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A systematic review of the use of in-vehicle telematics in monitoring driving behaviours

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ABSTRACT

Background: Road traffic deaths are increasing globally, and preventable driving behaviours are a significant cause of these deaths. In-vehicle telematics has been seen as technology that can improve driving behaviour. The technology has been adopted by many insurance companies to track the behaviours of their consumers. This systematic review presents a summary of the ways that in-vehicle telematics has been modelled and analysed.
Methodology: Electronic searches were conducted on Scopus and Web of Science. Studies were only included if they had a sample size of 10 or more participants, collected their data over at least multiple days, and were published during or after 2010. 45 relevant papers were included in the review. 27 of these articles received a rating of "good" in the quality assessment.
Results: We found a divide in the literature regarding the use of in-vehicle telematics. Some articles were interested in the utility of in-vehicle telematics for insurance purposes, while others were interested in determining the influence that in-vehicle telematics has on driving behaviour. Machine learning analyses were the most common forms of analysis seen throughout the review, being especially common in articles with insurance-based outcomes. Acceleration, braking, and speed were the most common variables identified in the review.
Conclusion: We recommend that future studies provide the demographical information of their sample so that the influence of in-vehicle telematics on the driving behaviours of different groups can be understood. It is also recommended that future studies use multi-level models to account for the hierarchical structure of the telematics data. This hierarchical structure refers to the individual trips for each driver.

1. Background

Globally there is an increasing trend in road traffic deaths, reaching 1.35 million in 2016 in comparison to 1.3 million a decade previously (World Health Organisation, 2018). Across all age groups, road traffic injuries are ranked as the eighth leading cause of death (World Health Organisation, 2022). Speeding is a contributing factor for 29 % of all traffic fatalities in the USA (United States Department of Transport, 2021). Fig. 1 displays the road fatalities per 100,000 inhabitants by region in 2021, with fatality rates being the highest in the African region. Low and middle-income countries are overrepresented in road traffic fatalities, with 93 % of all road traffic accidents occurring in these countries (World Health Organization, 2021). Preventable driving behaviours are a major issue, with speeding, driving under the influence of alcohol and fatigued driving being the leading causes of road traffic collisions in New South Wales, Australia (NSW Insurance Regulatory Authority, 2019).

Young people between the ages of 5 and 29 years old are the most at-risk demographic, with 73 % of road traffic deaths occurring in young males under the age of 25. In this age group males are almost three times more likely to be killed in a road traffic accidents than females (World Health Organisation, 2022). This is also the case in Australia, with motor vehicle accidents causing the most burden over the life course for males aged between 14 and 25 years (Australian Institute of Health and Welfare, 2022).

The use of in-vehicle telematics has increased rapidly in the last decade with the increase in mobile connectivity (Young drivers Telematics Trial, 2019). In-vehicle telematics typically gives measurements on acceleration, deceleration, turning manoeuvres, and the speed of vehicles, while also providing locational data, which can be used to

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understand the behaviours of drivers on the road. The use of telematics is becoming mandatory in some countries (Kirushanth and Kabaso, 2018), and most modern vehicles are equipped with or can be retrofitted with sensors that provide telematics data (Winlaw et al., 2019). The Australian government has called for insurance reforms incorporating the use of telematics data to facilitate speed management initiatives (Road Safety.gov, 2018). Previous studies have used telematics data to classify drivers as “safe” and “risky” drivers (Osafune et al., 2016), which is significant to insurers who offer pay-as-you-drive (PAYD) or pay-how-you-drive (PHYD) insurance schemes, as they can use these classifications to adjust the price of insurance premiums.

There has also been interest in the way feedback from in to vehicle telematics devices can influence driving behaviour. Evidence is emerging regarding the utility of in-vehicle telematics technology for direct driver feedback on driving behaviour, and for providing financial incentives for good driving behaviour (Wijnands et al., 2018). A study conducted by Peer et al. (2020) found that drivers exhibited better driving behaviours when receiving feedback on their driving along with incentives that promoted safe driving techniques. However, Stevenson et al. (2021) found no significant differences in driving behaviours measured by driving scores between those who received feedback and incentives, and those that did not receive feedback or incentives. While the results were not significant, the group that received both feedback and incentives had reductions in speeding, harsh braking, and harsh acceleration behaviours. This evidence highlights the promising effects of feedback on driving behaviour.

The purpose of this review is to firstly understand how data collected from an in-vehicle telematics device has been statistically analysed in previous research and what telematics variables have been included in these analyses. The review also aims to determine what issues in-vehicles telematics has been used to address and what outcomes were obtained from the use of in-vehicle telematics.

The rest of the paper will be divided into four sections. The first section, entitled methodology, will detail how the reviewed papers were selected and how the quality of these papers were assessed. A results section will follow, detailing the statistical analyses that have been used to model in-vehicle telematics data and what telematics variables were included in these analyses. The results section will also explain the aims, conclusions and issues raised by the reviewed papers. The implications for both driving behaviour and insurance companies will then be discussed before final conclusions are presented.

