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Legislative and Regulatory Frameworks: Regulatory Issue of Black Box Algorithms in Motor Insurance Pricing

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ABSTRACT

This study investigates the regulatory challenges posed by the integration of AI-driven black box algorithms in motor insurance pricing. The research employs archival techniques to select scholarly articles and thesis records from the period 2017 to 2025, focusing on topics such as unfair discrimination, transparency, fairness, and regulatory compliance requirements. The methodology encompasses a comprehensive literature review to identify existing regulatory gaps and challenges, and case studies to examine real-world applications and implications of black box algorithms. The study provides an in-depth examination of the current regulatory landscape, identifying specific gaps and challenges in overseeing AI-driven decision-making in motor insurance. The results highlight the inadequacies of current regulations in ensuring transparency, fairness, and accountability, and underscore the necessity for regulatory refinement. A comparative regulatory analysis across various jurisdictions reveals the effectiveness of different frameworks, while ethical considerations are integrated to address the broader implications of AI deployment in insurance. The study concludes that there is an urgent need for robust regulatory frameworks that mandate the use of explainable AI techniques to enhance model interpretability and mitigate biases. Recommendations include fostering public debate and interdisciplinary research, updating actuarial education to include AI and data science skills, and refining regulatory standards to protect consumer rights and promote ethical AI deployment. These measures are essential to ensure that AI-driven motor insurance pricing operates in an equitable and transparent manner, fostering trust and fairness in insurance practices

Keywords: Blackbox Algorithms, Artificial Intelligence, Discriminations, Fairness, Explainable AI.

INTRODUCTION

The integration of black box algorithms into motor insurance has fundamentally reshaped the industry, facilitating personalised pricing, fraud detection, and automated claims processing (Owens et al., 2022). These sophisticated models leverage vast datasets, including telematics from vehicles, driving behaviour analytics, and historical claims records, to assess risk with greater precision. While such advancements offer notable benefits in terms of efficiency, cost reduction, and risk assessment, they simultaneously introduce complex regulatory challenges that necessitate scrutiny (Xie, 2024; Aslam et al., 2022).

A primary concern arising from the deployment of these algorithms is their lack of transparency (Du Preez et al., 2024). Many AI-driven models function as black boxes, wherein their decision-making processes remain

opaque, even to their developers. This opacity raises significant ethical and legal questions, particularly in relation to fairness, accountability, and consumer rights (Brożek et al., 2024). Policyholders, for instance, may find it challenging to comprehend the rationale behind premium adjustments or claim rejections, potentially leading to disputes and regulatory interventions. The absence of clear explanations erodes consumer trust and exacerbates concerns regarding potential biases and discriminatory practices within the industry (van Bekkum et al., 2025).

Despite these regulatory concerns, AI-driven processes offer substantial value to insurers by embedding data-driven insights into core operational functions, such as sales, distribution, pricing, underwriting, and claims management (Rane, 2023). Financial service providers increasingly adopt AI-powered solutions to enhance customer engagement and align with regulatory compliance requirements (Reddy and Nalla, 2025). Moreover, innovative reward-based programmes enable insurers to offer tailored products and services, thereby incentivising responsible driving behaviour. As policyholders engage more extensively with digital platforms, the volume of available data for AI-driven analysis expands, fostering an ecosystem of mutual benefit for both insurers and the insured (Stevenson et al., 2021; Moodley, 2019).

However, while these advancements hold considerable promise, they underscore the necessity for a comprehensive regulatory framework to ensure that AI-driven decision-making processes are conducted with transparency, fairness, and accountability. This paper examines the existing legislative and regulatory landscape governing black box algorithms in motor insurance, identifying key gaps and challenges while proposing policy recommendations aimed at fostering a more equitable and responsible AI-driven insurance sector.

LITERETURE REVIEW

AI is rapidly transforming actuarial and financial sectors, yet its adoption raises critical ethical, professional, and regulatory concerns. Du Preez et al. (2024) highlight the risks of bias and discrimination in AI-driven actuarial work, particularly where proxy variables lead to unfair treatment in insurance pricing. The growing trend towards individualised risk assessment, while improving precision, threatens accessibility by excluding high-risk individuals from affordable cover. These concerns necessitate greater transparency in AI-driven decision-making to protect consumers. However, the opacity of AI models, often referred to as the Black Box Problem, poses significant challenges to interpretability and explainability, demanding the use of tools such as SHAP and LIME among others. Regulatory and professional bodies, including the Financial Reporting Council (FRC) and the Institute and Faculty of Actuaries (IFoA), are evolving their standards to mitigate these risks. Nevertheless, a key challenge remains: the actuarial profession's lack of AI expertise, which could undermine effective governance and oversight. To ensure AI is deployed ethically and responsibly, Du Preez et al. (2024) argue for robust regulatory adaptation, enhanced governance frameworks, and improved actuarial education.

