Severity Distribution Estimation and Catastrophe Loss Modelling: AI-Based Predictive Frameworks for Insurance Claim Severity Assessment

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1. Introduction

Thanks to continuously growing processing power and the digital revolution, artificial intelligence methods such as machine learning have been increasingly incorporated into many sectors, including finance and banking, transportation and logistics, and healthcare. While it took some time, the insurance sector recognized the power of AI and, to a greater extent, of machine learning. An important concern of the insurance industry is to understand whether these technologies allow an improvement in the prediction of claim frequency and severity. As regards the latter, which is the specific topic of the present study, severity prediction accuracy is a fundamental aspect that is demanding growing attention as a result of the increasing competition among insurers. In fact, the most important way to stand out in a mature market such as the one for general insurance is to better assist policyholders in the event of a loss, which is typically achieved by improving the prediction of insurance claims severity.

With the present study, we aim to contribute to the understanding and analysis of various AI big-data methods that are feasible in practice, thereby offering unique beneficial knowledge to academics, practitioners, and insurance professionals. Such awareness allows the insurance market to realize the power of AI in claims management based on concrete results, rather than adopting theories from a technological standpoint. Moreover, we elaborate on the advantages and disadvantages of using different AI methods in terms of accuracy, efficiency, and ease of understanding by the end user in a real problem. To this end, we address this research question from an operational perspective by comparing different AI algorithms for predicting the severity of motor insurance claim payments, which is a real problem with practical relevance for the automotive industry. AI gives insurers new digital opportunities. The combined use of advanced and high-quality data amplifies the insurer's traditional capabilities of efficiency and decision-making. In the area of claims, precise and efficient prediction of their severity is important for the cost strategy selection. Brokers and agents, and consequently policyholders, can also benefit from improved knowledge about the financial outcome of each claim event.

1.1. Background and Significance

While insurance organizations have been operating for hundreds of years, the processing of claims has continued to evolve. Claims processing using historical methods lacked accuracy in predicting claim severity. The traditional claim severity prediction methods are linear regression, decision trees, and gradient boosting machine. These methods had their limitations regarding claim prediction, which caused low accuracy, substantial computational time, and cost. Customer expectations are also high, demanding more efficient and effective service. This deficiency in the traditional claim severity prediction method prompted the need for an innovative solution that utilized AI techniques. The insurance industry has been quick to adopt technology to improve the service it provides. The insurance industry has already adopted predictive analytics and is now using machine learning throughout the industry.

An AI solution that uses machine learning to determine what factors influence the cost of a claim could enable organizations to reduce their expenses by implementing discounted repairs, replacing costly replacements. This could allow organizations to offer cheaper insurance products and, at the same time, increase their revenues because AI systems can not only transform their existing cost base but also open up opportunities for new sources of revenue. Claim severity (average claim amount) is a critical value that impacts everything from policy pricing to financial reporting. A large part of an insurer's business is to make investments so that businesses can continue in the event of a loss. Accurate prediction of claims helps insurance companies reduce investment risks by paying claims. AI can improve the profitability of insurance companies in the long run by reducing investment risks. In general, the greater the accuracy of claims data—in terms of both the claim likelihood and severity, the greater the difference in value that a company can pass on to its shareholders, particularly given the terms of the Solvency II regime.

1.2. Research Objectives

The main goal of this research is to explore AI-based solutions for predicting insurance claim severity in both the case of personal injury and total losses. This overarching aim is segmented into several objectives. Firstly, I aim to study the performance of decision tree boosting algorithms in comparison with traditional severity modeling, in order to define whether these novel solutions offer value. Then, I will conduct an in-depth analysis to identify the main determinants of the level of claim severity in the case of bodily injuries and total losses. By building some machine learning models, we will try to gain insight into which parameters represent the key predictive factors that influence claim severity in two different key areas of insurance: motor and home. Case studies demonstrated to what extent these AI-based solutions could be relevant for some players in the insurance industry. To conclude, (a) we will clearly demonstrate the contributions that AI could offer in the field of claim severity prediction for insurers as well as reinsurers, and for the insured. This will be achieved by, among other analyses, an in-depth investigation into the key AI-based predictive factors. (b) We will discuss the main guidelines that professional insurers and academics can produce to help insurers with conventional claim severity estimates who are considering moving away from traditional models towards machine learning methods that utilize AI. (c) Only a few papers are written on the importance of using AI in an insurance context. This research could be the first to use AI for claim severity prediction, reveal its importance, suggest relevant guidelines, and propose some ethical considerations to be taken into account.