2. Methodology

2.1. Eligibility criteria

Using in-vehicle telematics data to measure, monitor or classify driving behaviour was the main requirement for inclusion in the review. Only journal articles that used quantitative statistical analysis to identify driving behaviour outcomes and were written in English were selected. The extensive nature of the grey literature in this area made it impossible to do this literature justice, so it was excluded in this review. Articles were only included if they had a sample size of at least 10 participants. The in-vehicle telematics data used in the studies must have been collected over at least multiple days, preferably weeks or months, with participants being unsupervised while their driving data were being collected. Abstracts, systematic reviews, conference proceedings and meta-analyses were not considered in this review.

2.2. Search strategy

An online search was conducted using Scopus and Web of Science, with no restrictions on country of publication. The search was conducted on the 14th of April 2022 in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-analyses checklist (PRISMA). Articles published before 2010 were excluded due to the rapid advancements in in-vehicle telematics seen after this date. These advancements are linked to the increasing applications of the Internet of Things (IoT), which refers to the networking of physical devices, vehicles or any other connected device with electronics, software, sensors, and network connectivity, allowing for data to be collected remotely without human intervention (Desai and Phadke, 2017). Since 2010, a larger number of ‘things’ can be networked as an IoT due to advancements in intelligent sensors, low energy wireless communication and sensor network technologies (Li et al., 2015). The search terms “telematics OR OBD2 AND driv* AND behavio#r” were used on the Scopus database, while the search terms “Telematics AND driving AND behav*” were used on the Web of Science database. The search terms were

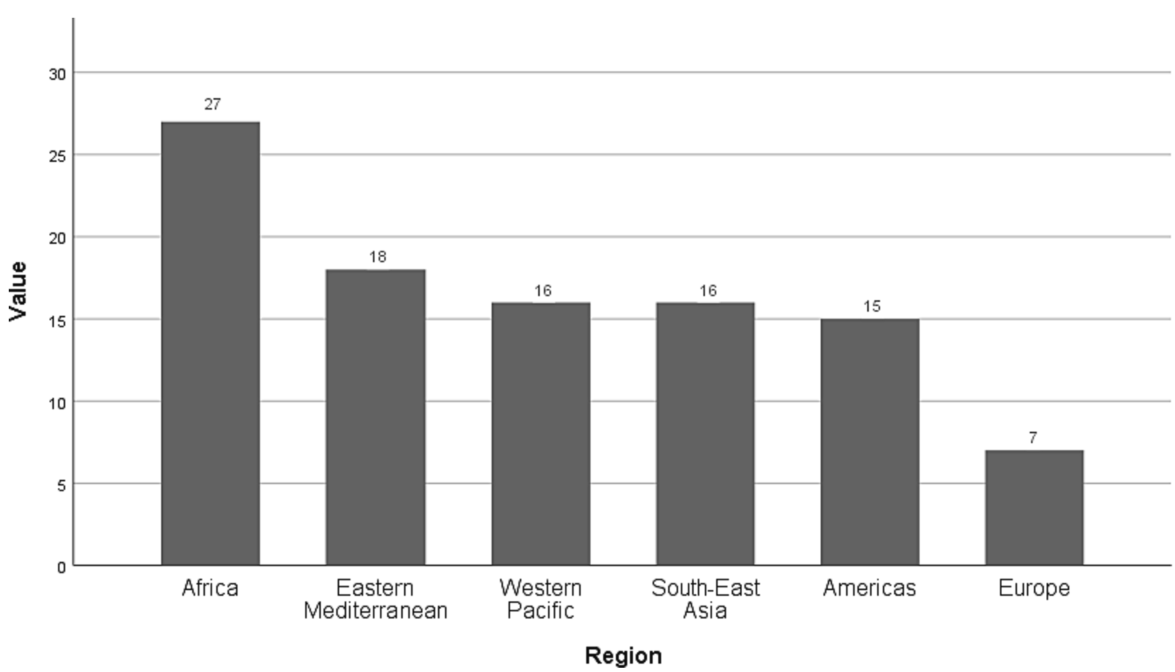

Fig. 1. Road fatalities per 100,000 inhabitants by region (World Health Organization, 2021).

modified for the Web of Science search due to the differences between the two search engines.

2.3. Study selection

The PRISMA flow diagram for this systematic review is illustrated in Fig. 2. A total of 297 records were identified using the combined keyword searches, leading to the 45 papers included in this review.

2.4. Quality assessment

The quality assessment was completed using quality assessment tools developed by the National Health, Lung, and Blood institute (United States Department of Health and Human Services, 2021). This tool was chosen due to the flexibility it has in assessing all types of study design. A checklist of items (10 items for observational studies, 12 items for case control studies, 11 items for pre-post studies, and 14 items for experimental studies) was completed for each article and a score of poor, fair, or good was then given. The number of "yes" responses required for each grading by study design can be seen in Table 1.

Table 1
Quality assessment scoring.

	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

Exceptions were made for studies with small sample sizes that recorded telematics data for a relatively short amount of time. These articles were put into the grading below what they would have otherwise scored. A distribution of the scores can be seen in Fig. 3.

