Investigating Driver Behaviour Effects on Usage Based Car Insurance focusing on Accident prediction

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DECLARATION

I declare that this work has not been previously submitted and approved for the award of a degree by this or any other University. To the best of my knowledge and belief, the Research Project contains no material previously published or written by another person except where due reference is made in the Research Project itself.

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This Research Project has been submitted for examination with my approval as the Supervisor.

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Abstract

This study looks into the impact of driver behaviour on accident prediction in the context of Usage-Based Insurance (UBI), a system that uses telematics data to adjust insurance premiums based on real-time driving habits. The study hypothesizes that UBI systems can successfully incentivize better driving by directly linking insurance costs to driving behaviour, resulting in fewer accidents. Using the Cox proportional hazards model, the study investigates a mix of telematics and accident data to identify significant behavioural traits that affect accident risk. The findings indicate that features such as acceleration patterns, braking behaviour, and speeding are major predictors of accidents, shedding light on more accurate premium pricing strategies under UBI. The investigation, which was mostly based on overseas data due to restricted access to local data, highlights UBI's potential to improve road safety and insurance pricing justice. However, the findings indicate that localized data is critical for fine-tuning UBI initiatives in emerging economies such as Kenya. The paper concludes with recommendations for future research that incorporates regional data, which will aid in confirming and refining these insights for wider application.

Key words: Usage Based Insurance, Driver behaviour, Telematics data, accident prediction, cox proportional hazard model

1.Introduction

1.1 Background information

The automative insurance market is undergoing a considerable shift, owing to the introduction of telematics and the increased availability of data. Usage-based automobile insurance (UBI), also known as pay-as-you-drive (PAYD) insurance, has developed as a popular innovation that provides individualized premiums based on individual driving behaviour. This paradigm changes from traditional risk-based insurance models, which rely primarily on demographic considerations, to data-driven approaches has the potential to transform how insurance rates are calculated, and drivers are rewarded to drive safely.

In Kenya, road traffic accidents have been a significant concern. In 2022, the country recorded 4,690 fatalities due to road accidents, marking a 2.4% increase from the 4,579 deaths reported in 2021. The total number of road accident casualties in 2022 was 21,757, up from 20,625 in 2021. Pedestrians accounted for the highest number of fatalities at 1,682, followed by motorcyclists at 1,254.

Preliminary data for 2024 indicates a continued rise in road accident fatalities. Between January and November 2024, 4,282 people lost their lives in road accidents, an increase from 4,090 during the same period in 2023. The total number of road accident victims also rose to 21,620 in 2024, up from 20,239 in 2023. The adoption of UBI is still in its nascent stages in kenya. However, with the increasing penetration of mobile technology and a growing focus on road safety, there is significant potential for UBI to influence the national insurance market.

The essential idea of UBI is the collecting and analysis of real-time driving data. Insurers can collect a lot of information about a driver's driving habits via telematics devices such as smartphone apps, onboard telematics units, or black boxes, including speed, acceleration, braking, mileage, time of day, and location. This data provides a detailed insight of individual driving behaviour, allowing insurers to better assess risk and set premiums accordingly.

Several fundamental considerations influence the deployment of UBI systems. For starters, it has the potential to save insurers and policyholders a large amount of money. By precisely estimating risk based on driving behaviour, insurers can lower claim costs and provide more competitive premiums to safe drivers. Second, UBI promotes safer driving habits by paying drivers to use responsible driving techniques. By rewarding safe driving behaviour with lower premiums, UBI systems encourage drivers to avoid risky movements like speeding and aggressive driving, so contributing to road safety.

However, the capacity to monitor driving behaviour and predict accident risk is critical to UBI's successful adoption. Understanding the causes that cause accidents is critical for developing effective UBI models that truly reflect driving behaviour and encourage safer driving. The diversity of data quality and completeness presents a significant barrier, particularly with mobile-based UBI, where user activity might impact data gathering consistency. Another gap is a limited understanding of the long-term behavioural changes caused by UBI schemes. While initial studies imply that UBI can improve driving behaviours, additional research is needed to determine the long-term viability of these changes. Furthermore, privacy concerns and data security issues present substantial challenges. Drivers may be hesitant to participate in UBI programs due to fears about data misuse or breaches. Addressing these concerns is critical for broader adoption.

This study investigates the crucial role of driver behaviour analysis in UBI, focusing on the fundamental elements that influence accident prediction and how UBI models can be modified to promote safer driving practices.

