest accuracy (91%) in classifying driving behavior into aggressive, semi-aggressive, and normal. The long-term short memory (LTSM) model had a similar accuracy (89%). Driver identification is also critical for insurance companies to ensure that only the insured driver(s) are driving the vehicle, as insurance payouts may vary based on who is driving at the time of an accident. Developed a Siamese temporal convolutional network model to identify drivers based on steering behaviors. The model had lower accuracy in detecting imposters (drivers who were not the insured driver). Developed an empirical likelihood approach for testing originate of two independent samples. Created a driver identification model using a random forest with a five-second sliding window and six minutes of training data, achieving 100% prediction accuracy. However, the model required four hours of driving data to reach 100% accuracy. Key variables included maximum brake pressure, mean engine speed, maximum engine torque, maximum engine speed, maximum steering value, mean steering speed, and maximum jerk. Insurance Claims and Accident Risks The review highlights various studies that utilized telematics data to enhance the prediction of insurance claim frequencies and accident risk. Here are some key insights:

Differentiate between accident-prone and accident-free drivers using telematics and geographical data. Method: Employed five machine learning classifiers. Findings: The XGBoost model demonstrated the highest accuracy. However, logistic regression was recommended for future studies due to its interpretability and comparable predictive power. Recommendation: Future research should integrate demographic data along with geographical data to enhance predictive performance. Improve classical Poisson Regression models for predicting insurance claim frequency. Incorporated a one-dimensional convolutional neural network (CNN) to score driving risk for individual trips. The CNN-derived risk scores were integrated into the original general linear model. This integration significantly enhanced the model's performance. Enhance claim frequency prediction models using telematics data. Method: Added driver behavior risk factors from neural network models into the Poisson General Linear Model. Findings: This approach significantly improved the model fit. They compared risk factors derived from feed-forward neural networks and convolutional neural networks (CNNs), concluding that both had similar predictive performance, though CNNs required fewer parameters. These studies underscore the ongoing improvements in modeling techniques and the integration of various data types to enhance the accuracy and interpretability of insurance claim frequency predictions.

Cleaning and Handling Data Telematics data presents several challenges due to its complexity, with each trip generating a vast amount of data points. Each trip produces thousands of data points, including acceleration and braking scores, which can vary widely based on the trip's length and conditions. Short trips often exhibit high variability in driving scores due to the more frequent occurrence of harsh behaviors over shorter distances. Removed trips shorter than 0.3 km and longer than 70 km to mitigate the impact of highly variable scores from extremely short or long trips. They also required drivers to complete a minimum of 10 trips to be included in the study. Noted missing values in speed, acceleration, and angle change data. They performed data imputation to address these gaps, given the time-series nature of the data. They also recommended using data from the middle of each trip to improve reliability, though defining this middle period was challenging. imputing mean values, highlighting a common approach to handle incomplete data. These approaches reflect a range of strategies to manage the complexity and variability of telematics data, aiming to ensure more reliable and accurate analysis.

4. Discussion

Measures Speeding variables were used in all studies examining changes in driving behavior, though methods varied. For example: measured the monthly frequency of events where the driver exceeded the speed limit calculated the percentage of kilometers driven over the speed limit. Harsh acceleration and harsh braking were also commonly assessed, appearing in 8 out of 10 studies. These were usually measured by counting the number of occurrences of these events: averaged the number of harsh events per minute. counted harsh events per 100 minutes. expanded the risky events category to include harsh left and right turns, alongside harsh acceleration, braking, speeding, and seatbelt use. They compared the number of risky events per 100 km before and after an intervention. Overall, speed, acceleration, and braking variables were identified as the most crucial for assessing driving behavior. Typically, the effectiveness of interventions was evaluated based on changes in these behaviors or a combination of them. Interventions Overall, telematics data proved valuable for evaluating a variety of interventions aimed at improving driving behavior. Different studies employed diverse methods: examined the effects of feedback and financial incentives on driving behavior. similar interventions but without a control group. Feedback was provided in various formats heavy goods vehicle drivers receiving coaching from supervisors and monitoring through cameras. mobile applications to deliver feedback. focused on older drivers (65 years or older) by providing web-based trip diaries that offered feedback and suggested safer routes. Other interventions explored included the impact of accidents on future driving behavior and the influence of speed cameras on driving behavior. A random effects meta-analysis was conducted to assess the overall impact of feedback from in-vehicle telematics on driving behavior scores. However, only a small meta-analysis was feasible, involving results from four papers due to the varied outcome measures used in other studies (see Supplementary Material).