Articles that were considered "Poor" typically did not describe their sample or their data to an adequate level, which made it difficult to understand how the participants were recruited to their studies or the measures that were used. They were also not forthcoming with the limitations of their studies. Articles given a "Fair" rating typically had suitable sample sizes and used suitable study designs, however most of these articles did not discuss controlling for confounding factors in their analysis. Articles that received a "Good" rating described their sample in detail, used suitable study designs and analysis to answer their research

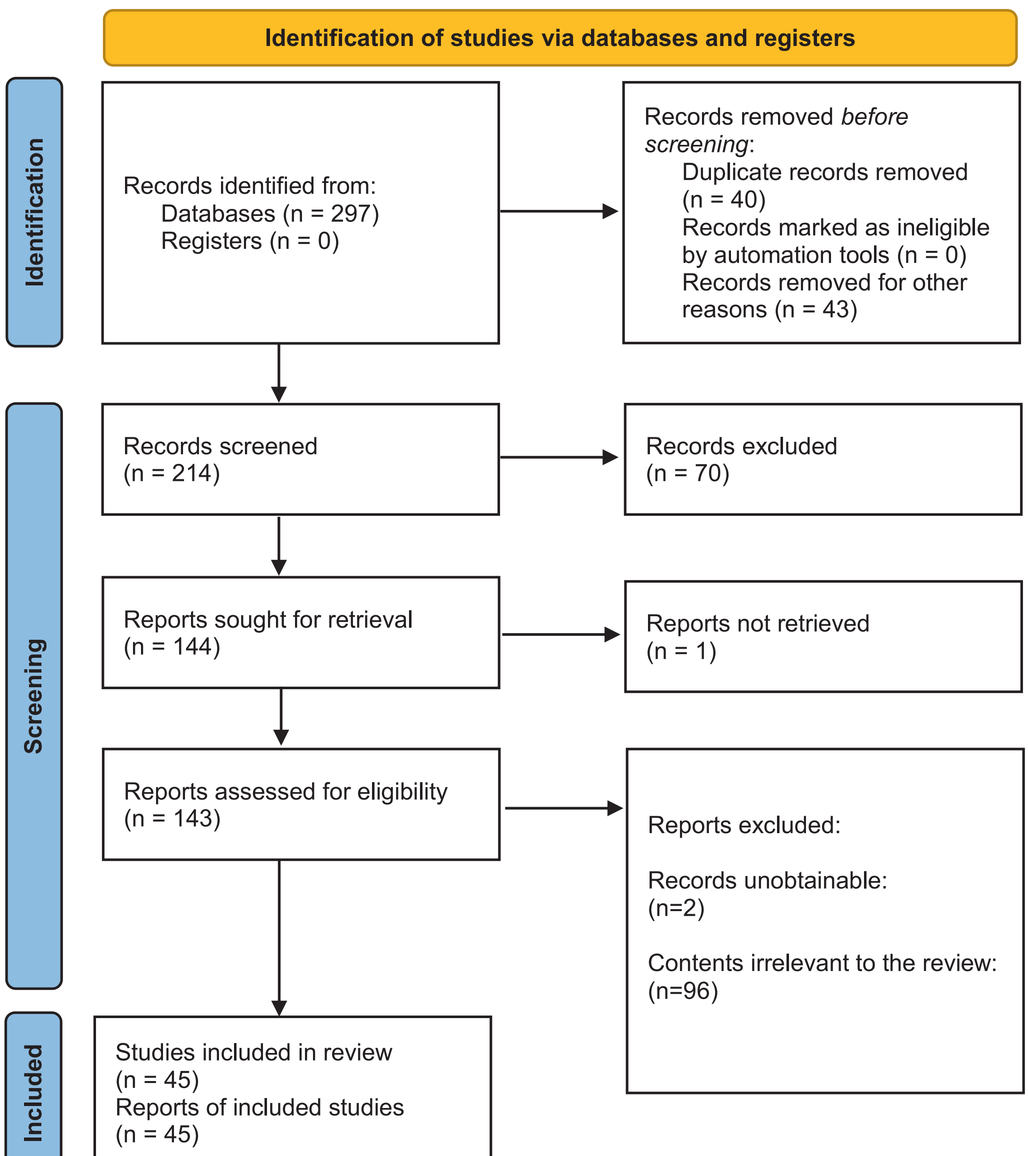

Fig. 2. PRISMA diagram.

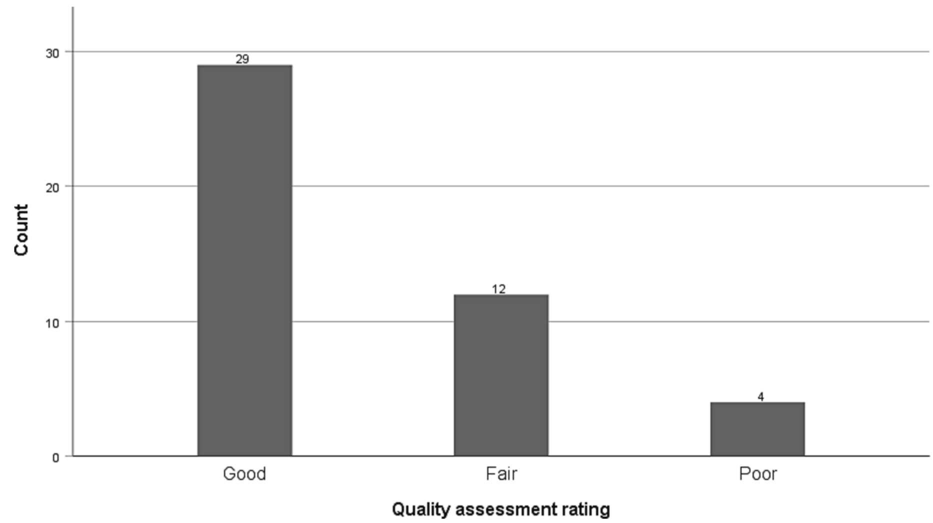

Fig. 3. Frequencies of quality assessment ratings.

questions, and were clear with what they were trying to achieve through their study.