Similarly, Makore (2024) explores AI's role in financial inclusion, illustrating how it enhances banking services, credit assessments, and risk management, particularly for marginalised populations. Yet, alongside these benefits, the study identifies substantial risks related to liability, cybersecurity, and ethical concerns, necessitating a well-structured regulatory framework. Drawing insights from the EU and UK models, Makore advocates for a decentralised, Afrocentric approach that balances technological innovation with consumer protection. In parallel, Brkan and Bonnet (2020) emphasise the importance of Explainable AI (XAI) in addressing the transparency gap in algorithmic decision-making. They argue that a clearer understanding of AI-driven outcomes can enhance trust, improve system reliability, and facilitate regulatory compliance. However, despite the EU's General Data Protection Regulation (GDPR) seemingly providing a right to explanation for data subjects in cases of automated decision-making, the practical enforcement of this right remains contentious. Legal barriers, such as algorithmic secrecy, alongside technical limitations in machine learning (ML), could obstruct the realisation of meaningful explanations. By taking an interdisciplinary approach, Brkan and Bonnet (2020) highlight how legal and technical constraints shape the extent to which AI-driven decisions can be explained in practice. In light of these insights, Zednik (2021) advances the debate by proposing a structured framework to assess the effectiveness of XAI techniques in mitigating the Black Box Problem. Without a normative evaluation framework, efforts to enhance AI transparency remain inconsistent and fragmented. Together, these studies underscore a pressing need for regulatory refinement, professional education, and explainability frameworks to ensure AI fosters fairness, inclusivity, and accountability across actuarial and financial sectors.

METHODOLOGY

The study employs archival techniques to select scholarly articles and thesis records addressing the regulatory issues of black box algorithms in motor insurance pricing. The archival technique is a method used to study historical documents, providing access to individuals and events from a distant past. It is also used by scholars in non-historical investigations of contemporary organisations and as a supplement to other research strategies

(Ventresca and Mohr, 2017). The methodology encompasses a comprehensive literature review to identify existing regulatory gaps and challenges, and case studies to examine real-world applications and implications of black box algorithms. Records from the last ten years, specifically between 2017 and 2025, were selected and analysed. These articles cover topics such as unfair discrimination, transparency, fairness, and regulatory compliance requirements. The study provides an in-depth examination of the current regulatory landscape, identifying specific gaps and challenges in overseeing AI-driven decision-making in motor insurance. It emphasises the need for regulatory refinement to address transparency, fairness, and accountability issues. A comparative regulatory analysis across various jurisdictions is conducted to evaluate the effectiveness of current frameworks, while ethical considerations are integrated to address the broader implications of AI deployment in insurance. The synthesis of these components culminates in the development of actionable recommendations aimed at enhancing transparency, fairness, and accountability in AI-driven motor insurance pricing.

RESUTLS

This section presents and synthesises the key findings derived from the analysis of explainable artificial intelligence, actuarial capability, and ethical governance in AI driven insurance pricing. The results are structured to reflect the multidimensional nature of transparency challenges associated with advanced machine learning models and the mechanisms required to address them. Specifically, the section examines the role of XAI techniques in mitigating black box opacity, the implications of skills gaps among actuaries for model governance, and the ethical risks related to fairness and discrimination in automated pricing systems. In addition, the findings highlight the critical role of human oversight throughout the AI system lifecycle. These results are integrated into a conceptual framework that illustrates how technical performance, interpretability, professional capability, and regulatory expectations interact to support transparent, fair, and accountable insurance pricing practices.

XAI in Mitigating Black-Box Transparency Concerns

The growing use of AI and ML in insurance pricing has been widely acknowledged for improving predictive accuracy, segmentation, and risk assessment (Blier-Wong et al., 2020; De Virgilis et al., 2022). However, the complexity of these models often results in limited interpretability, creating what is commonly referred to as the "black-box" problem (Brożek et al., 2024; Kuo and Lupton, 2023). This lack of transparency presents challenges for regulatory compliance, fairness assessment, and consumer trust, all of which are particularly critical in insurance pricing decisions that directly affect policyholders. XAI techniques have therefore emerged as essential mechanisms for addressing transparency concerns in complex pricing models (Du Preez et al., 2024; Brożek et al., 2024). Methods such as SHAP and LIME allow insurers and regulators to decompose model outputs and identify the contribution of individual predictors to pricing outcomes. Several empirical studies demonstrate that XAI enhances interpretability across a range of pricing analyses, including claims frequency, claims severity, and claim amount prediction (Masello et al., 2023; Masello et al., 2025; Byrne, 2024).