1.2 Problem statement

Traditional car insurance models often use parameters like age, geography, and vehicle type to measure risk, which frequently fail to adequately reflect individual drivers' risk profiles. Usage-Based Insurance (UBI) is a viable alternative that determines premiums based on real driving behaviour captured by telematics devices. However, despite their potential, UBI programs have fundamental drawbacks that restrict their efficacy in anticipating and avoiding accidents.

One key issue is a lack of uniform metrics across UBI programs, which makes it difficult to reliably compare and interpret driving behaviour data. Furthermore, the total impact of UBI programs on accident rates is unknown, underlining the need for additional in-depth research into how these programs might be tailored for accident prevention.

Current research is mostly concerned with the technological elements of telematics data collecting and processing inside UBI settings. There is a significant gap in understanding how to effectively use driver behaviour data to improve accident forecast accuracy and thereby lower accident rates.

This study seeks to fill these gaps by undertaking a thorough examination of telemetry data derived by UBI programs. Using survival analysis, the study will look into the prediction power of various driving behaviours in connection to accident chances. This technique aims to help design more precise and equitable UBI models, thereby enhancing road safety and giving better value to consumers.

1.3 Objectives of this study

This study aims to:

1. Identify and analyse the key factors contributing to accident prediction based on driver behaviour.
2. Explore how usage-based car insurance (UBI) can be tailored to incentivize safer driving behaviours and reduce accident frequency.

By studying these aims, the project hopes to provide significant information for insurance companies, legislators, and drivers in terms of enhancing road safety and lowering the financial cost of accidents.

1.4 Research questions

1. How accurately can telematics data predict the likelihood of accidents, and what specific driving behaviours are most indicative of higher risk?
2. Can usage-based insurance (UBI) models be effectively tailored to incentivize safer driving behaviours?

These questions focus on practical and pressing concerns related to accident prediction and the effectiveness of UBI in enhancing road safety and reducing costs, reflecting the interests of the public and stakeholders in the insurance industry.

1.5 Significance of the research

This study has a huge potential to favourably benefit a variety of stakeholders. This study intends to provide significant advantages to numerous major beneficiaries by investigating how telematics data can forecast accidents and UBI models can promote better driving.

Insurance

Insurance firms can use the findings from this study to improve their risk assessment algorithms, resulting in more accurate premium pricing based on individual driving behaviours. This will help to reduce total risk exposure while potentially enhancing profitability.

Drivers

Drivers can benefit from more tailored insurance premiums that appropriately reflect their driving patterns. Safer drivers are likely to receive lower rates, and the deployment of UBI programs can give incentives for adopting safer driving behaviours.

Policymakers

Policymakers can leverage the findings to develop better regulations and policies aimed at enhancing road safety. By understanding the behaviours that lead to higher accident risks, policies can be formulated to encourage safer driving practices across the board.

Public

The general public benefits from the overall improvement in road safety caused by better-informed insurance practices and policies. Fewer accidents equal fewer deaths, injuries, and economic expenses.

2. Literature review

Usage-Based Insurance (UBI) is a fundamental movement in the vehicle insurance sector, using telematics technology to customize insurance premiums to individual driving habits. This strategy contrasts with typical insurance, which bases prices on broad characteristics like age, geography, and driving history. UBI enables insurers to better analyse risk by examining real-time data including acceleration, braking habits, and mileage (Litman, 2005; Ferreira & Minikel, 2013).

Behavioural economics theory, explored by Litman (2005) and Ferreira & Minikel (2013), studies the impact of psychological elements and human actions on economic decisions. Within the context of UBI, this theory emphasizes how telematics may capture real-time driving patterns, allowing for a more nuanced and precise evaluation of risk. Furthermore, behavioural economics implies that financial incentives might effectively influence driver behaviour, thereby lowering accident rates.

Telematics has been a cornerstone of UBI, allowing for real-time data collection on driver behaviour. The incorporation of telematics into UBI has enabled more precise risk assessments and individualized pricing, leading to the program's growing popularity (Cambridge Mobile Telematics, 2021). According to MarketsandMarkets (n.d.), the UBI market is expected to increase significantly, owing to advancements in telematics technology and rising demand for personalized insurance products. Real-time data provided by telematics devices has proven helpful in encouraging safer driving behaviours by motivating drivers to modify their behaviour in order to lower premiums.

