Machine Learning-Powered Actuarial Science: Revolutionizing Underwriting and Policy Pricing for Enhanced Predictive Analytics in Life and Health Insurance

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KEYWORDS

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ABSTRACT

The integration of machine learning (ML) techniques into actuarial science is transforming the landscape of life and health insurance by enhancing predictive analytics, underwriting processes, and policy pricing models. This paper explores the potential of machine learning to revolutionize actuarial practices, offering improved accuracy, efficiency, and scalability. Traditional actuarial methods, which rely heavily on historical data and statistical models, are increasingly supplemented by ML algorithms capable of analyzing vast and complex datasets, uncovering hidden patterns, and making real-time predictions. By harnessing advanced ML techniques such as supervised learning, neural networks, and natural language processing, insurers can refine risk assessment models, optimize policy pricing, and personalize underwriting decisions. The paper also discusses the implications of these advancements for actuarial professionals, including the shift toward more data-driven, automated workflows, and the ethical considerations surrounding data privacy and algorithmic bias. Ultimately, ML-powered actuarial science promises to usher in a new era of precision in risk management and a more dynamic approach to insurance operations, benefiting both insurers and policyholders alike.

1. Introduction

The integration of machine learning in actuarial science has the power to profoundly transform how risks are underwritten and how policies are priced in life and health insurance. These techniques are expected to bring more dynamic and personalized underwriting strategies and to lead to a more granular pricing of risks. In view of that promise, current practices and future trends are analyzed, while examining the challenges to be met and the impacts expected on life and health carriers' pricing analytics and actuarial work. Over the past years, life and health insurance underwriting and pricing have seen a set of well-known technological advancements generating a soaring availability of data and an increased predictive power of models. This evolution could logically pave the way for advanced analytics, but adjusting current pricing practices to complex machine learning models remains a challenge for carriers.

The machine learning revolution in actuarial science is thus there to be monitored, as it is meant to transform – sometimes even deeply – insurance pricing models. From a statistical viewpoint, the reconcilement between traditional GLMs and complex tree- or neural-based models still has to be entirely written. These discussions define a framework that is particularly relevant now that all the actors – insurers, reinsurers, regulators – are looking to identify and assess the potential impacts of machine learning applications. Besides, current practices are also analyzed concerning the machine learning methodologies used by carriers in their pricing models and the specific points they pay attention to when communicating or monitoring these models. This part notably tackles the notion of model interpretability, which is a growing challenge and should be questioned in actuarial guidelines concerning the production and the review of machine learning based pricing models.

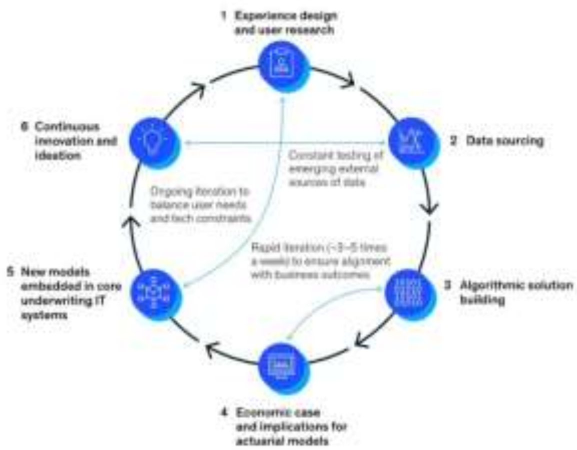

Fig 1: Machine Learning are Transforming Actuarial Science

1.1. Background of Actuarial Science Actuarial science undertakes an analytical approach towards long-term financial planning and the management of risks. The discipline dates back to as early as the year 1000, when options were first documented in Babylonian contracts detailing background risks. In light of the risks these merchants faced, actuarial science was developed in 1654 in London, when probability and interest were first combined and used in the pricing of life annuities. Work such as this produced the list of probabilities widely known as mortality tables, and practices established with the pricing of life annuities can be seen as the rudimentary form of life insurance as it is known today. The unprecedented growth of the insurance industry over the following centuries necessitated more intricate actuarial modeling and statistical understanding of risks, eventually leading to the emergence of the modern-day field. In short, the development and practice of actuarial science is deeply rooted in risk assessment, statistical analysis and financial forecasting.