Evidence from Masello et al. (2023, 2025) shows that SHAP is particularly effective in tree-based models such as XGBoost and Random Forests, enabling the ranking of contextual risk factors associated with hazardous driving behaviour. This capability supports not only technical model validation but also policy design, behavioural interventions, and regulatory evaluation (Kuo and Lupton, 2023; Du Preez et al., 2024). Reil (2024) further validates the role of SHAP and LIME in explaining ML models, concluding that SHAP provides more stable and reliable explanations in regulated environments, while LIME may exhibit inconsistencies when applied to complex models. Collectively, these findings reinforce the argument that XAI is fundamental to ethical, accountable, and transparent AI-driven insurance pricing (Brożek et al., 2024; Barry and Charpentier, 2023).

Skills Gap Among Actuaries in Artificial Intelligence and Data Science

Despite the demonstrated benefits of AI and ML in insurance pricing and reserving, the literature consistently identifies a significant skills gap among actuaries in advanced analytics and data science (Murphy and Burston, 2022; Friedrich et al., 2022). While awareness of AI and ML concepts has increased within the profession, practical experience and technical proficiency remain limited, constraining actuaries' ability to govern, validate, and explain complex models (Kuo and Lupton, 2023; De Virgilis et al., 2022).

Murphy and Burston (2022) report that although 94% of actuaries surveyed by the Institute and Faculty of Actuaries possess at least a high-level understanding of AI and ML, more than half lack hands-on experience in applying these techniques. Similar concerns are raised by Friedrich et al. (2022), who identify insufficient technical skills and weak senior stakeholder buy-in as major barriers to the adoption of data science methods within actuarial

teams. These limitations reduce the profession's capacity to critically assess ML models, particularly in high-stakes pricing and reserving applications (Blier-Wong et al., 2020).

The literature strongly advocates interdisciplinary collaboration as a means of addressing these challenges. Tripp (2018) argues that actuaries must work closely with data scientists and statisticians to combine domain expertise with analytical rigour. Blier-Wong et al. (2020) and De Virgilis et al. (2022) further emphasise that statisticians play a critical role in ensuring model robustness, interpretability, and compliance with ethical and regulatory standards. Without such collaboration and targeted upskilling, the actuarial profession risks lagging behind technological advances despite the proven effectiveness of ML techniques (Kuo and Lupton, 2023).

Ethical Risks, Fairness, and Discrimination in AI-Driven Insurance Pricing

As AI and ML models become increasingly embedded in insurance pricing systems, concerns regarding fairness, discrimination, and ethical accountability have intensified (Barry and Charpentier, 2023; Van Bekkum, 2025). Although these models improve predictive performance, their opacity can conceal biased decision-making processes, undermining consumer trust and complicating regulatory oversight (Brożek et al., 2024; Du Preez et al., 2024). Unfair discrimination is therefore identified in the literature as one of the most significant ethical risks associated with AI-driven insurance pricing.

Several studies emphasise transparency and explainability as essential safeguards against discriminatory outcomes. Du Preez et al. (2024) argue that advanced ML techniques may unintentionally amplify bias, making XAI a prerequisite for ethical pricing and sustainable consumer confidence. Brożek et al. (2024) similarly contend that opaque algorithms weaken accountability in legal and regulatory contexts, proposing conceptual frameworks to address the black-box problem and reinforce ethical integrity. These perspectives align with regulatory expectations that insurers must be able to justify and explain pricing decisions (Kuo and Lupton, 2023). Beyond transparency, the literature highlights the persistence of indirect and proxy discrimination in data-driven insurance systems. Van Bekkum (2025) demonstrates that behaviour-based underwriting and extensive data usage can exacerbate financial inequality through indirect discrimination. Barry and Charpentier (2023) show that biases rooted in stereotypes, non-causal correlations, and socially sensitive variables can persist even in fairness-aware algorithms. Lindholm et al. (2022) further warn that protected attributes can be inferred from seemingly neutral variables, leading to proxy discrimination. While technical mitigation strategies show promise, the literature consistently calls for robust governance frameworks, interdisciplinary oversight, and public scrutiny to ensure fair and ethical AI-driven insurance pricing (Du Preez et al., 2024; Brożek et al., 2024)

Human Oversight in AI system lifecycle.

