

# **Explainable Risk Factor Decomposition and Automated Underwriting Intelligence: AI-Based Decision Support Architectures for Insurance Underwriting**

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## **1. Introduction**

Traditionally, the maintained and evaluated records of Quiet often today, underwriters are having to develop stricter guidelines with regard to class evaluation, therefore putting more pressure on the increasingly data-driven decisions made by the underwriting teams. This trend is significantly impacted by the exponentially evolving technology, which is transforming processes previously governed by conventions and talent in taste. For this reason, this essay explores the role of AI-based decision support systems as a crucial tool for the underwriter in today's ever-changing and data-saturated underwriting area. The main purpose of this essay is to explore the role that AI-based decision support systems can play in increasing efficiency and accuracy in insurance underwriting, and how insurers make use of this essential tool. In detail, it will investigate the role that these decision support systems can play in providing critical insights into risk, enhancing the underwriter's decision-making workflow, and how these solutions can create value. Furthermore, it will provide an in-depth analysis of the implications of AI-based decision support systems, addressing the challenges presented in addition to the opportunities that AI may offer to the underwriting process. Finally, the essay will address the implications that AI and machine learning may hold for the processing of underwriting workflows and how insurers can unlock the potential of these developments. This essay becomes increasingly important as the emergence of data-driven methodologies undoubtedly has the capability to shape a new generation of underwriting.

### **1.1. Background and Significance**

Insurance underwriting represents a major operation in the insurance sector, designed to evaluate risks that can potentially affect the profitability of insurance companies. It is an age-old practice that has evolved over the years. Traditionally, the insurer with deep domain knowledge, tools, and calculative ability evaluated the risk and made the final decision. Over time, technological advancements have changed the decision-making ability and focused on data-driven decision-making, which increased the scope of the insurance underwriting process. This understanding enables underwriting, which directly contributes to the profitability of the company, enhancing an insurer's decision-making in terms of assessing risk and thus allowing for sound pricing and optimal utilization of resources. Underwriting involves two critical actions, namely: assessing insurability and calculating premiums. Based on historical data, the underwriters evaluate the risk by assessing proportions of what can potentially go wrong against what is good with respect to geographic locations, economic parameters, and behavior of people. In assessing the risk, the probabilities of undesired events are determined, and with regard to human behavior, predictive modeling and machine learning techniques are applied. Moreover, insurance companies are confronting much more diverse and complex data than ever before; the application of sophisticated risk modeling techniques is essential due to globalization and innovative products to reflect today's market realities. The utilization of predictive modeling and AI techniques is essential, considering the amount of data and diversity of the market. Building more technical sophistication into the system also helps to reduce manual errors, simplify system turnaround, and therefore improve overall operational efficiency. With the growing complexity of the insurance market, there always exists a trade-off between the complexity of decision-making and relevance to market needs. In this paradigm, there is a possibility of using technology to extract information and make rationalizations to supplement a top-down approach to underwriting. Moreover, the underwriting process also compels one to address issues of fraud in the early stages of processing insurance requests.

### **2. Fundamentals of Insurance Underwriting**

The underwriting is one of the core insurance processes carried out before agreeing to contracts with policyholders. It aims at appropriate pricing, appropriate risk selection, and appropriate terms and conditions. This chapter presents an intensively discussed

underwriting practice as well as the applications of artificial intelligence and operations research tools for decision support roles in underwriting.