3. Results

The final number of articles included in the review was 45 and the distribution of the locations where these studies were conducted is summarised in Fig. 4.

3.1. Study design

A divide was identified between the articles, with 28 of the articles being focused on the insurance implications of in-vehicle telematics and 17 of the articles being focused on measuring driving behaviour. Of the 28 articles focused on insurance implications, 21 aimed to calculate expected claims frequency or crash risk, while the remaining 7 were interested in driver classification and identification. The driver behaviour articles were divided into those that were interested in changes in driving behaviour (10 articles) and those that were interested in the factors that cause driving behaviours or just measuring driving behaviour (7 articles).

Due to the nature of telematics data and the fact that people need to drive to produce telematics data, many of the articles identified in the review used a naturalistic observational design. This design was popular due to the data being collected in many trips over several months or years, and due to its utility in allowing the data to reflect participants unsupervised driving behaviours. The naturalistic observational design was the most feasible design for studies that acquired their datasets from insurance companies or other organisations, as the data had already been collected prior to the start of the study. This was the most frequent design by far with 77.8 % of the studies in the review following this design. 13.3 % of the articles in the review used a control trial design. Control trials were adopted in articles that were more focused on changes in driving behaviour and understanding how incentives or feedback influenced these behaviours. These designs allowed the researchers to detect differences in behaviour between those who received

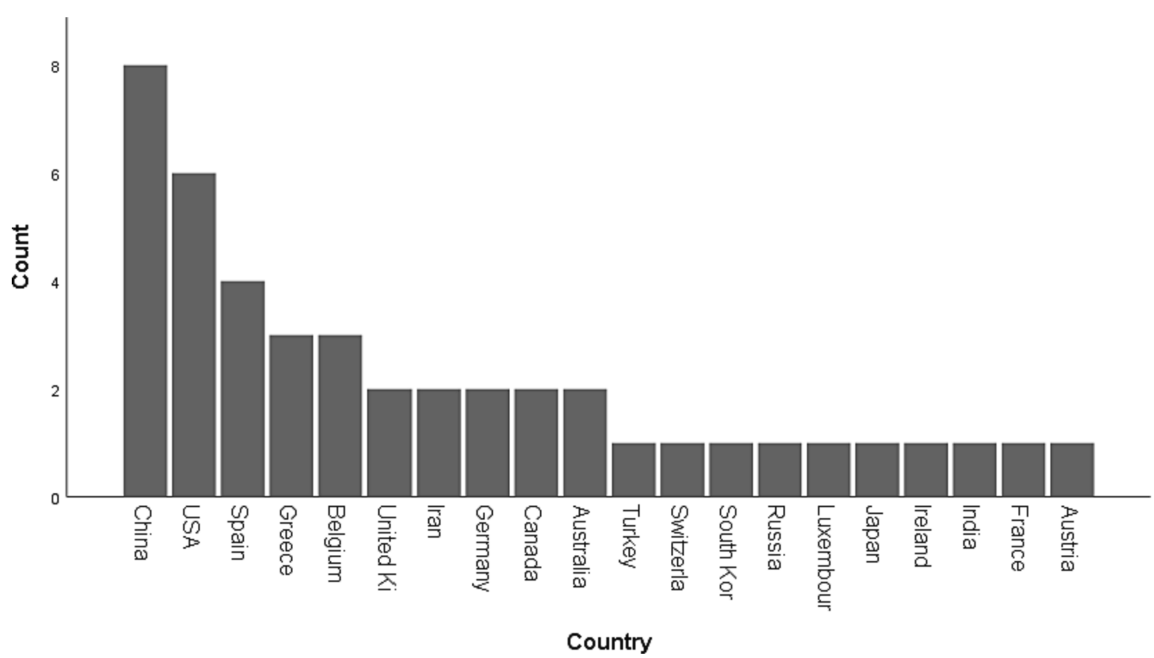

Fig. 4. Countries where the studies took place.

some form of intervention and those that received no intervention.

3.2. Participants and recruitment

The sample sizes of the studies were highly variable, with a maximum of 50,301 vehicles and a minimum of 10 vehicles. The large sample sizes were a result of the researchers having access to telematics data provided from insurance companies and government datasets, while studies with a smaller sample size typically recruited their own participants. The ages of the participants used in the 26 studies that provided participants' ages were highly variable, with a mean age of 35 years or less, and 14 articles considering drivers in all age groups.

