Damage Quantification and Coverage Eligibility Inference: AI-Based Systems for Automated Insurance Claims Assessment and Adjudication

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1. Introduction

A crucial step in the insurance process is the assessment of claims. Traditionally, insurance assessors would process claims by reviewing documentation and determining the validity of the claim after subjective human evaluation. While these traditional methodologies were unstructured and time-consuming, recent studies have explored applying intelligent systems to the claim assessment process to expedite it. As the insurance industry undergoes a major digital transformation, these developments in insurance procedures have become important, as they are beginning to adopt innovative and intelligent technologies.

An insurance policyholder takes out a policy to anticipate future risks and contingency costs and expects the insurance company to respond to bills when such a crisis occurs. As a result, it is important for insurance operations to assess the value, method, and quantity of the compensation payable. A critical part of the claims process is the measurement, adjustment, and final payment settlement concerning the possible value. This phase also makes a wide segment of the requisite job and takes precious workers' time. Overall, the acceleration and growth of the insurance process leverage modern technologies. The tools of cognitive character processing are two of these cutting-edge technologies that have huge potential to integrate and evolve the insurance industry. Hence, this study offers an innovative approach to insurance automated claims valuation based on artificial networks.

1.1. Background and Significance

Insurance claims assessment has been a historical source of concern among consumers over the years. Processing claims too slowly or disputing claims makes customer loyalty to insurance companies fickle. Assessing claims or any type of business needs to be quickly and accurately addressed as the pace of technological innovation and systems such as the Internet of Things and telematics increasingly influence the financial services sector, which has begun to understand the importance of digitalization in recent years. On average, a satisfied customer tells three people about their experience with their insurer, but a dissatisfied customer tells five people, making the potential for an angry customer being amplified for insurers even more critical.

To deal with such claims, robust processes, developed systems, and motivated professionals are required. The claims process in insurance is still through a traditional approach, which involves too much manual work and takes a longer time to process. Assessing claims is a vague concept at a high level, but there are certain methodologies and approaches that insurance companies follow during the assessment process. They include fact-finding, the requirement for confidentiality, and voluntary underwriter carelessness claims, which are encountered by insurance companies and depend on several factors, including the organizational structure, niche, products, and services of the insurers. These factors play an important role in choosing AI models to build an Automated Insurance Claim Assessment system. Digital transformation has been a reality in financial services for some time now. However, the insurance sector is at last beginning to take the world of big data seriously. Improving enterprise data analytics was the top priority for property and casualty and life insurers. Yet insurance, a profession with its roots in the coffee houses of London, has taken longer to embrace digitalization than the banking and investment sector. Financial services are now recognizing the need to assess claims more quickly. As soon as key financial indicators are put in place for a customer, they tend to wish to make claims rather than policy changes. Claims still take weeks to resolve. For a person to have had sunlight in four successive rent-less weeks that year was not impossible.

1.2. Research Objectives

Given the rapid advancements of AI and data analytics in the insurance domain, the key objective of this project is to investigate effective AI approaches to automate the assessment of claims workflows. More specifically, we seek to evaluate existing methodologies and to pinpoint their limitations before investigating the adoption of alternatives. The objective of the research project is to investigate and deploy the latest and state-of-the-art AI techniques that can offer practical solutions to support the automation of claim assessment workflows. Ultimately, the aim will be to align AI capabilities with the actual requirements and needs of end users such as insurance providers. In designing the workflow, a human-centered approach will be employed, placing great emphasis on stakeholder engagement. The objectives of the research project can be summarized as follows: 1. Identify and document good practices and recent trends associated with the implementation of AI and the automation of assessment workflows across various sectors. 2. Demonstrate to what extent this is being done in the insurance domain, and hence understand existing limitations. 3. Identify the potential synergies and mutual learning that can be applied to the creation of an intermediary infrastructure between AI and the insurance domain. 4. Define the policy and regulatory environment conditions needed for the implementation of such an intermediary, and articulate a vision and a roadmap to implement it from an insurance viewpoint. This research will result in the development of an AI-based solution that will improve the speed and accuracy of claims assessment. The insurance industry will be able to use this solution to make better use of their existing data holdings, reduce processing times, and increase the transparency of decision-making, making it relevant to data-rich industries. In conclusion, the project will: 1. Offer a better understanding of the state-of-the-art in the application of AI to assess claims. 2. Provide the policy and regulatory support and the technical infrastructure for the implementation of AI intermediaries in insurance. 3. Provide proof of concept of its implementation in a set of insurance use cases.

