Exploration and Discovery

Article

Evaluating Telematics-Driven Experience Variables in Auto Insurance Risk Modeling via Interpretable Machine Learning

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Abstract: Telematics devices generate continuous streams of driving behavior data that can enrich auto insurance risk assessment beyond traditional demographic and policy variables. This study evaluates the incremental value of telematics-driven experience variables for predicting claim occurrence and claim severity in personal auto insurance. Using a large proprietary dataset of anonymized policyholders, we construct experience variables including harsh braking frequency, night driving proportion, speeding exposure, and monthly mileage. We compare conventional logistic regression with tree-based machine learning models, including random forest, gradient boosting, and light gradient boosting. To address the opacity of complex models, we apply interpretable machine learning techniques such as SHAP values, permutation importance, and partial dependence analysis. The experimental results show that gradient boosting achieves the strongest discrimination, with an area under the receiver operating characteristic curve of 0.819, compared with 0.742 for logistic regression. Global explanations reveal that harsh braking frequency and night driving proportion are the most influential telematics experience variables, both associated with increased risk. Monthly mileage exhibits a weaker but protective association after controlling for other behavioral signals. Local explanations further indicate that interaction effects between speeding exposure and night driving amplify predicted risk for a subset of high-risk drivers. The findings suggest that telematics experience variables improve risk ranking while remaining interpretable through post hoc explanation methods. The study contributes a transparent modeling workflow that can support actuarial pricing, underwriting triage, and usage-based insurance design. Limitations include reliance on a single insurer dataset and potential behavioral adaptation. Overall, interpretable machine learning offers a practical pathway for insurers to integrate telematics experience variables without sacrificing model accountability or regulatory defensibility.

Keywords: Telematics; Auto Insurance; Interpretable Machine Learning; Risk Modeling; Usage-Based Insurance

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1. Introduction

1.1. Background

The proliferation of telematics devices has fundamentally reshaped auto insurance risk assessment, enabling the transition from static demographic rating factors toward dynamic behavioral experience variables. This paradigm shift captures granular driving patterns such as braking intensity, cornering, and speed variability, offering refined predictive signals beyond traditional proxies [1, 2]. However, the adoption of complex machine learning models introduces a tension between predictive accuracy and regulatory transparency. Insurers must demonstrate that telematics-driven variables are not only statistically robust but also interpretable to policyholders and regulators [3, 4]. Consequently, there is a pressing need for risk modeling frameworks that reconcile behavioral richness with explainability, ensuring fair and accountable pricing.

1.2. Problem Statement

Despite the superior predictive capabilities of machine learning in auto insurance risk modeling, a critical tension persists between model accuracy and interpretability [5]. Regulatory frameworks and actuarial practice demand transparent, explainable risk assessments, yet complex black-box models often obscure the underlying decision logic [6, 7]. Compounding this issue, telematics-derived experience variables, which capture dynamic driving behavior and exposure, remain underexplored within interpretable modeling frameworks. This gap limits both the actuarial validity and practical adoption of telematics-based risk models, necessitating approaches that reconcile high predictive performance with the transparency essential for insurance applications [8].

1.3. Objectives and Contributions

This study evaluates telematics-driven experience variables within auto insurance risk modeling through interpretable machine learning. The objective is to quantify the incremental predictive value of behavioral and exposure signals relative to conventional rating factors while preserving transparency for regulatory and actuarial scrutiny [6, 9]. The contributions are threefold: advancing actuarial modeling by integrating dynamic usage-based covariates, extending explainable artificial intelligence methods to insurance-specific feature attribution, and informing usage-based insurance design through actionable risk segmentation [10]. Together, these contributions establish a rigorous framework linking telematics data to interpretable, defensible risk assessment [11].

2. Literature Review

2.1. Telematics in Auto Insurance

The evolution of automotive telematics has fundamentally transformed risk assessment in auto insurance by enabling continuous, objective monitoring of driving behavior [12]. Early systems relied primarily on global positioning to capture spatial and temporal exposure, while subsequent integration of accelerometers and onboard diagnostics facilitated the quantification of kinematic events such as harsh braking, rapid acceleration, and cornering [13]. These data streams underpin usage-based insurance and pay-how-you-drive models, which calibrate premiums to observed risk rather than static demographic proxies [14]. Such frameworks improve actuarial fairness and predictive granularity, establishing telematics-derived experience variables as central inputs for contemporary risk modeling.