Risk can be defined as the possibility of a loss, injury, damage, liability, or any other negative occurrence that is caused by external or internal vulnerabilities and that may be avoided through preemptive action. Underwriting is the application of risk management principles to protect a company against some risk. In insurance markets, underwriting includes processes or practices to develop or contribute to the concepts, methods, and tools to be used in advancing the insurance knowledge and expertise of the company and ultimately leads to success. One important aspect of underwriting is to decide on the acceptance or rejection of risk and the pricing offer that indicates risk assessment. This makes everything done in the name of underwriting have a starting point from assessing the effect and frequency of uncertainties. Underwriting is about examining the impact of a collection of risks. The underwriting process involves evaluating, classifying, and pricing a proposed insured. In simpler terms, underwriting is about measuring the risk someone would like to pass onto someone or something. Whether, and under what insurance, someone can have a good or service, is an important consideration in Western society, where time has been developed. However, with the arrival of modern insurance in the past few years, insurance premiums are generally associated with a more fraudulent approach. In this context, the underwriting process boils down to answering two main questions: Firstly, what 'class' or level of risk does a particular client association of the policy cover? Secondly, at what price should the insurer 'associate' this policyholder with that policy?

### **2.1. Key Concepts and Terminology**

Underwriting is the process through which insurers decide which potential clients to insure and which premiums to charge them. The primary goal of underwriting is to predict and assess the economic costs and benefits of a potential client. The assessment proceeds through a "risk assessment," which is the process in which an underwriting decision maker tries to predict the magnitude, nature, and rate of a potential client's future claims without uncertainty, and a premium is calculated as a charge to the potential client that balances the insurer's expected costs from the potential client's claims, the insurer's expected costs, and the divestment if the client does not claim against the insurer. Insured persons are grouped according to the probability of making

claims and potential claim sizes forming risk pools. The premiums also cover acquisition and maintenance expenses.

Insurance companies underwrite thousands of policies every year, and their underwriting process is one of pricing the policy at a premium that reflects the absence of claims plus the insurer's costs and profit, a point known as the pure premium, together with the use of a few exclusions and restrictions to relieve the underwriter of any scope of claim. An underwriting year is the yearly aggregation of underwriting activities, including premium pricing, competition, underwriting quality, and the resulting loss ratio, which is the ratio of claims relative to the premiums earned in the underwriting year. An underwriting year covers the aggregation of the life histories of all the individual risks written and the net claims and premiums for existing risks, and only those. If the underwriting-year risk ratios are published quarterly, a counter-cyclical regulatory reaction function becomes much more elaborate, allowing the regulator to attempt to address an upsurge or a steep fall in underwriting risks much more quickly.

## **2.2. Traditional Underwriting Practices**

At present, the insurance sector employs traditional practices in the process of underwriting, which have a long history. Many of the processes and practices currently observed in underwriting are the same as those used for over a century. Throughout their history, insurance underwriters have mostly depended on expert judgment combined with statistical and analytical tools. They have relied upon their practical knowledge of their particular industry segment to assess the insurability of risk based on the evidence available to them. Underwriters have several tools at their disposal to help them make an assessment, including scorecards, rating systems, sticker guides, risk assessments, rate books, previously declined lists, automatic or referred cases checked by manual underwriters, referrals, flat extra and exclusions or justifications, ratings based on exposure and age, and business acceptance criteria by line. Although much of today's underwriting is based on descriptors, such as age and occupation, there remains the opportunity for detailed questioning of individuals through either intermediary or direct risk selection processes. The practice of using expert judgment to assess risk is time-consuming, often requires much evidence, and the outcome is often based on consistency of risk selection across individuals. This process can make assessments

subjective and lead to different outcomes between assessors and assessing systems. This can lead to bias in the decision-making process, which in today's climate is unacceptable. Many underwriting houses have already automated this process to a point, in order to aid the underwriters in their tasks of quickly and consistently allocating risk. However, where such assistance is provided, there is only a limited evidence base to suggest that this level of automation has a significant effect on policy and pricing. Nor is there a major difference in conversion or profitability between companies employing such systems and those not doing so. Non-automation can require more advanced levels of questioning by a human, who can often elicit finer point information not readily available through more basic questioning. It is also often possible to arrive at levels of assessment, and the outcomes themselves, more consistently via human questioning than through system questioning. In reality, businesses using underwriting tools often have a compromise between the two, skewing their questioning policy according to the available human and system resources. The questioning policy will also depend upon the tolerance of the underwriting organization to changes in policyholders' attitudes to questions.