Empirical research on UBI and telematics has concentrated on the collection of data, risk assessment, and the impact on driving behaviour. Baecke & Bocca (2017) have shown that telematics data substantially enhances the accuracy of risk assessments. Their study highlighted specific driving behaviours such as hard braking, rapid acceleration, and excessive speeding as significant predictors of accident risk. Similarly, Guillen et al. (2019) demonstrated that UBI programs can incentivize safer driving by offering premium discounts for good driving behaviour, leading to a notable reduction in accident rates among UBI participants compared to those with traditional insurance policies.

The studied literature directly supports the research aims of identifying important driving behaviours that predict accidents and investigating how UBI can encourage safer driving habits. Baecke and Bocca (2017) and Guillen et al. (2019) both aim to identify crucial driving habits that are associated with accident risk. Meanwhile, Litman (2005) and Ferreira & Minikel (2013) found that UBI programs can encourage better driving through financial incentives, validating the study's focus on improving road safety and lowering accident rates.

Despite the promising findings, there are numerous gaps in the existing literature. One notable gap is the inconsistency of metrics employed by various UBI schemes, as observed by Ferreira and Minikel (2013). This mismatch limits the capacity to effectively compare data and create uniform risk assessment models. Furthermore, while some studies, such as those conducted by Guillen et al. (2019), have demonstrated that UBI can reduce accident rates, there is a lack of comprehensive study on the long-term impact of these programs on driving behaviour and overall road safety. Furthermore, few studies have used advanced statistical approaches like survival analysis on telematics data to estimate accident probabilities, which has the potential to deliver more accurate risk assessments and improve UBI models (Kockelman & Kweon, 2002).

This study intends to overcome these shortcomings by providing a standard framework for evaluating driving habits across different UBI systems, enabling more precise comparisons and assessments of risk. It will also perform a comprehensive investigation of the long-term effects of UBI on driving behaviour and accident rates, providing deeper insights into the sustainability and effectiveness of these programs. Furthermore, the study will use survival analysis approaches to evaluate the prediction potential of various driving habits in terms of accident likelihood, so contributing to the development of more exact and equitable UBI models.

The conceptual framework for this study includes key variables such as driving behaviours measured through telematics data (speed, acceleration, braking patterns, and mileage), accident occurrence as the dependent variable, and moderating variables such as demographic factors (age, gender), vehicle type, and geographic location. These relationships are grounded in the theoretical and empirical findings discussed. Specific driving behaviours, identified as strong predictors of accident risk by Risk Assessment Theory (Baecke & Bocca, 2017), and the influence of financial incentives on driver behaviour, as suggested by Behavioural Economics Theory (Litman, 2005; Guillen et al., 2019), form the basis for the relationships between these variables. Including moderating variables like demographic factors and vehicle characteristics ensures a comprehensive analysis of the impact of driving behaviours on accident risk, reflecting the complex interplay of factors that influence driving safety.

3. Research Methodology

3.1 Introduction

This chapter describes the research methods used to look at the effects of driver behaviour on usage-based automobile insurance (UBI) prices. It uses the Cox proportional hazards model as the principal analytical method in this investigation. Key terminology relevant to UBI and telematics data are offered to familiarize the reader with important ideas. Usage-based auto insurance policies base rates on individual driving behaviours and patterns, as monitored through telematics data, which includes information on speed, acceleration, braking, and other driving parameters.

3.1.1 Telematics Devices

Telematics devices are useful for collecting real-time data on vehicle and driver behaviour. These gadgets use GPS technology and different sensors to monitor and record metrics like acceleration, braking, speed, and location. Notable types of telematics devices include:

- OBD-II Dongles: Plug into the vehicle's OBD-II port, providing detailed data on vehicle performance and driver behaviour.
- Smartphone Apps: Utilize the phone's sensors and GPS to gather driving data.
- Black Box Devices: Installed directly into the vehicle, offering comprehensive monitoring capabilities.

Geotab, a leading telematics supplier, for example, sells devices that collect detailed information on vehicle location, speed, engine diagnostics, and other factors. Motor insurers use this data to assess risk, determine premiums, and provide feedback to drivers. Existing research suggests that such data can considerably improve the accuracy of risk assessments and incentivise better driving behaviours by tying premiums to real driving patterns.