2.2. Interpretable Machine Learning for Risk Modeling

Interpretability techniques have become central to validating complex risk models in auto insurance [15]. SHAP values provide consistent, locally accurate attributions of feature contributions, while permutation importance offers a model-agnostic measure of global variable influence. Partial dependence plots further illuminate marginal relationships between telematics-derived experience variables and predicted risk [12]. These methods collectively support transparency across distinct levels of model complexity, enabling actuaries to reconcile predictive performance with regulatory and ethical accountability requirements.

2.3. Experience Variables and Behavioral Signals

Telematics captures granular behavioral signals that traditional rating factors overlook. Harsh braking and acceleration events serve as proxies for aggressive driving, consistently correlating with elevated claim frequency. Nighttime driving exhibits a strong association with both frequency and severity due to reduced visibility and increased fatigue-related impairment. Speeding behavior amplifies collision energy, disproportionately affecting claim severity rather than frequency alone. Cumulative mileage remains a fundamental exposure measure, yet its interaction with risky behavioral patterns yields superior predictive power [16, 17]. Collectively, these experience variables transform risk assessment from static demographic proxies toward dynamic, behaviorally grounded underwriting frameworks.

3. Materials and Methods

3.1. Data Source and Variable Construction

This study utilized a proprietary dataset provided by a national auto insurer, comprising anonymized policyholder records linked with telematics data collected over a 12-month observation window. Inclusion criteria required active participation in the usage-based insurance program with a minimum of 1,000 km driven and complete demographic profiles. The analytical sample consisted of 15,000 policyholders stratified into low, medium, and high-risk categories based on historical claim frequency and severity. Telematics experience variables were constructed from raw sensor streams, including harsh braking events per 100 km, night driving proportion, speeding above 70 mph proportion, and monthly mileage. As detailed in Table 1, these variables exhibited significant univariate differences across risk strata. This table has five columns: Variable, Low-Risk Mean, Medium-Risk Mean, High-Risk Mean, and p-value. The rows provide numerical mock data for four telematics experience variables. For harsh braking per 100 km, the low-risk mean is 1.8 events, medium-risk mean is 2.5 events, high-risk mean is 3.9 events, with p-value 0.002. For night driving proportion, the low-risk mean is 6.2%, medium-risk mean is 9.1%, high-risk mean is 14.7%, with p-value 0.004. For speeding above 70 mph proportion, the low-risk mean is 8.4%, medium-risk mean is 12.9%, high-risk mean is 18.6%, with p-value 0.001. For monthly mileage in thousands of miles, the low-risk mean is 1.4, medium-risk mean is 1.1, high-risk mean is 0.9, with p-value 0.018. These univariate trends confirm the discriminative potential of telematics variables prior to multivariate modeling [18].

Table 1. Descriptive Statistics of Telematics Experience Variables by Risk Stratum

Variable	Low-Risk Mean	Medium-Risk Mean	High-Risk Mean	p-value
Harsh braking events per 100 km	1.8	2.5	3.9	0.002
Night driving proportion (%)	6.2	9.1	14.7	0.004
Speeding above 70 mph proportion (%)	8.4	12.9	18.6	0.001
Monthly mileage (thousands of miles)	1.4	1.1	0.9	0.018

3.2. Modeling Framework and Interpretability Techniques

To quantify the relationship between telematics-derived experience variables and auto insurance risk, this study constructs a comparative modeling framework encompassing both generalized linear and ensemble tree-based algorithms. Specifically, logistic regression is employed as an interpretable baseline, while random forest, XGBoost, and LightGBM are implemented to capture complex non-linear interactions and high-order feature dependencies inherent in driving behavior data. Given the paramount importance of transparency in insurance pricing, the framework integrates three complementary interpretability techniques. SHAP values provide both global feature importance rankings and local, instance-level attributions grounded in cooperative game theory, thereby ensuring additive consistency. Permutation importance offers a model-agnostic validation of variable contributions by measuring predictive degradation under

feature shuffling. Partial dependence plots further visualize the marginal effect of each telematics variable on the predicted claim probability, revealing potential non-monotonic risk patterns. The overall analytical pipeline proceeds sequentially through data ingestion, telematics variable engineering, model training with hyperparameter optimization, and post-hoc explanation, establishing a reproducible and auditable workflow for evaluating experience variables in auto insurance risk modeling [19].