### **3. Role of AI in Insurance Underwriting**

Artificial Intelligence (AI) has the potential to revolutionize the underwriting process by transforming it from the traditional mechanism toward one of insurance preferences and risks. Several benefits can result from using AI to assist clerical tasks, such as improving the precision of assignments to underwriting, speeding up decision-making and response cycle time, reducing the cost of application cases by shifting it more closely to the risk factor itself, and providing data on policyholder habits and locations. Insurers can use many AI tools and processes to facilitate the underwriting process. For example, one large manufacturer is developing the use of algorithms in drones using predictive analytics to accelerate the underwriting phase and strengthen claims decision-making by using aerial imagery investigation through machine learning. The firm is using neural networks for computer vision and multi-label classification in addition to the use of drones. Another commercial insurance provider is working on the use of autonomous submarines conducting maintenance checks to protect businesses and monitor for any signs of damage, such as a commercial underwriting advantage. Many businesses in various forms across the industry are looking at using AI to measure the risk in various projects from liability to property scenarios and swap industries.

As with many structural shifts facing the insurance industry as a whole, the use of AI helps to lower premiums for insurance firms due to operational advantages. Furthermore, insurers and reinsurers embrace the new data sources reflecting the particular risk behaviors of the insured. Some insurance firms are also using new AI applications to give specialist programmers. The output of AI can also be used to create bespoke health insurance plans for customers based on their medical data and details accumulated by their wearables and gadgets. Finally, underwriters have policy expectations change because of the underlying development that AI uses. Other underwriters were consulted to provide advice and rating on the risk/reward construction of every UAV method. This assumption is that less coverage is servicing costs (good for the insurer) because AI can support preventive maintenance planning. Underwriters have created a company strategy for when they are expected to collaborate with an AI-driven review instrument and when not. The technique is both adapted to an AI-generated case and to either AI-operated. For companies that will not support an AI-driven and manned underwriting program, this study targeted underwriters.

### **3.1. Benefits and Challenges**

Artificial intelligence (AI) technology is increasingly integrated into underwriting for many types of insurance, from personal lines products to commercial insurance. The substantial benefits are driving the increased adoption of AI-based decision support systems in underwriting. One of the key benefits is the improvement in processing efficiency, as the new systems are able to automatically assess and rate entries and apply the insurance terms and conditions for most standard cases without manual intervention, resulting in considerable cost decreases. The increased processing speed will enable policyholders to receive quotes much more quickly, resulting in improved business retention rates. It also has great potential for decreasing paperwork, which could also contribute to reducing costs. Besides the efficiency gains for handling policyholder applications, AI ensures the accuracy, consistency, and fairness in risk evaluation for day-to-day operations due to the elimination of operational biases and human mistakes.

Although manual processes have supported a wide range of policyholder risk classifications, AI technology has the ability to look at diverse and vast datasets rapidly, providing enhanced insights for risk acceptance and pricing that were previously

unavailable. Yet, such efficiency gains also come with challenges, as insurance companies are pushed to balance the embedment of cutting-edge AI with tackling the potential disadvantages of using said technologies. This is particularly pertinent in the discussion of AI for insurance underwriting, where the potential for AI model bias can harm marginalized policyholders and damage both the reputation and bottom line of the carrier involved. Furthermore, transparency in decision-making is even more important for underwriting AI, where the consequences of rating errors and inaccurate predictive assumptions can have large implications on policyholders' coverage and insurance premiums. Legal compliance and trust are paramount in the underwriting context, where individuals are sharing sensitive data with carriers to receive a promise of risk transfer. Consequently, regulatory attention must also target the accountability of AI decision support systems in order to gain the trust of both users and regulators. Current regulatory instruments impose specific requirements on insurers in relation to oversight, traceability, and validation of AI-based underwriting tools. AI's complexity also complicates robust risk management and control when relying on AI decision support tools. As AI is increasingly embedded in underwriting practices, challenges to audit and evaluate AI model errors also become harder to trace, particularly when AI models generally rely on making predictions against the narrow tail of large loss events. Failure to verify the shelf life of an underwriting AI model risks significantly impacting the company's business-as-usual activities. Regulatory expectations in the insurance market are clear on the need for the ongoing validation of systems, algorithms, and tools. Failure to audit the continued performance of AI models for underwriting is, therefore, not only operationally and strategically expedient but also mandatory.