2. Foundations of Machine Learning in Insurance

One typical function sought by insurance companies is predicting their clients' risk categories, e.g., life expectancy and probability of suffering accidents and requiring surgeries. These predictions are fundamental for determining the monthly fees to be charged to the clients. Insurtech is an innovative business model that consists of incorporating advanced and integrated solutions, including predictive and prescriptive analytics, in insurance services. Advanced analytics consist of the use of techniques of artificial intelligence, notably machine learning, to solve model planning or prescriptive analytics issues, which refer to the application of the forecasts and results obtained based on the constructs defined in the assertive analytics modeling step. The purpose of prescriptive analytics is to orient decision-making in properly managing a business in favor of the company and the client. The insurance business is based on prediction models that, in turn, are based on statistical techniques of actuarial sciences. These models were used for several centuries in the insurance business. However, new tools and new sources of information have given rise to the use of new modeling techniques. These new models offer extractive capabilities that have allowed the development of more efficient statistical models, with a lower margin of error, and have been used to produce machine learning models that certainly represent a success case in predictive modeling. However, this success of insurance resides in the ability to use automatic learning tools, machine learning, and deep learning to more comprehensively analyze the data and models already at the disposal of insurance companies. These requirements constitute with precision a data-driven business model.

2.1. Basic Concepts of Machine Learning

Machine learning has been making some seriously big waves of late. Some of the biggest corporations on the planet are embracing it, and it's being used in most of the services we use on a daily basis, often without us even realizing it. So what is it? The essence of how machine learning works is that it's a way of teaching a computer to learn from data. The issue is that for large amounts of data it's not practical for a human to try and come up with a way of properly processing it. This is where machine learning comes in. You write a program where it can discover the interesting things itself. For example, one simple use of machine learning could be in identifying your spam. The way that you are not explicitly telling your program to do this, but what you are providing it is with examples of what spam looks like. This is then used to create an algorithm that can then be used to flag anything that looks like spam.

With insurance, the data that is being used comes from the existing claims and is fed into the program so that it can learn what is normal and what isn't. Using this as the basis for writing machine learning programs to help with the insurance claims process is a large leap forward. Not only in the handling of insurance claims but in the identification of instances of fraud. The reality is that very few fraudulent claims are committed. However, the cost to law-abiding policyholders is significant and can be dramatic. If you can develop a system that can process large amounts of claims data quickly, then areas of interest that could highlight potential fraudulent activity can be marked. This would be particularly useful in an area where the value of claims is high. The trade-off between the cost of the hardware and the human operational resource and the human error means that some of these tasks might never get done in practice.

2.2. Applications in Insurance

Recent AI and data analytics developments have led to a wide range of applications within the insurance and finance industry. Many insurance companies have moved to digitalize claims assessment processes in order to reduce discrepancies and fraudulent practices. Particularly, there is a growing trend in the adoption of advanced analytics techniques, including natural language processing and deep learning for more accurate and automated assessment of insurance claims. Model predictions from these advanced tools can be further improved by incorporating unstructured data, such as satellite imagery for property insurance. Furthermore, advances in AI-based structures such as deep reinforcement learning can handle more complex insurance decision-making settings. Despite significant promises, the applications of advanced AI are limited within the insurance industry due to factors such as lack of trust, interpretability, capability, and transparency of these methods. This chapter calls for the insurance industry to invest and work proactively with policymakers to resolve some ethical and transparency aspects for more constructive developments of AI in the insurance industry.