3.3. Statistical methods

One of the key objectives of this review is to understand how the telematics data was analysed. A list of the analysis techniques and their frequencies can be seen in Table 2. The split in insurance studies and behavioural studies was also evident in the analysis techniques, with insurance focused studies relying more heavily on machine learning techniques such as neural networks and random forests. These techniques were especially useful for articles focused on creating models for driver identification and classification. Machine learning was used in half of the studies included in the review (22 studies used some form of machine learning), while regression techniques were used in 30 of the studies. Neural networks, random forests, and support vector machines (SVM), and adaptive boosting algorithm were among the machine learning techniques observed in the review. These were used to create models with the greatest predictive power for crash risk and also for creating models that classified drivers into subgroups based on their driving styles.

3.4. Telematics variables

A wide range of telematics variables were used; however, speeding, acceleration, and braking were the most popular variables. A list of the variables and their frequencies can be seen in Table 3.

Speed variables were not consistent across studies. Some articles opted to measure speed using average velocity while others used time spent above the local speed limit or the number of occasions where the participant was speeding as their speeding measure. Multiple studies used thresholds to determine whether instances of acceleration and braking were dangerous or risky. Mao et al. (2021) used thresholds ranging from 0.3 g's to 0.7 g's for longitudinal acceleration, latitudinal acceleration and braking, considering events equalling or exceeding these thresholds to be "high G-force events".

Table 2
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 3
In-vehicle telematics variables observed.

Telematics variables used for analysis	No. of articles
Speed	32
Acceleration	32
Braking	24
Turning/cornering	14
Driving score	2
Torque	2
Lateral position	3
Distance/driving time	15
Mechanical measures	7
Other	12

The frequencies of turning/cornering events were used in some articles, while others used the severity of cornering events (measuring in 'g's' or m/s^2). The severity of the events can be measured by using values of lateral acceleration. Zhao et al. (2021) used a number of 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.

There were also some variations in the distance variables. Most articles that included a distance variable were looking at the distance of each trip or the distance driven over a period of time. However, some articles were interested in distance travelled at different times of the day (day or night) or distances travelled in urban or regional areas. Payyanadan et al. (2017) defined a trip as every time that the vehicle had moved, with the trip ending either when the ignition was turned off or when the vehicle had a speed of less that 1 km/h for more than 200 s. Admittedly, it is unclear what the majority of the articles in this review classify as a trip, making it difficult to understand whether a trip was recorded every time the vehicle's engine was engaged or whether there were minimum time and distance parameters in place.

Driving scores, computed using a number of telematics variables, were used in two studies. Eftekhari and Ghatee (2019) used accelerometer data to create safe driving scores and aggressive driving scores. Choudhary et al. (2019) used harsh braking and acceleration, speeding instances, time of day, distance travelled, and driving duration to create their driving scores.

Variables that were related to the mechanical function of the vehicle were grouped as "mechanical variables" to make Table 2 more concise. Steering wheel angle and steering wheel velocity (how fast the steering wheel is being turned), torque, yaw rate, engine speed, turning signal, fuel consumption, pedal position, and brake pressure were all considered to be mechanical variables for the purpose of this review.

Finally, the "other" variables were measures that were rarely used across the articles. This included coasting, idling, longitudinal jerk, time of day, driving frequency, phone usage, seatbelt usage, breaking of road rules, driving below speed limit, familiarity with roads, time of week (weekend or weekday), and if a crash occurred. These "other" variables will not be discussed in this review because they tend to be rare.

3.5. Influence of feedback on driving behaviour

Stevenson et al. (2021) used a randomised control trial study design to determine whether driving behaviour changes, depending on whether the participants received either feedback, feedback and incentives, or neither of these (control group). There were no significant differences identified between the groups, however, there were reductions in harsh braking and harsh acceleration in both intervention groups compared to the control group. Peer et al. (2020) were also interested in how driving behaviour changes with feedback and incentives and used a similar study design. While this study lacked a control group, there were improvements in driving behaviour for both the group that received feedback and the group that received feedback and incentives. These improvements were larger in the group that received monetary incentives and for participants who received more frequent feedback.

A randomised control trial was conducted by Sullman (2019) to determine whether feedback about driving behaviour obtained from in to vehicle telematics would reduce the number of risky driving behaviours observed. The treatment group received weekly feedback about their driving. A significant reduction in risky driving behaviours was observed for the treatment group, while no significant changes were observed in the control group across the study. Choudhary et al. (2021) conducted a field experiment focused on the influence of feedback on driving behaviour. They utilised "personal best", "personal average", and "last score" nudges to provide feedback to three different treatment groups. The groups that received "personal best" and "personal average" nudges displayed improved driving performance compared to the control group that received no feedback. Another study aimed to determine how "safe driving coaching" influences driving behaviour (Mase et al., 2020) and found that significant reductions in harsh braking and harsh cornering occurred when coaching was provided. The study was conducted across two companies that used heavy goods vehicles, one company provided feedback while the other did not.