#### **4. Machine Learning Models in Underwriting**

Machine learning algorithms are widely used in the insurance sector, especially in underwriting. Machine learning techniques are classified into two main categories: supervised learning, which is designed to build the predictive model based on the given input features and group target variable to define the risk, and unsupervised learning, which is used to summarize or explain the structure of the given input data. Supervised learning techniques can be used to predict and classify records using historical data. There are various machine learning supervised learning techniques used to classify and predict a target variable in the insurance sector. For example, a decision tree is a classification tool used to solve regression models. Other machine learning algorithms

utilized for classifying a target variable are Nearest Neighbor, Naive Bayes, Neural Network, Support Vector Machine, and Random Forest.

Examples of problems and decisions that can be solved using predictive models developed from supervised learning algorithms are: estimating the amount of car insurance premiums based on various factors such as vehicle type, the driving record of a person, and so forth; predicting whether a car accident will happen or not and how much the expense occurred during a particular period; predicting insurance cancellations; identifying fraudulent insurance claims; and determining the severity of a car accident based on various factors, such as a towing requirement, courtesy car requirements, and so on. Machine learning predictive models are important for insurance underwriting to predict the risk or the occurrence of an event based on prior claims files data. They can provide the distribution of different claim outcomes, dependent on the policyholder's characteristics. Supervised learning approaches can help in enhancing in-depth changes in underwriting by providing quantitative insights. On the other hand, unsupervised learning algorithms help in detecting similar groups representing alike characters in large data files or identifying anomalies and patterns.

#### **4.1. Supervised Learning Algorithms**

Supervised learning is the most popular paradigm for data analytics. In a broad context, decision support systems based on supervised learning can provide solutions like predicting future events and making classification decisions by evaluating input features, thus reproducing human inference, but not explaining how and why. Several supervised learning approaches exist and have found applications in insurance underwriting. A well-known and widely used technique is to overplot the input data in a multidimensional graphical space, separating unusual clusters from similar ones; popular supervised learning algorithms allowing such visualization of the 'anomalies' are clustering, k-nearest neighbors, k-means, support vector machines, some decision trees, etc. The most common types of supervised learning algorithms are: (1) Decision trees; (2) Regression models; and (3) Probabilistic models such as neural networks.

Based on the abovementioned learning method, a supervised learning algorithm in AI can accomplish effective predetermination for insurance underwriting. For example, suppose a life insurance company based an underwriting decision on underlying factors, such as education, profession, avocations, tobacco use, outstanding debt, and

insurance worth in order to compute an overall health index value as the discounted standard deviation and mean risk class value. If such index values are available, time to market could be reduced by artificial intelligence using linear regression and other learning techniques, thus predicting years of healthy life left for applicants. Given multiple modified index values of population data on an actuarial table, for instance, an insurance company might use artificial intelligence to develop a probability model predicting a range of diabetic conditions of applicants with certain index attributes, and implement a recommendation engine to provide underwriting guidance based on those predicted values for years of healthy life.