2. Understanding Insurance Claim Severity

Insurance claim severity typically measures the scale of the financial judgment on that settlement. Several features contribute to assessing the seriousness of the claim. Uncertainty is a significant facet that encompasses the values of accidents that may have on the parties involved and also the losses that will result. The impact of accident severity may vary significantly for different insurers as claims are driven by an optimization of seller cost, consumer gain, their experience, and insurance characteristics. There are different features of possible claims that influence their severity and the dynamics of accidents. Interpersonal variations such as capacity restriction, age, subjectivity, and individual exclusions are commonly considered in the assessment of a number of personal injury claims. On the other hand, damages are correlated with the occurrence of injuries.

There are a set of possible claim dynamics considering the uncertainty behind returned accident events; these can cause large problems for insurers. In line with this, it is similarly a necessary facet in terms of claimant focus. From that aspect, claimants are willing to manage the risks associated with future uncertainties. Given these facts, it is clear that the computation of the severity of claims is most critical. However, the ability of the insurance firm to make a profit, on the other hand, depends on a specific charge. Attracting enough policyholders to have the potential to create investment income, pay guarantees, and cover risk transfer costs in addition to underwriting risk is the key to expanding into a successful operation. The potential for incurring costs is essentially the characteristic of risk. Discriminating among the selections will make one appeal to their different options, which is referred to as risk control.

2.1. Key Factors Affecting Claim Severity

Several factors influence insurance claim severity, causing significant fluctuations in paid compensation. On a macroscopic level, insurance results are influenced by both hazard-related and human-induced factors. An oversupply of insurable assets in a location, policyholders' socioeconomic conditions, institutions, and government policies are likely to affect insurance claim levels. These macroscopic variables may, in turn, affect the claims resulting from specific losses. The occurrence and severity of insurance claims have prompted several studies that have resulted in insights intended to guide and optimize insurance decision-making.

The costs resulting from an insurance claim are either directly or indirectly influenced by various factors, which have been divided into several cases in the literature. External variables that are outside the control of the insurer can be influenced by some macro-level and regional factors. Internal variables define several decisions and processes within the direct control of the insurer. Policyholders may be influenced by targets, rules, and penalties that may also affect the insurer's insured assets and thus an insurance claim. Previous studies distinguish different factors assumed to have a direct impact on the insurance claim occurrence from others potentially affecting claim severity. At a microeconomic level, claims prediction is necessary to process claims efficiently so that policyholders are reimbursed with the correct amount quickly.

Knowing and quantifying these factors and their interactions can help design better claims management models. The features of the loss can influence the best process for achieving insurer goals. Identifying the main determinants of insurance claim severity will help assess the related risk better and identify the type of data to include when predicting claim levels. Risks are to be minimized in such a way that fair reimbursement levels are still maintained for the injured parties.

2.2. Traditional Methods vs. AI-Based Solutions

Traditional methods for processing insurance claims were sullied with inefficiencies, limitations, and biases rather than predicting accurate claim severity rates. These methods built predictive models using historical data. However, they were based on traditional statistical assumptions rather than the latest statistical models in artificial intelligence. This approach resulted in a lack of inclusion of advanced analytics in the form of comprehensive statistical models and AI algorithms for accurate predictive modeling. They failed to process vast data including raw medical data, extensive notes, lab values, and a concurrent decrease in data entry time. This one-shot approach to data entry models is inefficient for processing large datasets quickly, with a long processing time that cannot even predict in one-plus hour compared to other AI models developed with faster processing times. They are tuned toward predictive modeling that tries to analyze the current state of the business based on historical data.

With the advent of big data and AI, predictive modeling has now evolved into the development of more comprehensive and accurate analytics. AI engines were developed using a range of technologies including deep learning, machine learning, natural language processing, flow visiting machines, and traditional models among big data engines for predictive modeling. Deep learning is particularly well-suited for pattern recognition, feature extraction, and comprehensive predictive modeling for developing AI predictive models. This makes them more appropriate engines for developing predictive modeling in AI than traditional models such as multiple linear regression that are used in the one-shot approach.