3.6. Classification and identification

The classification of dangerous drivers and safe drivers is helpful to insurance companies so that they can adjust their premiums to account for the risk of an accident occurring. Machine learning techniques were the primary form of analysis for classifying and identifying these driver groups across most studies explored in the review. Osafune et al. (2016) utilised support vector machines to classify 809 insured drivers as safe or risky drivers. They determined that the frequencies of accelerations above a threshold of 2.4 m/s^2, decelerations exceeding 1.4 m/s^2, and left acceleration exceeding 1.1 m/s^2, differentiated the safe drivers from the risky drivers. Mantouka and Vlahogianni (2022) classified individual trips instead of a driver's overall behaviour, and utilised machine learning and a deep deterministic off-policy algorithm to classify the trips. Aggressive trips were characterised by higher levels of acceleration and deceleration, and higher frequency of harsh acceleration and harsh braking events per minute.

Figueredo et al. (2019) classified the drivers of heavy goods vehicles into one of eight unique driving profiles using cluster analysis and machine learning. After two stages of analysis only 317 drivers out of the sample of 21,193 were left unclassified. A Greek study (Savelonas et al., 2021) tested their classification models across three separate datasets using various forms of machine learning and found that gated recurrent unit (GRU) networks had the highest accuracy (91 %) in classifying driving behaviour into aggressive, semi-aggressive and normal driving behaviour. The long term short memory (LTSM) model had a similar level of accuracy (89 %). Thresholds were used in this analysis to split accelerations, braking and turning into three different levels of intensity.

Driver identification is also important to insurance companies so that they can ensure that only the insured driver(s) of a vehicle has been driving this vehicle. This is critical because the price of insurance payouts may differ depending on who is driving at the time of an accident. Driver identification models may be useful in detecting when an uninsured driver is driving at the time of an accident. Azadani and Boukerche (2022) created a Siamese temporal convolutional network model to identify drivers based on steering behaviours. They were also interested in imposter detection, however, their model had lower accuracy in detecting imposters (drivers who were not the insured driver). Wang et al. (2017) also used telematics data to create a driver identification model. A random forest was used and a five-second sliding window with six minutes of training data was able to achieve 100 % prediction accuracy. However, the model needed four hours of driving data to become 100 % accurate. The most important variables in their model were maximum brake pressure, mean engine speed, maximum engine torque, maximum engine speed, maximum steering value, mean steering speed, and maximum jerk.

3.7. Telematics and insurance claims/accident risk

Multiple studies explored in the review were interested in using telematics data to predict claim frequencies and accident risk**.** Brühwiler et al. (2022) utilised telematics data along with geographical data to train a model that could differentiate between accident and accident-free drivers. They used five different machine learning classifiers but found that the XGBoost model was the best performing model. While the XGBoost model had the highest accuracy, the researchers suggested that future studies should use logistic regression, as it was much easier to interpret, and the predictive power was not much less than the XGBoost model. Geographical data was crucial to higher predictive performances, but it was suggested that future studies should also use demographic information.

Improving existing insurance claim frequency prediction models was an objective of several studies. Meng et al. (2021) attempted to improve on the classical Poisson Regression model that is commonly used to predict insurance claim frequency. A one-dimensional convolutional neural network was used to score driving risk for individual trips, the credibility average risks scores calculated by the neural network were then incorporated into the original general linear model and were found to significantly improve the model. Gao et al. (2022) also discussed the increasing incorporation of telematics data for improving claim frequency prediction models. Also intent on improving the classical Poisson regression model, this study included driver behaviour risk factors calculated by neural network models in the Poisson General Linear Model, significantly improving the fit of the original model. A speed-acceleration heatmap was computed for each driver using telematics data. The researchers compared driver behaviour risk factors calculated by feed-forward neural networks and by convolutional neural networks, but concluded that the models had similar predictive performance although the convolutional neural network used fewer parameters.

3.8. Cleaning and handling of telematics data

Telematics data is complex, with each trip producing thousands of datapoints. Driving scores for acceleration and braking are often highly correlated with the time of trip, with extremely short trips producing highly variable scores, with harsh behaviours more likely for short distances. Choudhary et al. (2019) removed trips with lengths below 0.3 km and above 70 km and only included drivers in their study if they completed at least 10 trips. Meng et al. (2021) observed missing values for speed variables calculated using a GPS (Global Positioning System) device, and acceleration and angle change variables calculated using telematics. Data imputation was conducted and was deemed necessary by the researchers as they were analysing time-series data. The researchers also suggested using data from only the middle period of each trip to increase the reliability of the data, but also noted that it was difficult to define such a period. Priyadharshini and Ferni Ukrit (2022) also encountered missing values and accounted for these by imputation using mean values.

3.9. Calculation of driving scores

Multiple studies generated driving scores that allowed researchers to measure driving performances in a more concise way, rather than looking at several variables independently. Peer et al. (2020) created a scale from 0 to 100 with lower scores reflecting worse driving performances, using six variables (phone use, speeding, speeding in dangerous areas, braking, cornering, and acceleration) to create the scale. They placed more weight on illegal behaviours such as phone use, speeding, and speeding in dangerous areas. Choudhary et al. (2019) used a driving score computed by a mobile application that was visible to their participants. The score was computed using three user behaviours (braking, acceleration, and speeding) and two trip aspects (distance travelled and the hour of the day that the trip occurred).