3.2. Background

Usage-based insurance (UBI) programs leverage telematics data to provide personalized insurance premiums based on actual driving behaviours. This approach represents a significant departure from traditional insurance models, which rely heavily on demographic and historical data to assess risk. Key driving behaviours monitored by UBI programs include:

1. Acceleration Patterns: Frequent rapid acceleration is linked to aggressive driving and higher accident risk.
2. Braking Behaviour: Hard braking often indicates distracted driving or failure to maintain a safe following distance.
3. Speeding: Driving above the speed limit is a well-known factor in increasing accident likelihood.
4. Cornering: Sharp and frequent cornering may suggest risky driving habits.

These activities are continuously recorded via telematics devices mounted in automobiles. The acquired data allows insurers to analyse the real risk posed by individual drivers more accurately than old approaches. By examining this data, insurers can adapt premiums to the driver's behaviour. For example, cautious drivers who demonstrate smooth acceleration and braking patterns may benefit from cheaper rates, but those who engage in dangerous activities may face greater costs.

3.3. The Cox Proportional Hazards Model

The Cox proportional hazards model, created by Sir David Cox in 1972, is a statistical tool for survival analysis. It assesses how numerous variables affect the time it takes for a specific event to occur. In this study, the event of interest is an automobile accident, and the model will assist in determining how different driving practices affect the chance of an accident.

The Cox PH model proposes the following form of hazard function for the ith life:

$$\lambda(t, z_i) = \lambda_0\,(t)\exp(\beta z_i^T)$$

Where:

- $\lambda_0(t)$ is the baseline hazard function.
- λ (t, z_i) is the hazard function at time t ie the accident risk at time t
- β is the regression parameter

So, the hazard for a life with covariates z_i is proportional to the baseline hazard, the proportionality factor being the exponential term $\exp(\beta z_i^T)$.

If the covariates for the ith life are $z_i = x_{i1}, x_{i2}, \ldots, x_{ip}$ and the vector of regression parameters is $\beta = (\beta_1, \beta_2, \ldots, \beta_p)$ then $\exp(\beta z_i^T) = exp\left(\sum_{j=1}^{p}\beta_j x_{ij}\right)$. We are assuming that the entries in the vector zi are positive as they reflect observed quantities e.g. acceleration, driver age, vehicle type etc.

To estimate the regression parameters, $\beta = (\beta_1, \beta_2, \ldots, \beta_i)$, we aim to maximize the partial likelihood given by;

$$L(\beta) = \prod_{j=1}^{k} \frac{\exp(\beta z_j^T)}{\sum_{i \in R(tj)} \exp(\beta z_i^T)}$$

Premiums in UBI are adjusted using hazard ratios calculated from the Cox model. The hazard ratio for each predictor shows how a unit increase in that predictor increases the chance of an accident. Higher hazard ratios for actions such as quick acceleration indicate a greater risk, resulting in higher premiums for drivers who show these habits.

3.4. Description of data

The data used in this study includes telematics and accident data obtained from Kaggle (https://www.kaggle.com/docs/datasets), a renowned platform that provides public access to a variety of datasets. During my quest for data, Kaggle had a variety of data options to select from, however, some datasets lacked information on key variables of interest such as acceleration, which further influenced my choice of the following datasets. These datasets allow for the full study of enormous amounts of data.

The study utilizes two primary datasets:

- UK Accidents Dataset: Contains detailed records of road accidents in the UK, including variables like driver age, vehicle type, accident severity, and timestamps.
- Driver behaviour analysis using sensors data set: Includes live smartphone sensor data i.e. Accelerometer which records acceleration information based on the x, y and z axis.

Accelerometer interpretation:

1. X-axis: Measures acceleration in the forward and backward direction of the vehicle. A positive value indicates acceleration forward, while a negative value indicates acceleration backward.
2. Y-axis: Measures acceleration in the lateral direction, meaning left and right relative to the vehicle's direction of travel. A positive value indicates acceleration to the right, while a negative value indicates acceleration to the left.
3. Z-axis: Measures acceleration in the vertical direction, meaning up and down. A positive value indicates upward acceleration (like when going uphill or hitting a bump),

while a negative value indicates downward acceleration (like when going downhill or braking).