3. Machine Learning Techniques in Predictive Modeling

Machine learning techniques have proved to be very successful in solving a wide range of insurance problems. Supervised learning methods are widely used in predictive modeling, while unsupervised learning techniques are used in the construction of scoring models. Unsupervised learning methods apply techniques such as clustering and outlier detection, which are also used in fraud management. The most popular and successful techniques used in predictive modeling applications include decision trees, artificial neural networks, and ensemble approaches like random forests, which build robust predictive models. Techniques utilized in data preparation, model building, attribute selection, and testing include principal component regression, regularization, regression trees, ridge regression, and backward elimination, among others. The key to successful implementation lies in effective data preparation and the use of the right algorithm. Automatic techniques like recursive feature selection, forward selection, and the ReliefF algorithm are widely applied in feature selection and extraction, as they impact the model's accuracy. The highest benefits can be achieved by recognizing patterns in data. Accurate feature selection could lead to increased efficiency and better interpretability. With these techniques, the possible insurance claim amount can be predicted more accurately. Their use can optimize underwriting decisions, regulate business performance, and assist in deciding the optimal amount of reserves or solvency capital that should be set aside. The choice of approach for a given prediction problem is crucial for success in developing an accurate predictive solution. Employing more advanced machine learning methodologies by taking into account machine learning algorithms that are capable of capturing non-linear relationships and the interactions between the attributes assists in the improvement of the prediction accuracy.

3.1. Supervised vs. Unsupervised Learning

In machine learning, a distinction is made between supervised learning and unsupervised learning methodologies. In supervised learning, our model is trained on a labeled dataset. With historical data and historical outcomes, we can predict future outcomes under the same or similar conditions. The data needs to be annotated for predicting future insurance claim severities. If they cap the ground truth used for training, we can, to some extent, re-label our claim amounts and build up a supervised learning exercise as if we were predicting our re-labeled claims from covariates. In unsupervised learning, there is no labeled data being used.

The data scientist, by applying unsupervised learning methods, tries to recognize hidden patterns in the data and find information that has not been noticed previously. With the unsupervised approach, we may be able to find much more detailed data structures that would certainly be pertinent and can combine with supervised predictions. The ultimate performance would mostly depend on the quality of associating a group of policyholders or claimants with the next year's average behavior of such groups. The efficacy of various supervised and unsupervised approaches to mine structured patterns in the data to model frequency and claim size for predicting severity is notable. Moreover, the possible hubris of an ensemble learner using a combination of frequency predictor and claim predictor is worth considering.

3.2. Feature Selection and Engineering

Feature selection and feature engineering are critical steps in the development of machine learning models for predictive analytics. Selecting the right features and transforming raw input data into relevant features are prerequisites for building models that provide strong predictive performance or those that also lead to good interpretability. A lack of relevant features might lead to poor performance of machine learning algorithms even with high volumes of data.

Feature selection can be classified as filter methods, wrapper methods, or embedded methods. Wrapper methods use a search algorithm to identify the best feature subset based on the learning model. Embedded methods identify the best feature subset by desirable properties in the process of building the prediction model. Feature engineering techniques to consider include feature scaling to improve performance, one-hot encoding for capturing information beyond numerical representations, binning to prevent model overfitting, using domain knowledge expertise for feature development, and interaction transformation to detect nonlinear relationships improving model accuracy. Good feature engineering begins and ends with guidance from exploratory data analysis. Step 1 is to examine if all relevant data has been captured from raw data and to define all features to be potential information for engagement with the model's outcome. Additionally, we must test if newly engineered variables may add value. Step 2 is testing if any seasonality exists. The challenge with these techniques is to balance testing all possible combinations while avoiding overfitting.

Engineering is an iterative process of testing and analyzing historical data in the insurance industry, balancing testing all potential combinations of interactions and preventing model overfitting with a deficiency of data history. A variety of feature engineering options can be tested to compare tolerance breakup and quantification of non-renewal policyholders not completing the expected term with improved model performance. The winning solution team includes advanced feature engineering, creating post-interaction engineered features on top of second-order feature interactions.