4. Discussion

4.1. Insurance implications

The review was dominated by papers that were focused on strengthening insurance claim expectancy models, or models that were able to classify drivers as safe or risky drivers for the purpose of premium adjustment. Most of these studies were provided with their telematics datasets by insurance companies. These datasets were large. Guillen et al. (2018) were able to have a sample size of 25,054 insured vehicles, while So, Boucher, and Valdez (2020) acquired their dataset from a Canadian insurance company and were able to achieve a sample size of 50,301 insured vehicles. This meant that machine learning models could be successfully applied as explained below.

4.1.1. Measures in insurance

Expected claim frequency was a common outcome measure for insurance focused studies. This is an important measure as the more claims a client files, the greater the cost for the insurance company. The derivation of driving profiles or driving styles was also a common objective, with Figueredo et al. (2019) creating eight different driving profiles and Siami et al. (2021) identifying twenty-eight different driving styles. Speed, acceleration, and braking were the most common variables in articles focused on insurance-based outcomes. Distances driven and the trip duration, as well as the driving conditions of each trip, were also important variables, with researchers being interested in the number of kilometres driven at different times of day (e.g. during the night or day or peak hour traffic times), the number of kilometres driven on weekends or weekdays, and the number of kilometres driven in urban or rural areas. These variables were especially prevalent in articles with crash risk outcomes, with geographical data and kilometres driven in different driving conditions significantly improving claim frequency prediction models and crash risk analyses.

Speeding and harsh braking variables were the most useful variables for classifying drivers as safe or risky drivers. Winlaw et al. (2019), found that speeding was the only telematics variable linked to crash risk, while Mao et al. (2021) suggested that harsh braking events provided more valuable information compared to harsh acceleration events when profiling high-risk drivers. Distance driven variables were significant predictors of crash risk in multiple studies. It is recommended that future studies interested in modelling crash risk using telematics include harsh braking, speeding, and distance variables in their analysis.

4.1.2. Analysis in insurance

Machine learning techniques were the dominant form of analysis used in articles that aimed to improve expected insurance claim frequency models and in articles that aimed to classify safe/risky drivers, to improve the accuracy of insurance premium pricing. Neural networks were used in combination with Poisson general linear models on multiple occasions. Logistic regression was also commonly used in studies that classified the crash risk of their participants.

Henckaerts and Antonio (2022) used a Poisson Regression model to determine whether there were differences in expected claim frequency between insurance policy holders who had a telematics box installed in their vehicle and those that did not. After controlling for age, it was determined that there were no significant differences in expected claim frequency between those with a telematics box installed and those that did not, however, those with telematics installed did tend to have lower expected claim frequencies. Ayuso et al. (2019) included telematics variables, specifically distance travelled in different conditions at different times of day and in different settings, along with classical insurance pricing variables such as age and sex, in a Poisson Regression model, concluding that their model outperformed classical insurance pricing models.

Though machine learning techniques typically perform the best when predicting crash risk, logistic regression produces comparable results and is much easier to interpret. Brühwiler et al. (2022) conclude that if maximum possible model performance is not the only aim, then future studies should use logistic regression when predicting individuals' car accident risk. Poisson regression models perform strongly when predicting the frequency of insurance claims, with all studies that used Poisson regression able to outperform classical insurance models.

4.2. Behavioural implications

4.2.1. Measures used

A speeding variable was used in all of the articles that were investigating changes in driving behaviour, however, this variable was not always used in the same way. Mase et al. (2020) used a monthly frequency of all events where the driver's speed was over the speed limit, while Payyanadan et al. (2017) calculated the percentage of kilometres driven over the speed limit. Harsh acceleration and harsh braking were also common variables used in articles interested in changes in driving behaviour, with these variables used in 8 of the 10 articles. Typically, both variables were measured using a count of the number of times that these events occurred. Mantouka and Vlahogianni (2022) used an average of the number of harsh events per minute in their analysis, while Choudhary et al. (2019) used the number of harsh events per 100 min. Sullman (2019) included harsh left turns and right turns along with harsh acceleration, braking, speeding, and seatbelt use in their risky events categorisation, and compared the number of risky events per 100 km after an intervention to baseline.

It was determined that speed, acceleration, and braking variables were the most important outcome variables for assessing driving behaviour. Typically, interventions were introduced and the effectiveness of these interventions were determined through measuring changes in these three behaviours or in a combination of these behaviours.

4.2.2. Interventions used

Overall, it was found that telematics data in a variety of forms was useful for assessing a wide range of interventions. Stevenson et al. (2021) investigated how feedback and financial incentives influenced driving behaviour. These interventions were also adopted by Peer et al. (2020), but without a control group. Feedback was also given in multiple forms across the articles. A group of heavy goods vehicle drivers received coaching from the supervisors along with being monitored by cameras in a study by Mase et al. (2020), while mobile application-based feedback was provided to participants in studies conducted by Stevenson et al. (2021), Choudhary et al. (2019), Peer et al. (2020), and Choudhary et al. (2021).

Payyanadan et al. (2017) had a sample of older drivers (65 years or older) and gave them access to web-based trip diaries that provided feedback on their driving trips and suggested alternative routes with lower risk. Several other interventions were considered, with one article being interested in how involvement in an accident influenced future driving behaviour, and another being interested in how the installation of speed cameras influenced driving behaviour.