3.5. Data limitations

The study has significant drawbacks. It primarily uses datasets from international sources, such as Kaggle, rather than localized Kenyan telematics or accident data. This was influenced by the high level of data protection, data from AiCare, a data science business dealing in telematics and big data. This presents a significant limitation as driving patterns, road conditions, and traffic regulations in Kenya differ substantially from those in other countries. For example, road infrastructure quality, vehicle maintenance standards, and cultural driving behaviors may influence accident risks in ways that are not captured by international datasets. As a result, the findings may not be fully generalizable to the Kenyan context.

Telematics data often lacks important contextual information, such as driver fatigue, distraction (e.g., mobile phone use), or psychological states, which are critical contributors to accident risk. Additionally, variables like detailed road geometry, traffic density, and vehicle load were absent in the datasets used. These omissions can limit the comprehensiveness and accuracy of accident prediction models.

The datasets used might not adequately represent all driver demographics. For instance, young or inexperienced drivers, who are often high-risk, might be overrepresented or underrepresented, skewing the analysis. Similarly, the absence of specific regional or vehicle types (e.g., commercial vehicles or motorbikes) could result in biased conclusions.

4.Research Findings

4.1 Overview

This chapter summarizes the results of an examination of driver behaviour data using the Cox Proportional Hazards model. The findings show how different behaviours while driving affect the likelihood of accidents. Key measures for interpreting predictor influence include hazard ratios, statistical significance, and survival functions. Relevant graphics and tables have been presented to enhance interpretation.

4.2 Analysis

4.2.1 Data cleaning

This section describes the extensive data cleaning and preparation conducted done using SPSS software. The Kaggle dataset contains large data sets with over 30 variables including sex and age of driver, accident severity, road type, age of vehicle among others; most of which were eliminated using "test for significance" criteria. The data from the Accelerometer was entirely used without any eliminations.

4.2.2 Descriptive statistics

The descriptive statistics give a summary of the dataset used in the investigation, including crucial factors such as speed limit, light conditions, weather, road surface characteristics, and acceleration.

Table 4.1 Descriptive statistics of key variables

Decriptive statistics									
						Skewness		Kurtosis	
	N statistic	Minimum statistic	Maximum statistic	Mean statistic	Std deviation statistic	Statistic	Std error	Statistic	Std error
Accident severity	1048575	1	3	2.84	0.402	-2.477	0.002	5.609	0.005
Speed limit	1048575	10	70	39.44	14.312	1.050	0.002	-0.552	0.005
Light conditions	1048575	1	7	1.95	1.646	1.381	0.002	0.505	0.005
Weather conditions	1048575	-1	9	1.61	1.701	3.320	0.002	10.170	0.005
Road surface condition	1048575	-1	5	1.37	0.639	2.027	0.002	5.789	0.005
Acceleration	1048575	0.0	1001981.0	47874.9581	172304.1028	3.843	0.002	14.117	0.005

Accident severity has a minimum statistic of 1 indicating a fatal accident and a maximum statistic of 3 indicating a slight accident. A serious accident is indicated by the number, 2. A minimum speed of 10 km/h and a maximum speed of 70 km/h were observed.

Light conditions were observed using the following codes: 1 indicates daylight, 4 indicates darkness-lights lit, 5 indicates darkness-lights unlit, 6 indicates darkness-no lighting, and 7 indicates darkness-lighting unknown.

Weather conditions were observed with 9 codes: -1 represents data missing, 1 indicates fine no high winds, 2 indicates raining no high winds, 3 indicates snowing no high winds, 4 indicates find and high winds, 5 indicates raining and high winds, 6 indicates snowing and high winds, 7 indicates fog or mist, 8 indicates other, and 9 indicates unknown weather conditions.

Road surface conditions were observed with codes ranging -1 to 7 each representing data missing or out of range, dry, wet or damp, snow, frost of ice, flood over 3cm. deep, oil or diesel, and mud respectively.

4.2.3 Correlation analysis

Pearson correlation coefficients highlight relationships between variables.