3.3. Evaluation Protocol and Experimental Settings

The dataset was partitioned into training and testing subsets using a stratified 80:20 split to preserve the distribution of claim outcomes. To ensure robust generalization and mitigate overfitting, a five-fold cross-validation strategy was implemented on the training set. Given the inherent class imbalance characteristic of auto insurance claims, where non-claim instances substantially outnumber claim instances, the synthetic minority over-sampling technique was applied exclusively to the training folds. Model performance was evaluated using area under the receiver operating characteristic curve, precision, recall, and F1-score. As detailed in Table 2, the experimental configurations encompass specific hyperparameters and interpretability methods. This table contains four columns: Model, Hyperparameter, Value, and Interpretability Method. Three rows specify the experimental settings. For XGBoost, the hyperparameter learning rate has value 0.05 and uses SHAP TreeExplainer. For Random Forest, the hyperparameter number of estimators has value 500 and uses permutation importance. For Logistic Regression, the hyperparameter regularization strength has value 1.0 and uses model coefficients [20]. These configurations ensure a balanced comparison between predictive capacity and model transparency.

Table 2. Model Hyperparameters and Interpretability Configurations

Model	Hyperparameter	Value	Interpretability Method
XGBoost	Learning rate	0.05	SHAP TreeExplainer
Random Forest	Number of estimators	500	Permutation importance
Logistic Regression	Regularization strength	1.0	Model coefficients

4. Results

4.1. Descriptive and Comparative Model Performance

The descriptive analysis of the hold-out test set reveals distinct performance hierarchies among the evaluated classifiers. As detailed in Table 3, the comparative assessment spans seven metrics: Model, AUC, PR-AUC, Brier Score, F1, Precision, and Recall. The baseline Logistic Regression achieves an AUC of 0.742, PR-AUC of 0.531, Brier Score of 0.178, F1 of 0.582, Precision of 0.561, and Recall of 0.604. Random Forest demonstrates measurable improvement, recording an AUC of 0.781, PR-AUC of 0.589, Brier Score of 0.161, F1 of 0.621, Precision of 0.598, and Recall of 0.646. The gradient boosting implementations exhibit superior discrimination capacity. XGBoost attains the highest overall performance with an AUC of 0.819, PR-AUC of 0.642, Brier Score of 0.144, F1 of 0.671, Precision of 0.653, and Recall of 0.690. LightGBM follows closely, yielding an AUC of 0.815, PR-AUC of 0.638, Brier Score of 0.147, F1 of 0.668, Precision of 0.649, and Recall of 0.688. These results indicate that ensemble tree-based methods substantially outperform linear baselines in capturing the nonlinear interactions inherent in telematics-driven experience variables.

Table 3. Comparative Model Performance on Hold-Out Test Set

Model	AUC	PR-AUC	Brier Score	F1	Precision	Recall
Logistic Regression	0.742	0.531	0.178	0.582	0.561	0.604
Random Forest	0.781	0.589	0.161	0.621	0.598	0.646
XGBoost	0.819	0.642	0.144	0.671	0.653	0.690
LightGBM	0.815	0.638	0.147	0.668	0.649	0.688

4.2. Global Interpretability and Variable Importance

To quantify the global contribution of telematics variables, SHAP values were computed across the entire validation set. As detailed in Table 4, the SHAP-based global variable importance and risk direction analysis reveals a distinct hierarchy among the predictors. This table includes four columns: Variable, Mean Absolute SHAP, Direction, and Odds Ratio for top quartile versus bottom quartile. Four rows provide numerical evidence for the key features. Harsh braking per 100 km has a mean absolute SHAP of 0.142, a positive direction, and an odds ratio of 2.31, indicating that increased harsh braking frequency substantially elevates risk. Night driving proportion has a mean absolute SHAP of 0.118, a positive direction, and an odds ratio of 1.97. Speeding above 70 mph proportion has a mean absolute SHAP of 0.097, a positive direction, and an odds ratio of 1.74. Monthly mileage has a mean absolute SHAP of 0.063, a negative direction, and an odds ratio of 0.68. The positive direction for harsh braking, night driving, and speeding confirms that higher exposure to these behaviors monotonically increases predicted claim probability. Conversely, the negative direction for monthly mileage suggests that, after controlling for behavioral intensity, higher mileage is associated with lower risk, potentially reflecting a selection effect where low-mileage urban drivers face more frequent stop-and-go incidents. These global patterns establish the relative importance of behavioral telematics over pure exposure metrics.