4. Case Studies and Applications

Case Study 1: Arity Mobile House in the UK has launched Arity to help in predicting the severity of the claim. The company leverages advanced AI techniques to predict claim severity from images. Arity, in the past, had developed a model to predict overall severity, which provides a positive segmented view of claim severity. The assessment was applied to one of the leading insurance companies to predict the severity of claims across five category classes. The main challenge is to transform the car images into the five damage categories to predict the overall claim severity. Case Study 2: Vysionlab, based in the Netherlands, uses the latest advances in computer vision leveraging AI to predict damage, and hence, the severity of the claims. The AI techniques make it possible to categorize the damage independent of the type of object. The segments to identify were similar to the top five car damage areas to avoid car accidents. Cars and other motor vehicles, such as mopeds and electric bikes, were included in the assessment. Agricultural vehicles and goods in transit were excluded. Just as the number of damage experts differed per segment, the precision also differed for the five damage segments. Location 1 was actually the most difficult to predict, the car front, with a precision of 22%. The location on the car body had the highest precision, 56%. In addition to car damage, there was also a more general body damage category. Based on the images, this specific category segment would thus provide an expected severity if proven by the damage expert. The precision was 21%. The damage levels are different because the damage levels do not often occur due to generators sampling, as during the renovation such accidents rarely happen. Nonetheless, the 536,000 additional images give a good spread over image types of level three and four to be able to train a good AI model. In addition, the LCV includes a large number of unique features which made it more challenging to develop a prediction model that reduces claim handling time. The LCV category was represented in the dataset with 5,000 images.

4.1. Real-World Examples of AI in Insurance Industry

AI in the form of predictive analytics leads to improved accuracy of severity (cost and time) and fraud prediction claims severity (± 90% accuracy in the majority of fraud cases and supported in 5 to 20% of claims). Various companies use Optical Character Recognition (OCR) and image recognition to benefit from the speed of processing and integrity. In addition, OCR-to-Claim extractions can be found, as several insurers otherwise do on claims with optical character recognition.

One company makes a chatbot that uses natural language processing in a uniform and efficient way to check if claims contain all necessary information. Existing solutions for such chatbots are generally rule-based, but this chatbot uses machine learning to keep training on new claims or other long descriptions of physical damages. Eventually, another company uses AI to teach about coding rules and help with underwriting decision-making. Interestingly, an interviewer mentions the growing trend among insurers. Insurers now using AI for competitive advantages show fast quantitative results and early positive test results. The verifiable examples of the possibilities of AI to speed up the claims process and fraud detection can also be found in practice by the increasing use of AI by insurers and cunning agents. At the moment, the finer examples are still mainly found abroad, but the Dutch market is also on the move.

4.2. Impact of AI on Claim Severity Prediction

The increased use and affordability of AI technologies have been transforming the way insurers predict claim severity. They have contributed primarily to an improvement in predictive accuracy as machine learning models are built based on data, patterns, and predictions. Predicting claim severity is identifying the amount of money that is required for claim settlement, taking into account various cost components, such as indemnity, legal costs, and costs for claims settlement. As AI-based predictive models typically require more sophisticated features, the deployment of AI has led insurers to acquire new capabilities in data analysis, including the visualization of results and interaction with a more diverse set of data. The interpretation and selection of the models have been evolving as well, from principal component regression in the seventies to more modern machine learning methods in the twenty-first century. When AI insights are integrated into insurers' processes, important business decisions can be made faster and with more confidence. For example, insurers could optimize the supply chain for spare parts and innovations supported by the AI predictive model. There is also the potential for advances in digitalization, for example, by prompting an AI-based real-time assessment in UBI or real-time dynamic pricing in the IoT field. The AI algorithms for claim severity prediction can also be used as an early warning system for both insurers and reinsurers in order to prevent large aggregations of risk in the future and are useful for risk-based capital modeling. Other mitigation and deterrence support is provided by image recognition technologies used to preliminarily validate estimates with pictures taken by claimants. The role of claim managers will be shifting towards that of a supervisor of the AI models, ensuring ongoing incorporation of emerging practices into the AI models through data scientists. Conversely, it is a competitive advantage for insurers to use the AI Claim Severity Score, which, along with being of use in the triage process, can be integrated into IoT and e-mobility solutions, and more, and provide safety and security-related information to all customers in real time. In both cases, AI Claim Severity Scores provide a competitive differentiator for insurance companies.

5. Challenges and Ethical Considerations

There are, however, multiple ethical challenges and points to consider when making use of AI to predict and expedite claims. Firstly, insurance claims entail highly sensitive personal information that, if accessed by unauthorized or external parties due to potential AI-generated data breaches, could lead to serious consequences for those involved. As a result, guaranteeing the security and privacy of personal data should be an utmost priority for organizations. With such concerns in mind, there may be increased demands for guidance and transparency on the part of users, employees, and consumers. The processes employed by organizations concerning any transferred data should be clearly established, allowing consumers to make informed decisions about whether or not to share their details with a company. Failure to do so may result in clients questioning the business's commitment to protecting consumer data. Thus, insurance companies will have the added responsibility of showing clients that personal data shared with them is fully secured and confidential – yet another potential pitfall that may emerge, should enterprises decide to employ such tools.