The proliferation of AI across high-stakes domains such as biotechnology and insurance introduce unprecedented challenges for meaningful human oversight, owing to the increasing complexity, autonomy, and opaque nature of many AI systems. The necessity of human involvement is not merely procedural but foundational to governance practices that ensure transparency, accountability, and fairness, particularly where AI outputs materially affect individual rights and socioeconomic outcomes (Holzinger *et al.*, 2025; Kandikatla and Radeljić, 2025). Human-in-the-loop (HITL), human-on-the-loop (HOTL), and human-in-command (HIC) models have been proposed as structured oversight mechanisms that calibrate human engagement according to the risk profile of AI systems, reinforcing ethical alignment without unduly constraining innovation (Kandikatla and Radeljić, 2025; Ntoutsi *et al.*, 2025).

The literature on XAI further emphasises that interpretability and transparency are prerequisites for trust, enabling stakeholders, whether clinicians in medical triage or underwriters in insurance to scrutinise, contest, and validate algorithmic decisions (Barocas, Hardt and Narayanan, 2019; Papanikou *et al.*, 2025). In insurance contexts, the risk of algorithmic bias is heightened by models trained on historical data that may embed socioeconomic or demographic disparities. Without transparent mechanisms to detect, explain, and correct such biases, AI systems risk perpetuating unfair outcomes and eroding consumer trust (Eling, Nuessle and Staubli, 2021; Koster *et al.*, 2020). Ethical and governance frameworks consistently position human oversight as critical to upholding accountability and mitigating the "responsibility gap" that arises when autonomous systems make consequential decisions (Floridi *et al.*, 2018; Langer *et al.*, 2024). Regulators across jurisdictions are formalising these expectations. For example, the European Union's Artificial Intelligence Act explicitly requires high-risk AI systems to be designed in a manner that allows effective oversight by natural persons, allocating responsibility between system developers and deployers to reduce automation bias and oversight failures (Butt, 2024). Moreover, research demonstrates that AI governance cannot rely on technical safeguards alone; effective oversight must integrate

social and ethical considerations, including fairness metrics, bias audits, and stakeholder engagement, to ensure both procedural justice and substantive equity (Jobin, Ienca and Vayena, 2019; Ntoutsi *et al.*, 2020).

In insurance, these principles translate into regular model audits, robust data governance, and transparent consumer-facing explanations for automated underwriting, pricing, and claims adjudication decisions, practices that strengthen regulatory compliance and public trust while addressing algorithmic opacity and discrimination risks (Puchakayala, 2022; Infantino, 2024). Ultimately, as AI continues to transform industry practices, human oversight remains indispensable not only for error detection and risk mitigation but also for embedding ethical values, fairness, accountability, and respect for individual agency throughout the AI system lifecycle.

Overview of the Conceptual Framework

Figure 1 presents a conceptual framework that integrates the empirical findings on XAI, actuarial skills gaps, and ethical risks in AI-driven insurance pricing. The framework illustrates how advanced AI and ML models influence pricing outcomes, the risks introduced by black-box decision-making, and the mechanisms required to ensure transparency, fairness, and regulatory compliance. It positions XAI and actuarial capability as central mediators between technical model performance and ethical pricing outcomes as explain. In summary, the conceptual framework shows that advanced AI and ML pricing models improve predictive accuracy in insurance pricing but introduce black-box risks, including opacity, bias, and regulatory challenges. These risks undermine transparency, consumer trust, and the justification of pricing differentials. XAI techniques, particularly SHAP and LIME, act as a critical mediating mechanism by enhancing interpretability, enabling bias detection, and supporting regulatory compliance. The effectiveness of XAI is moderated by actuarial and organisational capability, as limited AI and data science skills can constrain proper model validation and interpretation. When supported by interdisciplinary collaboration and regulatory oversight, the framework demonstrates that XAI-enabled models lead to more ethical, fair, and explainable insurance pricing outcomes.