In insurance companies, actuaries are responsible for managing financial risk of claims, both in terms of defining the types of risks the company wants to cover and at what cost they are willing to cover these risks. Premiums are set so that the projected claims, given the covered risk, can cover operating costs, level of investment expected income and make a profit, usually within legal constraints. Actuaries actively participate in the decisions of which risks to cover and at what price. Along with the rapidly increasing importance of insured systems, obligations, and liabilities in the widest range of applications, it is more important than ever for actuaries to accurately assess the financial health of covered transactions. Over the past decades actuarial science has proven invaluable to step over the bounds of individual entrepreneurial activity and field of activity, first through adopting the Keynesian innovation of pioneering innovative risk financing mechanisms, later on with the employment and stimulation of highly developed mathematical models.

Equ 1: Random Forest Model for Underwriting (Ensemble Learning)

$$\hat{Y} = \frac{1}{T} \sum_{t=1}^{T} h_t(X)$$

Where:

- $\hat{Y}$ is the predicted outcome (e.g., risk score or claim probability).
- $h_t(X)$ is the prediction from the t-th decision tree.
- T is the total number of trees in the forest.
- X represents the input features.

1.2. Evolution of Machine Learning in Insurance Although machine learning has recently become popular, it is of way older date, with Samuel's artificial intelligence (AI) programs able to play a better game of checkers than he could before 1962. Insurance companies have started using machine learning models for a variety of different applications, even before high-resolution data became that easily available. However, the computational power constraints experienced a couple of years ago did not allow the use of highly complex predictive modeling tools based on algorithms that require extensive computations. This is why statistical models were preferred instead of more advanced machine learning techniques. Nevertheless, the recent advancements in computational power have made machine learning and tree-based models in particular a common choice in the insurance industry with significant improvements for those who have adopted this technology. A broad range of studies now see insurance companies explaining the tariff plan instead of simply releasing it. Insurers are using tree-based machine learning models to rank different statistics based on their impact on the pricing model. Also, insurers are constructing complex interactive models by combining explanatory information on factor impacts from tree-based models. By unveiling the insights gained by insurers in the tariff setting process through tree-based machine learning models, this paper attempts to address the current gap in the available literature. Additionally, a novel methodology is presented that relates the tree-based models to popularly accepted insurance pricing models in an expedited fashion while circumventing the need for a full parameterization of the tree models. Machine learning algorithms are increasingly being used in insurance to model frequency and severity, assess risk, and predict claims. With the increased focus on the use of machine learning in insurance pricing and reserving purposes, the need to understand the model results and ensure models are not unfairly biased has never been more important. Amid COVID-19, the FDIC has continued to see an increase in the use of alternative data sources and the use of non-traditional underwriting methods, such as machine learning and AI. As institutions consider the use of alternative data sources and machine learning in their underwriting models, it is crucial that these models are transparent and can be reviewed to ensure controls are in place to limit unfair treatment of applicants.

2. Theoretical Framework

This article investigates one of the prime tasks of actuaries; assessing and pricing risks. Theoretical concepts that are basic for understanding the current practices in both the actuarial and the machine learning field are set out first. Given that the article's main audience is actuarial researchers, the presentation of machine learning refers to the modeling techniques used in the case studies. A comprehensive overview of all existing machine learning models would be beyond the scope of this article. Then the synergy of both fields is illustrated through a few representative examples. Traditional concepts of actuarial science relating directly to the assessment and management of risk are laid out. As such, concepts such as risk, affordability, equivalence, pooling, experience rating, risk class and insurance system are introduced. Traditionally, actuaries deal with risk assessment and management in insurance underwriting and policy pricing. However, discussing the whole process in a competitive insurance market involves some macroeconomic and regulatory aspects that go beyond the actuarial view and hence are left aside. Actuarial science is thus brought down to the micro level of the insurer. Then a review of the various risk assessment models built and updated by insurers is given. Nevertheless, while illustrating actuarial risk assessment and pricing models, separately built stochastic and deterministic models are discussed. This contrasts with the current market practices, as it is widely accepted that combining both leads to better results in terms of profitability, risk selection, solvency and fairness. Finally, the issue of the growing use of machine learning by insurers is discussed with its implications for actuarial practice. In order to understand it, beyond being aware of the black box issue, which will be addressed later, actuaries must be acquainted with the most common machine learning algorithms and their applicability in insurance. Halfway between statistics and artificial intelligence, machine learning covers a wide range of algorithms, methods and techniques. The most used techniques by insurers and which are the discussion focus here are ensemble methods, and specifically: random forests, gradient boosted decision trees, extreme gradient boosted decision trees, and their regularized versions.