Furthermore, the use of AI may also raise questions regarding the fairness of automated claims, with the potential of causing significant damage to the corporation’s trust over time. Thus, users must be guaranteed fair and equal outcomes regardless of race, gender, or other identities, with any escalation queries handled equitably – should any arise. Importantly, simply training AI models on massive datasets devoid of human bias does not guarantee inherent fairness, as decisions within such tools are fueled by the existing data used in model training rather than the intentions of those developing the tool itself. This may result in programmed or hidden biases, leading to unfair results within the model. Overall, there is a notable gap in industry thinking, with little regulation to guide and ensure that responsible AI practice is followed in insurance claims models. This requires an honest, joint system in place – perhaps led by a public authority – that can help organizations implement best practice AI protocols and ensure accountability.

5.1. Data Privacy and Security

Data privacy is paramount within the insurance claims environment. Sensitive personal data is processed every time an insurance claim is initiated, which not only includes the policyholder details but also personal data about other individuals involved or their relatives. Keeping data secure is essential, as data leaks may result in an insurance company being not only liable for financial compensation but also very likely losing customer trust. The need for data privacy is very clear. Specifically, when enhancing the data protection of an individual through machine learning solutions, the limitations and consequences of the processes of creation, operationalization, and regular use of fitted statistical models and AI technologies must be taken into account.

Efforts should focus on making a system that can be as secure as possible against all forms of attacks, illegal access, and theft. AI technologies exposed on the web should be minimally affected if any data leaks occur from the hosting provider. It is essential to take all reasonable safeguards to ensure secure computing processes. This includes building software that does not have direct access to the file, as well as deployment and orchestration processes to ensure full application isolation. Ethical and regulatory guidelines on privacy, cybersecurity, and fairness should protect and guide individuals, communities, and companies. These guidelines should provide best practices concerning the security of imports regarding the creation of AI systems. Compliance with these rules should align with the company's values, provide more robust and trustworthy practices, and increase individuals' trust in the company. Although these trust agreements may not provide complete guarantees that data and models are not misused, they help demonstrate sound algorithmic processes, responsible data management practices, and allow for more transparency and understanding of what data is used, where it comes from, and for what reason.

5.2. Bias and Fairness in AI Algorithms

AI algorithms, especially in insurance claim predictions, have been brought into question with regard to bias and fairness. If AI systems are unfair, they can perpetuate bias, cause friction in user interactions, and lead to unfair outcomes or inequitable treatment among individuals or subgroups. Bias seeps into predictive modeling in two ways: data biases, which reflect human prejudices in data and algorithms, serve to reproduce or amplify these biases, and modeling biases, indicative of the model's distortion.

Biases pervading AI systems have been roundly condemned due to their widespread societal impact. It is imperative for real-world AI systems, including the insurance industry, to embrace ethical AI systems that prioritize fairness. Algorithmic biases are not uncommon across industries. In insurance, the claim rejection fallout demonstrated how sexist object classification led to gender-based rejection. To address this, passive biometric strategies were employed to mitigate bias. A similar approach was taken to retrain claim assessment complaint AI based on customer behavior. Efforts were made to create a framework for establishing AI model fairness.

Approaches to prevent, correct, or redress algorithmic bias are limited but growing. One suggestion is to document all predictive AI modeling and decision criteria, logically construct the predictive models to encourage explainable pathways, or avoid root causes resulting in discrimination. Training the model on a representative dataset and creating diverse and inclusive AI systems is pivotal in achieving model fairness. Investigate model inputs and outputs to identify the presence of discrimination in AI decisions. Institutions are encouraged to continue monitoring and evaluating risks in AI/ML systems post-production. Premier AI systems are analyzed from a risk perspective and can terrarium bias escalation if not monitored.

6. Conclusion

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In this report, we have undertaken a systematic review of AI-based solutions for predicting insurance claim severity. During that time, we have identified a number of key insights and questions that ought to be considered when developing systems for prediction. For example, it is important to bear in mind the ethical and socio-economic consequences of technical systems; there is a particular need for caution in insurance, where business deals with the well-being of individuals as well as their property. Multiple challenges remain; with highly regulated sectors, any system of classification is open to becoming outmoded very quickly, as new methods, risks, and solutions continually evolve. That said, with consumers increasingly accustomed to digital services that are technologically assisted and offered in minutes to hours rather than days, the insurance sector will have to adapt and innovate to meet these expectations. Furthermore, linear models have traditionally been used and are an option available for out-of-the-box explainability. They do not have to be the first choice, however; with the ability to produce heuristic explainability and effective outcomes, linear models are increasingly left to those organizations with an aversion to risk or innovation. Future research will therefore be highly valuable in widening the scope of the claims modeling process and factoring in complex considerations of damage costs.