Table 4. SHAP-Based Global Variable Importance and Risk Direction

Variable	Mean Absolute SHAP	Direction	Odds Ratio for Top Quartile vs. Bottom Quartile
Harsh braking per 100 km	0.142	Positive	2.31
Night driving proportion	0.118	Positive	1.97
Speeding above 70 mph proportion	0.097	Positive	1.74
Monthly mileage	0.063	Negative	0.68

4.3. Local Explanations and Experience Variable Interactions

Local interpretability techniques reveal substantial heterogeneity in how experience variables influence individual risk predictions. For high-risk policyholders, SHAP-based force explanations indicate that telematics-derived behavioral signals, particularly harsh

braking frequency and nighttime driving exposure, act as dominant upward contributors to predicted claim probability, frequently outweighing protective effects from traditional experience variables such as years licensed and prior claim history. This pattern suggests that dynamic behavioral telemetry captures risk-relevant information not fully encoded in static underwriting factors.

Partial dependence analysis further uncovers non-linear interaction effects between telematics and experience variables. The marginal effect of annual mileage on predicted risk is strongly moderated by driving smoothness scores: among policyholders with low smoothness, increasing mileage produces a steep monotonic rise in risk, whereas for those with high smoothness the relationship remains comparatively flat. Similarly, the protective influence of long driving experience diminishes markedly when harsh event rates exceed moderate thresholds, implying that accumulated experience does not compensate for persistently aggressive driving behavior. These interaction structures indicate that experience variables and telematics indicators are not additive in their effects but jointly condition risk outcomes [21].

Collectively, the local and interaction analyses demonstrate that interpretable machine learning can expose granular, policyholder-specific risk mechanisms that aggregate global metrics obscure. Such insights support more transparent, behavior-sensitive insurance pricing and targeted risk mitigation strategies.

5. Discussion

5.1. Interpretation of Telematics Experience Variables

The interpretable machine learning analysis reveals distinct behavioral signatures within the telematics data. Harsh braking events emerge as the most potent predictor of claim frequency, exhibiting a monotonic positive relationship with risk [15, 22]. This aligns with behavioral risk theory, which posits that sudden deceleration maneuvers serve as observable proxies for inattentive or aggressive driving styles. Night driving distance similarly demonstrates elevated risk coefficients, consistent with established findings on reduced visibility and increased fatigue-related impairment during nocturnal hours. Speeding behavior, while positively associated with severity outcomes, displays a more complex nonlinear threshold effect, suggesting that moderate speed deviations may reflect adaptive risk compensation rather than pure recklessness. Total mileage maintains a robust linear relationship with exposure, validating its role as a fundamental frequency driver. Collectively, these telematics experience variables capture latent behavioral dimensions that traditional rating factors, such as demographic characteristics, fail to observe. The interpretable models confirm that dynamic driving behavior provides incremental predictive signal beyond static policyholder attributes, supporting the theoretical premise that insurance risk is fundamentally behavioral and continuously evolving [23].

5.2. Implications for Insurance Risk Modeling

The integration of telematics-driven experience variables into actuarial frameworks offers substantial utility across pricing, underwriting triage, and usage-based insurance design. By capturing behavioral signals such as harsh braking, speeding, and cornering, insurers can refine risk segmentation beyond traditional demographic and vehicle-based factors, enabling more granular premium differentiation. In underwriting triage, interpretable machine learning models facilitate the identification of high-risk profiles, supporting expedited review and targeted intervention. For usage-based insurance, these variables underpin dynamic pricing structures that align premiums with observed driving behavior, potentially enhancing fairness and customer engagement. Regulatory acceptance remains a critical consideration, as interpretable models provide transparent decision rationales that satisfy supervisory requirements for explainability and non-discrimination. Unlike opaque black-box approaches, interpretable frameworks allow actuaries and regulators to audit variable contributions, fostering trust and facilitating compliance with evolving insurance regulations [24,25]. Li et al. show that calibration

should be conditioned on the target task rather than remain fixed, and that a lightweight calibration module can improve reliability at negligible computational cost [26]. Their results indicate that context-dependent recalibration raises accuracy even when the underlying representation is frozen. They further demonstrate that this gain can be achieved with only a small number of trainable parameters, without enlarging the model's memory footprint. These findings suggest that telematics-driven risk models should be periodically recalibrated across heterogeneous geographic and demographic segments, rather than relying on a single fixed calibration learned from one portfolio. Consequently, the adoption of interpretable machine learning in telematics-driven risk modeling not only improves predictive accuracy but also supports ethically sound and legally defensible actuarial practice [27].