2.1. Actuarial Science Principles Actuarial science is a discipline that applies mathematical and statistical methods to assess financial risks in order to maintain the financial sustainability of insurance products. The historical principles of actuarial science are deemed vital in helping insurers to evaluate risks behind policyholders and set fair premiums. Insurance is all about the evaluation of risk to provide compensation against it. All the risks within the scope of policy coverage are agreed in the policy contract. But evaluation of the risk itself is uncertain. A fair premium is required to cover expected claim costs and other expenses, including the determination of the expected values of these uncertain future costs, with extra margins added to ensure financial sustainability. As a protection to both the policyholders and the policy providers, the contract must be set up fairly, the so-called actuarial equivalence.

At the core of the mathematical foundations of life and health insurance is the concept of multi peril mortality rates. Risk pooling is the idea that by merging the uncertain losses of many policyholders, the resulting average loss per policyholder decreases. The increasing death rates with age lead to the establishment of the actuary profession. Actuarial aging is the transformation of random future lifetime into deterministic future lifetime. The establishment of a financially sound life insurance company by setting a life table containing the distribution of future lifetime is the process of calculation of annuities. The construction of tables relating future widowhood and divorce rates is the financial DHCM. For λtw finite, setting aside the case of accidents, male mortality dominates female mortality at every age. For λtw infinite, on the other hand, there exists a threshold at age ω, for which male mortality dominates female mortality for ages before ω and vice versa for ages after ω. A fair price policy will be a barter trade where the future random losses are exchanged before their realization. The Lehmer property was handy for the establishment of accurately projected future widowing rates, leading to the construction of ω. Characterization of ω was made easier with the transformation of bidecadal future widowhood rates into a calendar table.

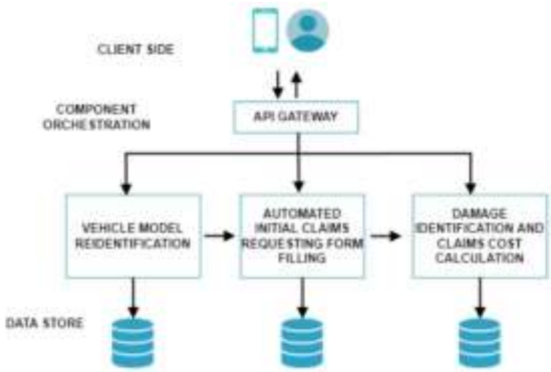

Fig 2: Actuarial Science

2.2. Machine Learning Algorithms and Techniques Machine learning (ML) is an umbrella term for a family of algorithms that learn patterns from sample data to improve their error or accuracy. These algorithms are particularly interesting for the insurance sector, where they can automate and generalize processes that would otherwise require expertise and experience. Insurance underwriting is the acceptable class of risks, based on guidelines produced by underwriters. Insurance pricing is the practice of setting prices for insurance services. In the life and health insurance subsectors, the mortality and morbidity risk are the most important, so understanding the insured's health is crucial for underwriting. Unfortunately, this information is not available to the insurer in the right granularity. However, it leaves traces that can be analyzed, such as the number and type of doctor visits. Pricing becomes more challenging due to the large variety of products available. Varying the characteristics introduces different levels of risk into the insurance pool. Jointly, underwriting and pricing policies deeply influence the policies perpetration and have a broader impact on social welfare. The number of lives with life and health policies is ten times greater than the number of non-life covers, causing the former to be burdensome to both the state and the insured. Machine learning algorithms have the ability to analyze datasets thousands of times larger than traditional actuarial tools. They can find patterns in data that can inform a set of guidelines. This can be extended to the underwriting and pricing proposals, as well as to their understanding. An analysis is conducted on how the implementation of several machine learning algorithms, suggested guidelines, changes in the claim data, or pricing can affect some macroeconomic indicators of welfare. The framework allows for the comparison of distinct underwriting and pricing suggestions based on the solutions. Population variables are to understand how those choices interact with economic and social aspects. As a result, the framework intends to support the explainer and rationalize the choices currently made regarding the underwriting pricing field.

3. Applications of Machine Learning in Underwriting

Underwriting, the process of assessing risk prior to policy issuance, plays a core role in the insurance industry. And it historically depends on actuarial tables often manually-driven. Within the underwriting process, transformative potential is seen in machine learning with data-based algorithms. The underwriting progress is being streamlined and the decisions become more precise as a wide variety of learning algorithms, comparison methods, and data sources. Machine learning is about making data-driven predictions or decisions based on applying algorithms that learn their pattern of the data.

Machine learning has various applications in underwriting. The first of these is risk assessment. Life insurance underwriting considers medical history, family medical history, risky behaviors, dangerous hobbies and jobs, and driving records. And when it comes to health, medical malpractice, and long-term care, the standards become even more complex and detailed. It means there are a number of opportunities to decrease the error that can be made here, and actuaries have had a lot of success in doing so with the advent of machine learning. The process can be made more accurate, and relying on misleading proxy variables can be avoided. An example of a subfield within risk assessment is that of fraud detection in underwriting. This mechanism of fraud detection is generally predictive, looking for patterns indicative of deceiving the insurer. Fraud prediction comes in one of three tastes: settler (ex-ante), provider (during the policy term), and payer (post-claim).