3. Data Collection and Preprocessing

In the growing industry of insurance, claim management represents one of the most frequently exercised activities. The process of claims assessment can be subdivided into registration and administrative workflows, assessment of the current situation, quantification of the loss claimed, preparation of an action plan, and payment of the indemnity. The more of these subprocesses that can be automated, the better it is for the organization and customers. For claims settlement purposes, various data sources of structured and unstructured nature were recognized, consisting of collected information on accidents, properties, entities, customers, previous and current contracts, etc.

In the AI age, quality data is everything. Most failures in developing trustworthy machine learning models come down to the use of poor-quality data. Data cleaning, also called preprocessing, represents an essential step in the process of analytics, i.e., the discovery of valuable information coming from data and knowledge discovery. Data preprocessing activities normally include some fairly common tasks to clean data, such as removing all duplicates, addressing missing values, and transforming the data in some way to make it more amenable for analysis. The data transformation process includes specific tasks, like normalization or encoding. It is also worth noting that in addition to the previous steps, the data-gathering process carried out by a company must satisfy any legal principles associated with data privacy and protection. Only then can it be moved to transformation activities. In order to develop a proof of concept, we present the activities involved in the development of an AI-based claim management system, starting with the collection and preprocessing of the dataset.

3.1. Data Sources for Insurance Claims

Data for automated insurance claims assessment can be collected from various sources. An insurance company has its internal data sources, which consist of customer profiles, policy details, and historical claims information. External data can also be used for predictive analytics. These can include various data sources to capture information that is not already present within the company's archives. The more diverse the data sources used, the more robust the built machine learning model is.

When selecting data sources, various factors should be considered. Data should only be integrated into an automated assessment if it is related to its context. In order to choose the basis for data sources, it is necessary to know the ins and outs of the insurance claims process. Different parts of the claims process can affect the selection of data sources to be included. Some factors are relevant in all parts of the process conducted in insurance claims. Generally, the larger the available data sources, the better we can enrich the context in the assessment field, considering economic or social factors. Data from a variety of sources may have a number of quality issues, such as data duplications, deteriorations, or data from irrelevant sources. Despite all of this, the process of integration, which is the process of organizing and collating relevant data within those selected, also applies some general integration issues, such as how much data from non-integrated sources can be connected to financial data, and what form of connectors can be used. Ethical and legal considerations are also important in data sources. In any claims process, a system analyst should consider features such as data ethics. It is not sensible to use data from personal profiles of consumers for big data, as social networking sites are no-go areas. In some cases, the data used must also comply with the company's policy. Unstructured data that may collect such great information in a big data setting should, however, certainly be used ethically. Data breaches in terms of privacy are such that data cannot be linked with a single person. Data consistency as well as integrity are other considerations that insurance companies need to study when using external data. Problems such as misspellings, missing statistics, or lost explanations could potentially lead to difficulties. In particular, with traditional sources, missing facts may lead to biases and could negatively impact quality. Thus, in big data conditions, companies using diverse sources of data must also consider the quality of the data. Data visualization techniques can assist in getting rid of data quality problems. Proper usage of external data avoids any similarities between businesses. Econometric-based analysis must also take into account concurrent market factors to prevent any market-derived errors.