Analysis Used The articles examining behavioral changes employed various forms of analysis. Regression models were the most prevalent, but other methods such as analysis of variance, machine learning techniques, generalized linear models, generalized estimating equations, and simpler analyses like t-tests were also used. A common issue in control trial designs was the failure to control for driver differences, such as age, gender, residence, and whether they drove on rural or urban roads. For example, used analysis of variance to detect differences in mean levels of risky driving behavior events per 100 km during baseline and treatment periods, without considering driver behaviors for each trip. Mirbakhsh et al in 2023 descripted CAV system as a control on traffic and chaos. Introduced an ATSC scheme using DRL techniques with efficiency optimization rewards and speed modules to smooth traffic flow, achieving both efficiency improvement and decarbonization. Given that each trip occurs under different circumstances and locations, it would have been insightful to analyze differences in risky behaviors during shorter versus longer trips or during night versus day trips. Were unable to control for the duration and nature of each trip in their analysis, whereas managed to control for total trip duration under different conditions, such as night driving and peak hour traffic. Discovered that average trip length was negatively associated with improvements in driving scores, underscoring the importance of controlling for this variable. Accurate analysis of telematics data requires addressing the hierarchical nature of the data, with trip telematics data nested for each driver/vehicle. However, only three of the reviewed articles addressed this, and these models proved to be the most effective for measuring the effectiveness of driving behavior interventions.

Literature Limitation A notable issue across many studies was the insufficient description of the sample. Critical demographic details, such as sex, which significantly affect insurance pricing, were often missing. Ideally, studies should have controlled for these demographic variables. Furthermore, many articles lacked a thorough description of the telematics data. Some studies did not provide descriptive statistics for key variables like acceleration and speed, and the distributions of these variables were rarely depicted.

Another oversight was the neglect of vehicle differences among participants. Variations between manual and automatic transmissions were generally ignored, and vehicle age, which is pertinent to assessing risky events or errors, was seldom considered. Pointed out that older vehicles are more prone to technical defects, increasing crash risk. Given the hierarchical nature of telematics data, it is surprising that hierarchical linear modeling was not more commonly employed. This approach is essential for accounting for variables at both the driver level (e.g., gender, age) and the trip level (e.g., location, duration, timing), which is crucial for a more nuanced understanding of risky driving behaviors.

5. Conclusion

This review extensively documents the use and applications of in-vehicle telematics in vehicle insurance. Most studies focus on leveraging telematics data to enhance traditional insurance claim frequency prediction models. Machine learning techniques are predominantly used for analyzing and modeling this data, particularly in insurance-related research due to the large datasets involved. Variables related to speed, braking, and distance traveled are commonly used to measure driving behavior, with regression models and machine learning proving to be effective techniques for analysis.

Several key gaps were identified: 1. Impact of Telematics Feedback: There is a lack of understanding regarding how real-time telematics feedback influences driving behavior. 2. Age Group Differences: The effect of telematics on different age groups has not been well explored. 3. Vehicle Attributes: There is no consensus on how various vehicle attributes affect driving behavior. 4. Behavioral Implications: The effectiveness of telematics in modifying driving behavior and reducing risky behaviors remains under-researched. 5. Pre- and Post-Installation Comparison: There is limited research comparing driving behaviors before and after the installation of telematics devices. 6. Intervention Effectiveness: The potential of telematics for evaluating the impact of interventions, such as road safety campaigns, has not been thoroughly examined. Future research should aim to: 1. Detailed Data Descriptions: Provide comprehensive details on the data collected, including demographic information to better understand how responses to telematics vary by sex, age, and socio-demographic factors. 2. Vehicle Type Effects: Consider how different vehicle types influence telematics data. 3. Feedback Mechanisms: Clearly describe how feedback is provided and the frequency of feedback to participants. 4. Trip Variability: Account for differences in trip characteristics, such as the likelihood of risky behaviors during longer highway drives, by utilizing hierarchical modeling techniques to analyze telematics data [29,30].

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