Supervised learning techniques are commonly applied to classify high-risk from low-risk applicants in their group of potential policyholders. As the current market value of an individual seeking insurance is time-consuming in health examinations, underwriting costs, and in dire situations. An example of a recommender toolkit based on supervised learning algorithms for health insurance underwriting can be found in the work of others. In this context, the predictive model is able to discover additional related conditions in the records of hypertensive policyholders. Supervised learning models are only able to maximize the effectiveness of health insurance assessments, thus identifying potentially high claims. Consequently, the investment in a prescriptive analytics model suggesting recommendations according to the amount of identified proposed conditions increases the overall potential and improves the management of the perspective of the insurance claim. In other words, prescriptive analytics is employed to provide personalized underwriting recommendations as a decision support tool. Application of machine and deep learning algorithms as well as various traditional machine learning algorithms, such as time series regression approaches, for such underwriting complexity.

#### **4.2. Unsupervised Learning Techniques**

The second AI mainstream, which grows in popularity among marketers and now begins to breach the insurance underwriting, continues to be unsupervised learning. This section focuses on uncovering unsupervised methods and highlights how underwriting could benefit by employing them. Unlike supervised learning, which employs datasets rich with historical records, unsupervised methods typically work

with unlabeled data. They allow us to find patterns, structures, and rules within the data. We discuss some of their main representatives.

First, the most basic unsupervised approach is clustering, which segments risks into groups based on some interconnected attributes. Another promising technique that can bring value closer to the decision-makers is association rules, which reveal the co-occurrence of risk factors. With these methods, we can group individual risks by commonalities; in other words, we segment the book of business. The results enable the identification of regions with high concentrations of unexplained deviation or the detection of anomalies within the portfolio. The methods that work with unlabeled data can bring to light insights that might have been submerged under the data volume. The key challenge lies in operationalizing the results. A model is as good as its findings are reliable and can be used efficiently. In insurance, implementing unsupervised results into the underwriting strategy tends to translate into creating new risk profiles. When selecting customer segments, it helps to rerate the risks according to their newly taken out position within the portfolio. Thus, unsupervised learning aids both customer segmentation and risk profiling. Oftentimes, customer profiling and risk profiling share the same attributes. Hence, the emerging finding can improve both supervised models and unsupervised methods.

## **5. Case Studies and Applications**

The following case studies illustrate practical applications that enhance the underwriting process using AI-inspired technologies.

5. Case Studies and Applications The following case studies demonstrate the practical, real-world applications of AI and related technologies in the insurance industry. Innovation inspired by these technologies can reduce costs, increase efficiency, minimize processing errors, reduce processing time, and open up new markets. These case studies are not exhaustive but have been selected to provide a flavor of large-scale, landmark initiatives that have been completed to date.

5.2. Motor Insurance Gjensidige Forsikring is the largest general insurer in the Nordic and Baltic regions. The company, headquartered in Oslo, has a market share in the region of about 6.5%. Gjensidige recently completed a proof of concept using a commercializable product. As part of the proof of concept, analysts used technology to

generate customer behavioral attributes such as profitability by predicting customer retention and claims. They also combined audio data with in-vehicle device data, including real-time speed, acceleration, usage, and calendar data, to generate individual driving score data. In this way, analysts demonstrated how the solution could provide insights into customer risk or behavior and how the company could have new ecosystem-based sources of data. During the proof of concept phase, solutions calculated individual key value variables and delivered results in scorecards and dashboards. The analytical approach had a performance value of 96.00 on a 0-100 scale. In customer interviews, several of the participating insurers said that the technology could be standardized on the physical and mental aspects of home insurance, accident and health/wellness insurance, travel insurance, and vehicle insurance products. Implementing such a solution would allow customers to improve the customer experience of tailored questions during onboarding processes or through the policy period.

### **5.1. Real-World Implementations of AI in Underwriting**

#### Real-World Implementations of AI in Underwriting

Despite these restrictions, there are several examples of real-world AI underwriting use, where the deployment is not just conceptual but already a reality. Practically all (re)insurers that we contacted mentioned attempts, successful or unsuccessful, to automate at least some stages of their underwriting. Manulife Canada, for instance, best known for customer-focused initiatives using AI, has established an AI Hub to contribute to multiple business orientations. The P&C underwriting group at Manulife uses AI on a daily basis, including ML-based rule extraction for novel coronavirus, drastically reducing underwriter workloads. Via this AI Hub, they also formed a 'direct electronic access' specialist team focused on access to care, engaging with innovative care providers. Hartford additionally uses AI in underwriting to provide an automated risk assessment with flexible options for value drivers, cat capacity, and cat deductible.