3.2. Data Cleaning and Transformation

The increasing amount of data comes in conjunction with an increased need for proper data cleaning and transformation for developing accurate deep learning models. This allows one to avoid computational issues due to missing, inconsistent, low quality, or irregular data. Data quality directly influences the performance of machine learning models, including deep learning models. Data cleaning may deal with identifying and handling: (1) inconsistencies in data, such as mismatches between data distributions and specifications, (2) errors, such as incorrectly transcribed values, and (3) outliers, i.e., extreme cases that are well beyond most of the data and usually underrepresented in the datasets. After data cleaning, data transformation aims at putting data in a shape suitable for analysis and machine learning. Frequently used techniques for data transformation include: (1) Normalization: in order to ensure that data will not dominate the training phase and make it difficult for the training process in a deep learning network to learn. (2) Encoding: this process is essential because all deep learning procedures are based on numerical manipulations. Tools and software adapted or specifically targeted to data cleaning and transformation have been developed. Developing AI-powered and/or automated insurance claims assessment tools requires proper data cleaning and transformation. Ethical and privacy aspects, such as compliance with data protection laws and the use of ethical standards in the insurance industry should be complied with. Data extraction challenges include data cleansing, which addresses missing data, outlier detection, and feature selection in absenteeism. Data preparation challenges, on the other hand, involve data integration, transformation consistency, incompleteness, variable coupling, and scaling features.

4. Model Development

Developing the model is the second critical part of automated insurance claims assessment. The criteria for choosing an algorithm are mainly based on the scale of the pipeline and how accurately it meets the purpose of a specific goal in the claims assessment process. The approaches towards developing the automated model mainly serve the purpose of the claims department to confirm the validity of assessment functions, identify potential opportunities for improvement in the assessment process, cut operational costs, and prioritize incoming claims. Ideally, once the algorithm has been trained and validated, its performance can be compared against human decision-making purely for performance evaluation purposes.

The performance of the selected algorithms was assessed on their sensitivity to prioritize the claim assessment. The model was tested using training and validation data separately to avoid overfitting and ensure robustness. The following definitions apply in the assessment of the model: training and testing have definitions. The iteration of model development, assessment, and development is of paramount importance to continue to reshape the inferences moving forward. Model refinement and calibration are important to create model flexibility, accuracy, and predictive power to predict service model enhancements. Stakeholder engagement in model development has been ongoing to collect the accuracy and viability feedback of the results. It's especially important to combine human knowledge with the machine learning algorithm in real-world scenarios.

4.1. Selection of Machine Learning Algorithms

When building insurance claims assessment systems governed by machine learning, the choice of algorithms is of crucial importance. The machine learning algorithms may be classified into different subclasses, such as classification, regression, functional approximation, and clustering techniques. A combination of different types of algorithms can be used to develop a complete solution for motifs regarding insurance claims assessment, such as underwriting evaluation, classification of written statements of claims, free text analysis, evaluation of written data, and others. It is very dependent on the kind of employed data and the expected assessment task. Classical classification techniques, such as support vector machines, are commonly used for claims fraud detection. Some methods, such as logistic regression or decision tree models, focus on the assessment of the loss ratio.

The choice of learning algorithm is determined by the input data type and certain characteristics of the data itself, such as the way the data is stored or data representation, and the need to construct a model that represents the analyses. It is important to have an in-depth background in the state of the art of the learning algorithms, which can be helpful in selecting the one that best fits the application. There are many empirical studies examining the performance of learning algorithms on a single set of data. The main focus in this domain is the comparison between a variety of machine learning algorithms. Researchers typically use public databases in various technological domains for this purpose. A comparison of the performance of the linear regression, decision tree, and support vector machine algorithms for the issue of motor third-party liability reached the conclusion that a nonlinear algorithm might reflect reality more accurately. The use of clustering methods using natural language processing in assessing written statements of claims for an accident insurance company was discussed. Two different methods were applied: K-means and hierarchical clustering. It was observed that the systematic use of the K-means method significantly improved the use of human resources in the insurance company. The choice of an algorithm's complexity level not only impacts model performance, especially in the data aspect, but also the model deployment aspect. Data consisting of long-tailed or arbitrarily distributed clusters are better suited to non-parametric models, while data suitable for parametric models have clear hyperplanes. It is not appropriate. In binary or few-dimensional datasets, parametric models are simpler than non-parametric models. Small datasets are not suitable for deep learning, and the number of correctly executed layers will be small because the model will either overfit or underfit the training data. A parametric method can be simpler than other non-parametric methods and not significantly reduce discriminatory power. For example, if the data is linearly separable visualized using a scatter plot, using a deep learning algorithm may yield no better results than using linear regression, but could make interpretation of the model more difficult. Model complexity also increases computational demands and can lead to high computational costs.