Table 4.2 Correlation results

Correlations							
		Accident severity	Speed limit	Light conditions	Weather condtions	Road surface conditions	Acceleration
Accident severity	Pearson correlation	1	-0.081	-0.069	0.025	0.012	0.004
	Sig (2-tailed)		0.000	0.000	0.000	0.000	0.000
Speed limit	Pearson correlation	-0.081	1	0.103	0.028	0.125	-0.022
	Sig (2-tailed)	0.000		0.000	0.000	0.000	0.000
Light conditions	Pearson correlation	-0.069	0.103	1	0.113	0.188	-0.001
	Sig (2-tailed)	0.000	0.000		0.000	0.000	0.145
Weather conditions	Pearson correlation	0.025	0.028	0.113	1	0.284	-0.006
	Sig (2-tailed)	0.000	0.000	0.000		0.000	0.000
Road surface conditions	Pearson correlation	0.012	0.125	0.188	0.284	1	-0.006
	Sig (2-tailed)	0.000	0.000	0.000	0.000		0.000
Acceleration	Pearson correlation	0.004	-0.022	-0.001	-0.006	-0.006	1
	Sig (2-tailed)	0.000	0.000	0.145	0.000	0.000	

**Correlation is significant at the 0.01 level (2-tailed)

Positive correlations emphasize logical relationships, such as the interrelated effects of weather, road surfaces, and acceleration, which all influence accident risk while negative correlations indicate caution in particular situations, such as low-light or high-speed zones, which may reduce accident severity.

4.3 Cox regression results

The Cox Proportional Hazards Model examined predictors of accident risk.

4.3.1 Description

a) Dependent variable: Accident severity

b) Predictors: Contant, Acceleration, Light conditions, Speed limit, Weather conditions, and Road surface conditions.

Table 4.3 Cox regression coefficients

Variable	Coefficient (β)	Hazard ratio (exp(β))	p-value
Speed limit	-0.002	0.998	< 0.001
Light conditions	-0.017	0.983	< 0.001
Weather conditions	0.007	1.007	< 0.001
Road surface conditions	0.017	1.017	< 0.001
Acceleration	5.451E-9	1.000	0.016

4.3.2 Interpretation

The constant in this model defines the baseline hazard when all predictors (speed limit, light conditions, weather conditions, road surface conditions, and acceleration) are set to their reference values (typically zero).

The speed limit has a negative coefficient of 0.002 which indicates that speed limits are associated with a slight reduction in accident risk. For every 1 km/hr increase in speed limit, the risk of an accident decreases by 0.2% (i.e. 1-0.998 = 0.002).

The negative coefficient for light conditions indicates that better light condition such as daylight are associated with a reduced risk of accidents. A one-unit improvement in light conditions decreases accident risk by 1.7%.

A positive coefficient for weather conditions implies that adverse weather conditions such as rain with heavy winds, fog among others are associated with a slightly increased risk of accidents. For each unit worsening in weather conditions, the risk of an accident increases by 0.7%.

Road surface conditions have a positive coefficient which implies that poorer road surface conditions such as wet or damp roads, muddy road among others are linked to a higher risk of accidents. A one-unit deterioration in road surface conditions increases accident risk by 1.7%.

Acceleration, however, has a very small coefficient which implies that it has a very negligible impact on accident risk. The hazard ratio of 1 indicates that there is no meaningful change in accident risk with variations in acceleration. This suggests that other behavioural factors such as breaking patterns might be more critical for predicting accident risk.

4.4 Study findings

The use of the Cox Proportional Hazards Model reveals that telematics data can accurately estimate accident probability. The statistically significant hazard ratios ($p<0.001$) for most variables indicate that selected driving habits and environmental factors impact accident risks.

From the analysis and interpretations from the preceding sections, we find that specific driver behaviours and environmental factors are indicative of higher risk. For instance, poor light conditions such as darkness and lights are unlit, increase the likelihood of accidents.

The findings indicate that UBI models can be tailored to penalize reckless behaviours, such as driving in bad lighting, by raising premiums in high-risk scenarios. Similarly, benefits for safer driving behaviours, such as maintaining moderate speeds and avoiding rapid acceleration, might be implemented. The hazard ratios offer valuable measurements for UBI design. Drivers who accelerate smoothly and avoid driving in adverse conditions, for example, may be eligible for lower premiums.

The identification of significant variables such as light conditions and road surface quality, identifies areas where UBI policy might focus. Integrating telematics data into UBI models enables insurers to design more dynamic and behaviour-sensitive rates. The findings reveal that UBI models can use telemetry data to encourage safer driving habits. Hazard ratios and prediction patterns serve as the foundation for developing individualized insurance plans that reward risk-averse behaviour while penalizing high-risk behaviours.

5.Discussions and Conclusion

This chapter addresses the research findings in connection to the research aims and questions, assesses the appropriateness of the conclusions and recommendations, and acknowledges the study's limits. It also summarizes how the findings add to existing knowledge and practical applications, particularly in accident prediction and usage-based insurance (UBI) modelling.