Conceptual Framework for Transparent, Ethical and Effective AI-Driven Insurance Pricing

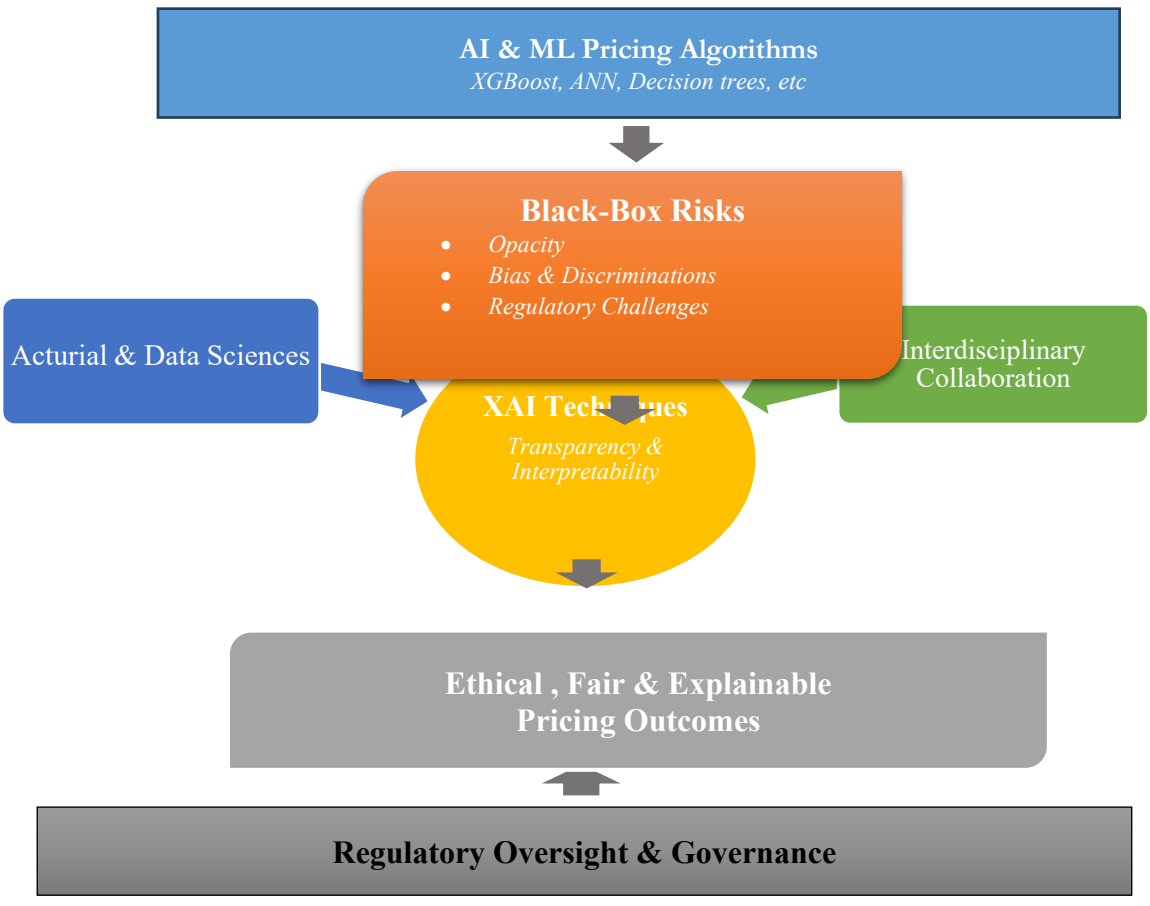

Figure 1: The Conceptual Framework

DISCUSIONS

The integration of black box algorithms, particularly those driven by AI, into the motor insurance sector has significantly transformed the industry. These models, while enhancing operational efficiency and personalised services, present substantial regulatory challenges. The discussions in this paper focus on the critical issues of transparency, fairness, accountability, and compliance with existing legal frameworks.

Transparency and Fairness

One of the primary concerns with AI-driven models is their lack of transparency. These models often function as black boxes, where the decision-making processes are opaque, even to their developers. This opacity raises significant ethical and legal questions, particularly regarding fairness and accountability. Policyholders may find it challenging to understand the rationale behind premium adjustments or claim rejections, leading to disputes and regulatory interventions. The absence of clear explanations not only erodes consumer trust but also exacerbates concerns about potential biases and discriminatory practices within the industry. To address these issues, it is essential to implement XAI techniques such as SHAP and LIME, which can help elucidate AI-driven predictions and foster transparency.