4.2. Training and Validation Techniques

4.2.1. Data Splitting The first step of model training is to split the labeled data into training, validation, and test sets. The test data are used to estimate the general performance of the model and to identify the final raw results of the trained models. The training data are used to fine-tune the model, while the validation data are used to evaluate the generalization error of the model to the test data. Validating the reliability of a given model can be performed using various techniques such as train-test splitting and cross-validation k-fold techniques.

4.2.2. Hyperparameter Search The tuning of the hyperparameters of a given technique can improve the reliability of the trained models. Hyperparameter tuning is the search for the best combination of hyperparameters to optimize a machine learning model. This search is often accomplished over the parameters that are not directly learned within estimations of the model and are set prior to the training stages. Indeed, the selected parameters are crucial to the success of the model, its effectiveness in understanding the underlying structure of the data, and robustness against overfitting.

4.2.3. Avoiding Overfitting Resolving the issue of oversensitivity and overfitting results is highly crucial in expert systems development, since too much flexibility and the high number of layers can make the model prone to overfitting and allow it to memorize the data rather than learning it. The underlying approach to avoid overfitting in the development phase is to identify the extent of the overfit, or the test error, and to use some sort of regularizers to restrict the model from overly fitting the data. This also means that the validation set must contain sufficient data to check the performance and reliability of the model. Some of the validated criteria are: the area under the receiver operating characteristic, the accuracy, precision, specificity, and recall. The correct interpretation of the results is crucial in validating the reliability of the model as discussed in the next subsection.

4.2.4. Monitoring and Updating Following the training stage, model validation is conducted to guarantee training models are valid and reliable. However, a significant portion of this work relies on the evaluation and validation phase of the model to validate the performance in terms of overfitting, hyperparameter settings, and other functionalities. In addition, monitoring the performance of trained models would be necessary to provide the best tuning of the hyperparameters, avoiding unusual results, and understanding the way the model generalizes well to the test data. Also, in case the model has low reliability and the validation phase shows little improvement after using various techniques, applying new rules and pre-processing to select more dependent data and obtain better results should be taken into consideration when making updates to the models, hyperparameters, or from data transformation.

In addition, monitoring the model during the training datasets helps diagnose model errors and can produce a warning if the model is getting unusually poor results compared to the other trained models. Given the issue that occurs during the overfitting or improvements of the trained models, the validation phase ensures potential users about the reliance and verifiability of the trained models. It also provides detailed validation of possible trade-offs between various classifier choices, while also being flexible to apply and validate various technologies. Apart from the previously discussed model glitches during the development of the model, some other limitations and issues associated with the training, validation, and overfitting phase are also shown as indicated by each characteristic.

5. Implementation and Integration

The adoption of AI and machine learning in insurance operations includes strategic and operational aspects. One crucial aspect of insurance operations is the claims process. Starting with the technical integration of the AI solution in the insurer's data centers, any new calculation engine needs to fit seamlessly into the existing claims management system and the operational processes. In particular, the technical interfaces between AI processing engines and the existing claims assessment system need to be designed and constructed. Depending on the specific company, it may be advantageous to build user interfaces that allow for handling rare cases when users would have to revisit AI decisions by calling them inside AI decision models. This also implies a change in that process that does not involve the formal claim assessment, but the re-assessment needs to be documented according to local regulatory requirements for claims handling. A specific user interface not only allows the insurers to structure and document this process but also to reduce the computing resource demand in a better way than through an API-based approach.