Customer segmentation and pricing is another area where actuarial and underwriting practices within the insurance industry have much to gain from predictive analytics. Innovative products and premium rates are required to mitigate such risks in an industry where undesirable selection is a perennial problem, and those who price and segment risk accurately will be best poised to provide the attractive deals. Customer segmentation is important here because an insurer can tailor the policy type and premium of a customer in accordance with their predicted probability of loss. The companies that are winning customers are more likely to remain competitive because they retain capital that others lost to payout as claim benefits.

Fig 3: Applications of Machine Learning Actuarial Science

3.1. Risk Assessment and Selection The algorithmic approaches of the fourth industrial revolution are likely to make an impact on many modern professions and jobs in the upcoming decade. Professionals such as accountants, lawyers, and pharmacists, as well as architects, insurance underwriters, generally operational staff, medical research staff, and likewise industrial manufacturing employees had relatively little worries about their job security. In particular, the problem of actuarial science might be relevant as often this profession is reckoned as an example of a high degree of skill and expertise, complex math for handling big data, survival-benefit models with potential for external digital transformation, and which also has legal side as legally admissible explanation is required for the conclusion of the end product calculated. Notwithstanding that, algorithmic decision making is sharply underway in the discipline of actuarial science. Modern underwriting boot camp is presented where algorithmic machine learning approaches to augment the huge amount of varying data available and prevent a step down approach in price competition, loss of capability to handle complex cases, and hence losing a rational level pricing of the policies, even up to failure and bankruptcy.

The application by evident domestic insurers and recent technological developments signify the expansion of it, as the general purpose of the underwriting process to provide an examination of the risks being reassured is highly aimed to effect the analysis of only temporally and structurally obtainable risks. Subsection 4.1 is dedicated to the Risk Assessment and Selection within the context of the underwriting process, which is holding the risk analysis base of multi-step actuarial calculations, classified in the most important actuarial bases by the risks' duration. An Array of actuarial metrics that quantify the goodness of the loss size prediction of emerged risks are used, discrete and continuous since modern underwriting risk selection refers to the decision-making, executed exploiting the examination results and predictions obtained through the algorithmic machine learning models, giving the spark to the eventual legislative alterations to hold the invulnerable areas of the profession.

3.2. Fraud Detection In recent years machine learning has become an essential tool for data analysis across many industries. It can help automate and optimize many of the processes associated with everyday operations and inform better decisions. Life and health insurance market is no exception. Many insurers have transitioned to machine learning-powered actuarial backbones that help manage a business from underwriting risks to policy pricing. They automate initial risk assessment by processing large amounts of historical data on the client and the type of insurance being applied. Insurance policies are automatically graded, renewals are offered to clients or their old policies are adjusted. Some claim decisions have also been moved to machine learning algorithms that can estimate the chances of different outcomes and decide on the best course of action. This machine learning-driven environment is designed to assist the human underwriting staff by providing necessary information faster and more accurately .

One of the machine learning-powered actuarial parts of life and health insurers that were slow to move to machine learning-driven automatic calculations is insurance underwriting. It's considered the financial analysis and valuation of the risk associated with a potential client. It relies on the calculation of individual prices and the specification of terms and conditions to close the deal. Underwriting utilizes the client onboarding data and the historical claims data to make an assessment. Human underwriters can quickly check for any inconsistencies or readily identify fraudulent activity. They can also turn down deals based on their experience and intuition that the machine learning algorithm may not be able to flag. Throughout the discussion, recommendations are made to combine the best aspects of both the machine learning-backed underwriting and the old school approach to ensure the best client experience. Underwriting process is also affected by other parts of the market around it - both suppliers and consumers.

Equ 2: Neural Network for Claim Prediction (Artificial Neural Network)

$$Y = f(W_2 \cdot f(W_1 \cdot X + b_1) + b_2)$$

Where:

- Y is the predicted output (e.g., claim probability, premium).
- X is the input vector of features.
- W_1, W_2 are weight matrices for the layers.
- b_1, b_2 are bias terms for the layers.
- f is the activation function (e.g., ReLU, sigmoid).