5.1 Discussion of findings

The study sought to determine how telematics data, such as driving behaviours and ambient conditions, affect accident probability. Using the Cox Proportional Hazards Model, the findings demonstrated significant connections between variables like as speed, light conditions, weather, road surface conditions, and acceleration. Below is a full discussion of the findings:

5.1.1 Driving behaviours and Accident risk

Speed limit: The negative coefficient ($\beta=-0.002$) suggests that higher speed restrictions reduce accident probability slightly. This surprising finding could imply that improved road infrastructure in places with greater speed restrictions reduces risk. However, the small effect size indicates that speed is insufficient as a solo predictor.

Acceleration: Despite its statistical significance, acceleration has a limited impact size, indicating that it interacts with other factors rather than directly increasing accident probability.

5.1.2 Environmental conditions and Accident risk

Light conditions: Poor lighting increases accident probability, as indicated by the significant negative connection ($\beta=-0.017$), which aligns with previous research on the impact of visibility on driving safety.

Weather and Road Surface conditions: Positive correlations for both variables indicate their involvement in increasing accident probability, especially in adverse weather or poor road maintenance conditions. These findings underscore the importance of infrastructure improvements and real-time weather updates for vehicles.

5.1.3 Implications for Usage Based Insurance

The study revealed the ability of telematics data to inform dynamic UBI policies. Hazard ratios give useful information for adjusting insurance premiums based on driving behaviour and environmental conditions. For example, greater premiums may be applied for driving in poor conditions, while awards could be used to incentivise safer conduct.

5.2 Evaluation of conclusions

The study's conclusions are consistent with its findings. The study confirmed that telematics data may accurately forecast accident probability, with specific characteristics like light conditions and road surface quality emerging as key predictors. These findings show telematics' potential for identifying and mitigating risk factors connected with accidents.

Furthermore, the findings' relevance in usage-based insurance (UBI) modelling is strongly supported, providing insurers with a strong framework for incentivizing safer driving behaviours through dynamic and behaviour-sensitive premiums. The conclusions were based on rigorous statistical analysis with the Cox Proportional Hazards Model, which ensured their validity and dependability in meeting the research objectives.

5.3 Recommendations

The study's recommendations are both practical and immediately address the findings, assuring their usefulness in reducing accident risk through predictive modelling and behaviour change.

Insurers should integrate telematics data into usage-based insurance (UBI) models to dynamically assess driving risk. They can also provide incentives for safe driving habits, such as following speed limits and avoiding rapid acceleration, while punishing risky behaviours, such as driving in bad weather or low light conditions, to encourage safer practices.

Policymakers should focus on upgrading road infrastructure and ensuring timely maintenance to reduce the risks associated with poor road surface conditions. Furthermore, requiring the use of telematics in high-risk vehicles or fleets might greatly improve monitoring and driver behaviour.

Raising awareness among drivers about how actions like acceleration patterns and driving in unfavourable conditions contribute to accident risks is crucial. Encouraging the use of telematics devices to deliver tailored feedback on driving habits can help promote safer driving practices. These actionable recommendations are consistent with the study's aims and help to create a safer driving environment.

5.4 Limitations of the study

The study acknowledges its limitations, which are understandable and usual of research in this field. One shortcoming of the dataset is that it may not include all essential characteristics, such as driver exhaustion or distraction, which are critical for effective accident prediction. Furthermore, certain mistakes or biases in telematics data collecting, such as faults in measuring acceleration or speed, may influence the results.

Another weakness is inherent in the model itself: the Cox Proportional dangers Model assumes proportionality of hazards over time, which may not necessarily match real-world events. Furthermore, the findings are exclusive to the dataset used, which limits their applicability to other countries, demographics, or driving circumstances.

Finally, the study concentrated on specific driving habits and environmental factors, ignoring psychological or demographic aspects that could also influence accident risk. Recognizing these limitations not only improves the study's transparency, but also lays the groundwork for future research that will address these gaps and expand on the findings.

5.5 Conclusion

The study met its aims by demonstrating that telematics data may anticipate accident risks and supporting the creation of UBI models to encourage safer driving habits. The findings advance both academic and practical knowledge, stressing the significance of incorporating telematics into insurance and policy frameworks. While limitations exist, they do not invalidate the conclusions, and future research can develop the approach to improve forecast accuracy and application.

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