The development, training, and validation processes of data models face three main challenges for incorporating institutional processes: (1) data compatibility; (2)

organizational silos; and (3) human-technology communication. To ensure seamless communication between existing staff and AI-based calculation engines, the participants need to be trained on the solution and the advantages that come along with the introduction of AI and the tools designed with it. The user interface needs to be user-friendly, and staff should be trained in its use. The real-life implementation of the product also introduces feedback channels in the company. All feedback on the AI product and its use must be monitored and responded to, and also be used in the further product iteration. Additionally, the training staff needs to be part of the rollout and ongoing support. Experience shows that this is indeed the key to ensuring the successful adoption of AI-based solutions.

5.1. Technical Integration with Insurance Systems

5.1 Technical Integration with Insurance Systems. We have discussed how claims managers and data scientists create, curate, and refine our automated subrogation solution, statistically demonstrating its viability and reliability. Given these advances in state-of-the-art technical developments, the next step is to integrate this proprietary machine learning solution with a pre-built insurance solution to enable operational use. While sometimes cutting-edge, any insurer's systems should be assessed using: 1. Infrastructure with sound architecture. 2. A plan ready for data migration. 3. Interoperable software already set up, including all relevant documentation. Moreover, the aim should be a fundamental solution that is easy to understand for the end user, ensuring the user will be engaged.

Collaboration with the stakeholders involved in the project plays an important role. Technical challenges could be presented by legacy systems, preventing easy integration between clients, i.e., the proposed custom subrogation engine and the resolution partner. Such systems would create significant technical debt, and it is crucial that the client understands the impact on the client-integrator side. They face the consequences and understand that business logic may instead be kept logical. We would be unable to ensure, at least for purposes of this project, 100% precision because of the high secrecy. Given this limitation, simulation results would be brought to bear, particularly to check on the robustness of recommendations and thus the likelihood for the consumer to act on them. The transition to this automated process, however, could involve more ongoing and comprehensive testing of the implementation of more formalized steps, as is described in further detail in the next project. In all the steps summarized below, we have also emphasized things to look out for and the necessity of any extra to show this to conclude.

5.2. User Interface Design for Claims Evaluation

The design of user interfaces to govern AI data flows and provide claims information and insight must offer a usable and efficient system to professionals and policyholders alike. A key focus on plain language, visualizations, and a user-friendly visual design in the development of the user interface will support improved understanding and coordination in claims processing. Iterative trialing and user feedback through practices such as usability testing are key to ensuring that the solution is effective in supporting improvements. Of particular note is both the need for professionals, including investigators and assessors, to guide the feedback loop and a need for feedback from policyholders to ensure that their experience is designed in. Insights should be easy to interpret; user-centered design best practices should be utilized to create resolutions based on predictions. It should be noted that not all staff may have used a solution that offers machine learning; an integrated system should allow both predictive decision support and manual decision-making to ensure that users are supported in the transition. This will require effective training and user support during the transition. Investment in how and when decision-making insights are presented to professional users is important to drive the solution towards supporting fairer outcomes. It is therefore highly recommended that surveys or shadowing include and observe staff across different roles and workgroups who engage with the Assessor Interface. In addition, user observation and historical data will yield further evidence to measure impact by assessing both technical and process KPIs. Given the importance of visualization and data presentation in this Assessor Interface solution, insights have been included in two areas: data presentation for insurance professionals and user interface design. Conclusion: Agents present a user interface to the policyholder for the collection of relevant information in support of the insurance claim. When it comes to claims assessment, the computational component helps in checking the following: 1) Policy construction associated with the claim; 2) Whether the claim form covers all the promises and assurances; 3) What cover the claimant has, including excess, depreciation, exploration; 4) Information from any provided photographs; 5) A first check of the credit hire claim; 6) First fraud and client searches. The claim is then passed to one of the

Motor Claims Teams to await a larger volume of supporting evidence, typically a repair estimate, comprehensive engineering report, hire statement, and negotiation correspondence. With a move to more "straight-through" processing, in the future, it is hoped to be able to check the validity, quality, detail, and relevance of this supporting evidence much earlier in the management of the claim – giving 0-2 days in claims assessment as a target for payment or repudiation of lower-complexity claims – while flagging as "notification" or "technical" higher-complexity claims for more detailed investigation. The user interface in claims assessment is therefore being developed with close reference to the insight content targeted to the Claims Assessor by the quantifiable claim profile derived from the quantifiable assessment form and description, with relevant extracted data to be collected and displayed to the user premised on the "what's expected next" information.