Similarly, firms such as Zurich and Sompo International have already faced the challenge of implementing AI in underwriting. For Zurich, it was about a new dynamic pricing and underwriting system, while for Sompo International executives, it was about reducing the workload of manual activities such as document and scanning handling and increasing the likelihood of fraud detection. Prudential, Coface, Chubb, and

investors who started trying to automate underwriting in 2019 highlight AI-based fraud detection tools. A host of insurers similarly mentioned involvement as proof of concept, with notable early participants across the globe being companies such as Blue Cross Blue Shield, Aioi Nissay Dowa Insurance, Reliance Nippon Life Insurance, and Tokio Marine Asia, as well as Europ Assistance. LIDOR's AI in insurance further assists underwriting for risk management purposes by providing content-based deep search for policyholder behavior. In general, the indicators of success of AI-based initiatives focus on measurement against competitive KPIs. Sometimes external benchmarks are not available, and so simple indicators versus before-technology levels can be appropriate.

## **6. Future Direction**

We can expect that AI technologies will further evolve in the future. Deep learning, which is used in various general and specific tasks, including scene recognition in photographs and speech and video processing, is an actively pursued research area. This highlights the degree to which numerous facets of insurance underwriting may be reshaped by AI. Insurance businesses are under increasing pressure to rethink the suitability of their current procedures and the consequences of their future AI path. This will ensure that AI technologies are regulated using sophisticated frameworks, ensuring the confidentiality and privacy of the companies and their clients' personal and financial details, and that the recommendations and projections are not affected by potential prejudicial algorithms.

AI is also projected to place an emphasis on corporate accountability. There might be legal repercussions that call into question the liability of people and institutions who make decisions about machines. In this respect, collaboration is key to developing and administering AI-supported premium assessment and in properly calibrating uncertainty in the application of modern tools. The previously described barriers to such cooperation may require interactive forums in order to overcome them. AI underwriting is expected to expand predictive analytics in insurance markets, thus sustaining the trend towards increasingly personalized insurance. Future work will have to address both existing and emerging issues in the face of the expected challenges. Alongside the development of further advanced and extensive AI underwriting software, research will become of immense importance to expand AI to entirely new subjects in order to capitalize on corresponding opportunities early.

## **7. Conclusion**

This essay has made the argument that artificial intelligence is proving to be transformative to insurance underwriting. The use of AI-based decision support systems has the potential to support and even replace the traditional practices of individual judgment by underwriters. The shift to AI technology seems inevitable, and yet there are challenges associated with it. AI technologies are often seen as a black box, with individual decision-making processes obscured and hard to understand. This raises ethical questions over the potential bias or discrimination of such systems. It has also been noted that there is the potential for such systems to fail to engage with older and more traditional market participants who have a strong skill base in traditional underwriting. The practices of insurance underwriting have gone through significant change over its history. Further installation of new AI systems must be supported by a common recognition of the significance of human judgment by underwriters, and yet an approach that is also amenable to continued learning and adaptation in the advent of AI technologies. Thus, underwriting agencies must ensure that the human values of their judgment are embedded into new AI risk assessment systems and collaborate with other insurance companies and technology suppliers. Within this collaboration, it is important that regulators appreciate the opportunities and limitations of new AI-based decision systems in insurance underwriting to support a better understanding of them. While these new AI assessment technologies bring new complex challenges, insurance underwriting is likely to transform into a leaner and more effective practice with the potential for improved risk management and the generation of new profitable business with improved customer satisfaction.