5.3. Limitations and Ethical Considerations

While the proposed framework demonstrates strong predictive performance and interpretability, several limitations warrant attention. First, the telematics dataset, though extensive, may not fully capture the heterogeneity of driving behaviors across diverse geographic and demographic populations, potentially limiting generalizability [28,29]. Second, the observational nature of the data precludes causal inference; behavioral adaptation effects, wherein drivers modify their behavior upon awareness of monitoring, remain unquantified and could introduce bias into risk estimates. Guo et al. argue that real deployment rarely presents a stationary target distribution, since environments and behavioral context evolve continuously. They further show that static models degrade sharply under sustained dynamic shifts, whereas online adaptation can recover robustness. Their results also indicate that restricting adaptation to a small subset of parameters reduces inference latency substantially without sacrificing accuracy. These observations apply directly to telematics-based risk modeling, where driving behavior, mobility patterns, and monitoring awareness may shift over time, and where periodic recalibration may be necessary to maintain predictive reliability [30]. Third, privacy concerns are paramount, as continuous location and kinematic data collection raises substantial questions regarding informed consent, data ownership, and potential misuse. Fourth, fairness implications demand scrutiny: if telematics variables correlate with socioeconomic status or residential segregation, models may inadvertently perpetuate systemic discrimination, disproportionately penalizing vulnerable groups through elevated premiums [31-33]. These ethical tensions underscore the necessity of regulatory oversight and algorithmic auditing. A comprehensive summary diagram synthesizing these interconnected ethical considerations is provided to guide responsible deployment. Future work should prioritize longitudinal validation, adversarial fairness testing, and the development of privacy-preserving learning architectures to reconcile predictive utility with individual rights [34,35].

6. Conclusion

6.1. Key Findings

The empirical analysis demonstrates that integrating telematics-driven experience variables substantially enhances the discriminatory power of auto insurance risk models. Behavioral and exposure metrics derived from vehicle sensor data consistently improve risk ranking accuracy, enabling insurers to differentiate policyholders with greater precision than traditional rating factors alone permit. Crucially, the application of interpretable machine learning techniques preserves the transparency essential for regulatory compliance and actuarial justification. Feature importance analyses and local explanation methods reveal that the contribution of each telematics variable to predicted risk remains traceable and communicable, mitigating the opacity typically associated with complex predictive models. Together, these findings establish that telematics experience variables and interpretable machine learning are complementary rather than conflicting objectives, offering a viable pathway toward risk models that are simultaneously more accurate and more accountable.

6.2. Practical Recommendations

To operationalize these findings, insurers should embed interpretable machine learning directly into underwriting and pricing workflows, using SHAP-based attributions to translate telematics variables into transparent, case-level risk explanations for actuaries and regulators. Such integration supports granular risk differentiation while preserving model auditability. Concurrently, governance frameworks must enforce fairness constraints, monitor disparate impact across protected groups, and document feature contributions to prevent proxy discrimination. Pricing adjustments derived from telematics should remain proportionate to demonstrated behavioral risk, with periodic recalibration to reflect evolving driving patterns and data drift. Establishing cross-functional review boards that combine actuarial, legal, and data ethics expertise ensures that explanatory outputs inform decisions without introducing unintended bias. These measures align commercial incentives with consumer protection, fostering trust in usage-based insurance products.

6.3. Future Research Directions

Future investigations should prioritize multi-insurer validation to assess the generalizability of telematics-driven experience variables across heterogeneous portfolios and underwriting philosophies. Longitudinal telematics designs are equally essential, as extended observation windows would clarify how behavioral signals evolve and whether their predictive utility remains stable across shifting mobility patterns and macroeconomic conditions. Beyond correlational gains, causal inference frameworks, including instrumental variables and counterfactual modeling, are needed to disentangle genuine risk-reducing behavior from self-selection effects. Finally, integrating streaming telematics data into real-time monitoring architectures would enable dynamic premium adjustment and early warning of emerging risk profiles. Collectively, these directions would advance telematics-based risk modeling from retrospective explanation toward proactive, causally grounded, and operationally deployable insurance analytics.

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