A random effects meta-analysis was conducted to determine the overall effect of feedback from in to vehicle telematics on driving behaviour scores, however, only a very small meta-analysis of the results for four papers was possible because the other papers tended to use a range of different outcome measures (see Supplementary Material).

4.2.3. Analysis used

The forms of analysis used in the articles interested in behavioural changes were varied. The most dominant types of models were regression models, however, analysis of variance, machine learning techniques, generalised linear models, generalised estimating equations, and simpler forms of analysis such as t-tests were also used.

A common issue in the analyses used in the articles with control trial designs was a failure to control for driver differences in terms of age, gender, where participants lived, and if they drove on rural or urban roads. Sullman (2019) used analysis of variance to detect differences in mean levels for risky driving behaviour events per 100 km in baseline and treatment periods, rather than considering driver behaviours for each trip. Each trip is driven under different circumstances and in different locations, so it would have been interesting if the researchers had analysed differences in the risky behaviours exhibited in shorter and longer trips or in trips that took place at night or the day. Payyanadan et al. (2017) were unable to control for the duration and nature of each trip in their analysis. However, Choudhary et al. (2021) were able to control for total trip duration in different conditions such as night driving and driving during peak hour traffic. Peer et al. (2020) found that average trip length was negatively associated with improvements in driving scores, highlighting the need to control for this variable.

The most accurate analysis of telematics data requires that the hierarchical nature of the data, with nesting of trip telematics data for each driver/vehicle, be addressed. However, this occurred for only three of the articles considered in this review. These models were the most useful for measuring the effectiveness of driving behaviour interventions.

4.2.4. Limitations observed in the literature

The most glaring issue observed throughout the review of insurance articles was the lack of a suitable description of the sample used. Demographical information about the sample was often missing, and, with sex having such a large impact on insurance pricing, ideally demographic effects should have been controlled for. Many articles also failed to appropriately describe the telematics data, with some articles not including any descriptive statistics for any telematics variables. The distributions of telematics variables such as acceleration and speed were also not commonly illustrated.

Typically, differences in the vehicles that the participants drove were not accounted for, with most studies neglecting to account for differences between vehicles with manual and automatic transmission. The age of the vehicles was also rarely taken into account, which is especially important in studies that analysed risky events or errors that can be related to vehicle age. Høye (2019) suggested that the increasing occurrence of technical defects in older vehicles contribute to higher crash risks.

With telematics data being hierarchical in structure it is surprising that hierarchical linear modelling was rarely seen in the articles included in the review. Accounting for driver level variables such as gender and age, and trip level variables such as location, duration, and the timing of a trip is needed in order to better understand risky driving behaviours.

5. Conclusion

The use and applications of in-vehicle telematics in vehicle insurance has been thoroughly documented in this review, with most studies found to be using in-vehicle telematics data to improve upon classical insurance claim frequency prediction models. Currently, machine learning techniques are the most frequently used way to analyse and model in-vehicle telematics data, with these techniques being especially popular in studies with insurance-based outcomes due to the large data sets available. Speed, braking, and distance travelled variables are typically the most useful in-vehicle telematics behaviours for measuring driving behaviour, with regression models and machine learning being the most useful techniques to analyse these variables.

Several important gaps were identified by this review. Currently, it is unknown how telematics feedback to the driver while they are driving influences driving behaviour. It is also unknown how in-vehicle telematics influences the behaviour of different age-groups in comparison to each other, and there is no consensus on what vehicle attributes cause differences in driving behaviour. Additionally, the efficacy of in-vehicle telematics in altering driving behaviour and reducing risky driving behaviours is still relatively unknown as there have been relatively few studies investigating the behavioural implications of telematics data. Also, little has been done to compare the behaviours of vehicle insurance customers before and after an in-vehicle telematics device has been installed in their vehicle. The applications for in-vehicle telematics for testing the effectiveness of interventions such as road safety advertising campaigns on driving behaviour have not been identified.

Future studies should describe their data in detail and obtain demographic information for drivers so that differences in responses to in-vehicle telematics can be better understood between sexes, age groups, and different socio-demographic groups. In addition, the effects of different types of vehicle on telematics data needs to be considered. It is also recommended that future studies that are interested in the behavioural implications of in-vehicle telematics describe in detail how the telematics data feedback is being provided to participants and find ways to record how often participants are receiving this information. Furthermore, it is also recommended that future studies account for differences in trips. For example, longer trips often include highway driving where risky behaviours such as sharp acceleration and braking are less likely to occur. This can be done by allowing for the hierarchical nature of the data when analysing telematics data rather than simply aggregating the data for each driver.

Author contribution

The study design was created by all authors. JB conducted the initial search and screening, and together JB and WSC made the final selection of articles with disagreements adjudicated by DM. JB conducted the quality assessment, data analysis and the initial draft of the paper, while all authors contributed to the final paper editing.

CRediT authorship contribution statement

James Boylan: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing. **Denny Meyer:** Conceptualization, Project administration, Resources, Supervision, Writing – review & editing. **Won Sun Chen:** Conceptualization, Funding acquisition, Project administration, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The articles included in the systematic review are shown in the supplementary material.

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Appendix A. Supplementary material

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