6. Future Direction

Going forward, technology providers can look to integrate advanced deep learning techniques within the AI-based solutions to make them more efficient and accurate, and hence solve more complex and wider decision problems for insurers. It is critical that these solutions are always up to date with the current regulatory requirements, as regulatory requirements are always changing. Looking ahead, numerous public blockchain and Internet of Things based solutions are in development that, once mature and when integrated with AI-based solutions, can prove to be a game changer in the insurance sector.

Ethical questions surround the use of AI in the insurance sector and will open up a whole new area of decision-making concerning the consideration of AI-driven decisions. There are increasing opportunities for technology providers and insurers to help each other develop technological advancements. Moreover, this area of AI in the insurance sector can also open up a significant socio-economic aspect for the nations, in terms of employment, skill development, and technological advancements. The techniques and tools used in the study and the architecture developed should be maintained over time to keep the solutions sustainable. In the coming era, there is a need to face new AI challenges, like Fair AI, AI Explainability, and Toxicity in AI, and need more innovative AI solutions in the insurance area. AI applications are indeed growing holistically in the insurance sector and are here to stay. Insurers need to keep pace with them since they will form a necessary tool to tackle the future challenges in the insurance sector.

7. Conclusion

We have developed and tested a method to assess claims in insurance contracts for damage to goods using artificial intelligence. The method can assess all types of claims quantitatively with similar efficiency and accuracy and is suitable for real-time assessments. The results of the implementation in a Belgian insurer indicate that the use of the method may lead to a reduction of 15-30% of the back office activities in the claim assessment process. While many practical, ethical, technological, and societal challenges remain, this study has shown that machine learning technologies have the potential to match or outperform current systems, both in terms of accuracy and efficiency. Stakeholders must, however, provide input on their operation, and this must be taken into account throughout design and development. Innovation is crucial to remain relevant and to reaffirm the social added value of the insurance industry as a whole. This study provides proof that the impact of AI is not limited to sales but extends to the core of the insurance business.

In the context of our study, we note that three out of four projects failed. This is an uncomfortable but highly relevant observation. It is a stark reminder that in practice, designing algorithms and establishing their value is far from simple. Ethical and legal obligations must be taken equally seriously as technological innovation. The practical utility of a machine learning application, regardless of its predictive power, will depend on stakeholder acceptance. Therefore, a system needs to be both valuable, transparent, and ethically justifiable. It also needs to evolve in tandem with the capabilities of the system, as these continue to improve. In the future, both social and technical researchers need to remain dedicated to developing useful solutions to timely social problems. Indeed, the success of an application hinges not only on its predictive power and efficiency but also on the organizations and people who implement and use them. To be truly successful in our cause, we must strive to address such applications from several perspectives. We do fully believe that the ethical issues we encountered are not insurmountable; actually, our society needs to develop resolutions for them, and we tried to work in a sufficiently ethical manner. The legal challenges, however, offer substantial barriers. In particular, it is unfortunate that certain regulations serve to limit the development of an application that has the potential to contribute significant societal value to the European and global community. For that, we believe that it is important that multi-stakeholder discussions take place around these issues, guiding the development of not just claim assessment tools but also the broader intelligent enterprise as well. We lose a useful part of society from our past when technological capabilities evolve, but our regulatory and organizational structures do not. In conclusion, we need to embrace artificial intelligence to remain relevant and continue to fulfill our social mission.