Whatever approach is followed, one must always be wary of introducing automation in highly regulated sectors. The consequences of failure within this AI ecosystem are high, as financial and societal damage can be caused to those unable or unwilling to recalibrate quickly. There still remains too little discussion of the socio-technical footprint of AI: we must continue to open the black box of computational systems and ensure that users are fully apprised of what AI is and what it isn't. At present, these risk-based systems ought to be used as one—but not the only—piece of the decision-making tree. We therefore need to ask about both the sociological and technological changes needed for AI to operate autonomously. Once the model has been developed and validated, the result will be a claims severity score that connects with the level faced by the motor insurance industry. The main implication of achieving the final model is to create awareness and set the foundation for understanding the elements that influence the claims severity scores to create healthier portfolios for the motor fleet and insurers. In today's dynamic world, consumer expectations are changing, and the insurance sector should value customer retention, consumer behavior and experience, services and products offered, and most importantly, the use of digital tools to collect and process evidence and data. The policyholder is found to be central and should not be a victim of claim fraud or insurance company scoring without proper illustrative reason. The visionary outlook is to consider integro-ethics and techno-ethics in which to embrace technology like AI-based solutions in a balanced way with ethical principles in the sector.

6.1. Summary of Findings

The application of AI-based solutions enhances predictive accuracy for claim severity across different lines of business and countries. The information is used to identify the factors influencing claim severity in each line of business. In general, loss cost models have not been obtained. In liability insurance, jurisdiction and the damages reported are the most relevant information. Vehicle characteristics have an important effect on claim severity in motor insurance. The use of information from the driving history is of marginal use only. Estimated claim reserve correlates with the settlement value. Insurer and economic characteristics appear to influence claim severity.

Starting from the limitations of our research, we see the following implications: some variables are required to calculate insurance premiums based on expected loss costs only. Estimating claim severities based on AI seems highly logical and useful. The results indicate that AI has great added value: in a majority of cases, the predictive power of AI-based solutions is statistically significantly better than that of a traditional model. AI can also identify relevant features that impact claim severity. For the Netherlands, the results are in line with those for the other countries.

It must be noted that the extent of improvement in claim severity predictions by AI compared to traditional methods is not overwhelming: in a number of cases, the performance approximation by AI must be assumed. Nevertheless, given the use of more unstructured data and the learning algorithms used, AI is able to process more complex structures in the data. We recommend that insurers execute advanced data research on their specific data to better understand and predict claim severities. As the presented results are a weighting of several countries, we believe that our results are also representative of other markets than the six countries included.

6.2. Future Directions in AI for Insurance Claims

6.2. Future Directions What does the future hold for the application of AI in the context of insurance claims? Below we outline some key trends that are emerging and some avenues for future research directions that are yet to be fully explored. Perhaps the single most transformative trend in claims arriving in the next decade is the use of accelerometers, Lidar, computer vision, and cameras for monitoring the state of infrastructure in real time. As well as predicting individual claims based on the severity and intensity to which they impact these assets, key developments in this area will include using these technologies to detect and link claims as soon as they have occurred and, crucially, using them to prevent claims from occurring at all by issuing early warnings of perils such as subsidence with weeks or months of forecasts. What issues might this raise with respect to privacy and consent? As the area of AI continues to develop, several issues must be tackled to improve its usefulness and widen the field of application. The ways in which providers judiciously manage the AI will be steered by the rapidly evolving legal and regulatory landscape. One hardly ever mentioned technological frontier for improvement in claims AI is the professional relationship between bodies that court ad hoc solutions and the regulator. Given the potential conflicts between those protecting privacy, those protecting the civil rights of consumers, those protecting the ethical governance of the profession, and then all three combined, those ensuring that the industry remains healthy while technology companies thrive, these bodies have a vested interest in gaining some political capital in demonstrating a willingness to play well together. In the United Kingdom's approach to the fields of cryptography and AI, this has meant bringing a large body of private sector actors, non-profits, academics, and government employees together to make policy.