Unfair Discrimination

Advanced ML techniques can inadvertently introduce biases, leading to unfair discrimination in insurance pricing. This includes indirect discrimination, where protected characteristics can be inferred from non-protected ones, leading to proxy discrimination. The persistence of fairness and discrimination problems in insurance, whether through traditional statistics or ML, highlights the need for a regulatory framework that ensures transparency, fairness, and accountability in AI-driven decision-making processes. Public debate and contestation are crucial to making biases visible and addressing them effectively. Personalised algorithms should be scrutinised to ensure they do not reinforce individualised perceptions that hinder collective mobilisation.

Regulatory Gaps

The current regulatory frameworks are insufficient to ensure transparency, fairness, and accountability in AI-driven decision-making processes. There is a pressing need for regulatory refinement to address the ethical, professional, and regulatory concerns associated with AI in insurance. Ensuring ethical AI deployment is imperative to protect consumer rights and promote financial inclusion. This includes fostering public debate and contestation to make biases visible and address them effectively. Regulatory and professional bodies, including the Financial Reporting Council (FRC) and the Institute and Faculty of Actuaries (IFoA), are evolving their standards to mitigate these risks. However, a key challenge remains the actuarial profession's lack of AI expertise, which could undermine effective governance and oversight.

Skills Gap

A significant skills gap exists among actuaries in the areas of AI and data science, impacting the profession's ability to effectively govern and integrate these technologies. Targeted education and interdisciplinary collaboration are essential to bridge this gap. Actuaries should collaborate with data scientists to combine business problem understanding with analytical rigour. This collaboration is seen as essential for actuaries to contribute effectively to the evolving landscape of data science and AI. By addressing these challenges, the actuarial profession can better harness AI and ML for more robust and equitable insurance pricing and reserving strategies.

Explainable AI

The application of XAI techniques is crucial to mitigate transparency concerns. Techniques such as SHAP and LIME contribute to model interpretability, ensuring that insurers and policymakers can derive meaningful insights for refining pricing structures and shaping informed regulatory frameworks. By evaluating model superiority and

XAI outcomes, the role of explainability in advancing ethical and accountable AI-driven insurance practices is underscored. Ensuring that AI-driven decision-making processes remain transparent, fair, and accountable is essential for fostering consumer trust and promoting financial inclusion.

CONCLUSION

In conclusion, the integration of black box algorithms driven by AI into the motor insurance sector offers significant benefits in terms of operational efficiency, personalised services, and enhanced risk assessment. However, these advancements come with substantial regulatory challenges, particularly concerning transparency, fairness, accountability, and compliance with existing legal frameworks. The lack of transparency in AI-driven models, often referred to as the Black Box Problem, complicates accountability and fairness, raising ethical and legal questions. This opacity can lead to consumer distrust and potential biases, necessitating the implementation of XAI techniques such as SHAP and LIME to foster transparency and interpretability. Advanced ML techniques can inadvertently introduce biases, leading to unfair discrimination in insurance pricing. Addressing these issues requires a robust regulatory framework that ensures transparency, fairness, and accountability in AI-driven decision-making processes. Public debate and interdisciplinary research are crucial to making biases visible and addressing them effectively.

Current regulatory frameworks are insufficient to address the ethical, professional, and regulatory concerns associated with AI in insurance. There is a pressing need for regulatory refinement to ensure ethical AI deployment, protect consumer rights, and promote financial inclusion. This includes fostering public debate and contestation to make biases visible and address them effectively. A significant skills gap exists among actuaries in the areas of AI and data science, impacting the profession's ability to effectively govern and integrate these technologies. Targeted education and interdisciplinary collaboration are essential to bridge this gap. By addressing these challenges, the actuarial profession can better harness AI and ML for more robust and equitable insurance pricing and reserving strategies.

In summary, addressing these key issues will enable the insurance industry to work towards fairer, more transparent, and ethically sound AI-driven insurance practices. This includes leveraging novel data sources and addressing challenges related to interpretability, regulatory compliance, and ethical considerations. The foundational knowledge of statisticians is essential to ensure these models are both accurate and interpretable.

RECOMANDATION

To address the regulatory challenges posed by AI-driven black box algorithms in motor insurance, it is recommended to implement robust regulatory frameworks that ensure transparency, fairness, and accountability. This includes mandating the use of explainable AI (XAI) techniques such as SHAP and LIME to enhance model interpretability. Additionally, fostering public debate and interdisciplinary research is crucial to identify and mitigate biases. Actuarial education should be updated to include AI and data science skills, promoting collaboration between actuaries and data scientists. Finally, regulatory bodies should refine their standards to protect consumer rights and promote ethical AI deployment.

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