4. Enhanced Policy Pricing Strategies

Machine learning advancements allow improved customer and policy pricing and underwriting strategies for life and health insurance. Among other changes to the status quo, it allows for the idea of dynamic pricing to enter life and health insurance policies. The customer's life expectancy changes and so does the cost for the insurance provider. Dynamic pricing models enable insurance companies to adapt their premium calculation based on real-time data analysis of risk combinations, medical state of the insured, changes to policy conditions, and many other factors that are involved. Fixed pricing policies of today, on the other hand, rely on generalized estimates of the future and do not allow providers to successfully compete. The life insurance company will be able to reach an agreement with its health insurance counterpart and offer personalized prices for the customer, according to the analysis of their risk profiles, combined with their own preferences. Indeed, a client in good shape can achieve a ‘safe-driver’ status and significantly reduce their total insurance costs, while still keeping the individualized conditions of the contract. As a result, customers receive the fair price for their policy that is always up to date with current personal conditions and insurer’s strategy, improving satisfaction and potential for retention. In response to the fluctuating market conditions and the constant changes in the policy holder’s life, the pricing market algorithm is continuously re-optimized. An insurer can, therefore, stay on top of the competition and adapt their policies to maximize the profit.

Fig 4: Pricing Models

4.1. Dynamic Pricing Models Life and health insurance are major business lines in the global insurance industry with a high value for policyholders, as they bring financial security to people’s lives. Life insurance secures dependents financially by managing risks and is a crucial part of financial planning for individuals and business firms. Health insurance protects individuals and families from sudden medical costs and encourages lower-cost care in the intended healthcare system, thereby stabilizing financial health. The core of life and health insurance is underwriting and policy pricing. With the advance of machine learning technologies, insurance practitioners are leveraging actuarial science to optimize pricing strategy and underwriting, creating favorable scenarios for policyholders while maintaining the insurer's financial viability. The underwriting process assesses risks and determines if and on what terms coverage should be provided to the applicant. As underwriting is an essential process for selling an insurance policy in the realm of adverse selection, the insurer must have a solid underwriting guideline. Pricing a policy determines how much premium will be charged to transfer risk. It is vital that the proposed premium covers the expected loss and provides a sufficient addition to account for the insurer's costs and desired profit, with the competition also considered. Moreover, as pricing innovation may bring a competitive advantage, insurers are pushing the boundaries of it. The actuarial modeling of insurance markets has gone through revolutionary changes within the last decade. Actuaries now make use of models that deal with high-dimensional data and take advantage of big data technology. However, the application of the most recent models has been hampered by slow adoption by regulatory authorities and academia, which has slowed the transmission of best practices to the entire professional community. This paper argues that machine learning-powered actuarial models help in setting adequate premiums and guidelines by investigating dynamic pricing models widely adopted by insurers.

4.2. Personalized Premiums Since the emergence of actuarial science, risk exposure has been quantified in insurance on a group basis, which led to the establishment of a fixed tariff system. Premiums were calculated by determining the portfolio's average risk and setting prices accordingly. Personal risk assessments through machine learning analytics are now reaching life and health insurance. Consequently, the possibility of calculating premiums that more accurately reflect the customer's individual risk profile is growing. Personalized insurance premiums have the potential to offer customers more precise coverage adapted to each situation. A personalized premium would ensure that the price aligns with individual circumstances and would thus increase the satisfaction of the insured, as research has indicated. In life and health insurance, the arrival of cloud computing and the increased attention to individualized risk assessment supported by AI will increase the use of customer behavior analysis in pricing. The collection and processing of individual data is expected to lead to important changes in policy pricing. Acting in a competitive market is a fundamental part of a business strategy. There are good reasons to believe that companies will increasingly use AI to extract information from markets and thereby offer better insurance prices to customers. Along with the potential advantages related to knowledge of the market and the need to retain policyholders, the use of machine learning-powered actuarial science in insurance pricing also poses some questions about ethics. To establish a transparent and fair approach to pricing is an ongoing issue for both the culture of the company and the regulators.

5. Challenges and Limitations

Machine learning is making a significant impact on the role and function of actuarial science as it pertains to underwriting and policy pricing in life and health insurance. Advances in algorithms and data collection have led to the development and adoption of machine learning models throughout insurance companies, including being used for purposes of underwriting risk classification, ratemaking, and pricing recommendation systems. The fast pace of development has regulators considering updated standards and best practices. These challenges follow the profession groundswell in its interest and use of machine learning.

Yet the leap from design to implementation of machine learning poses a unique dilemma for actuaries: confidence in its use and deployment requires a level of interpretation and explainability that might not be directly compatible with the cutting-edge techniques actuaries seek to employ. Imagine going to an analyst for help, but the entire thought process is permanently hidden. This is the growing dilemma in risk classification using black-box models and machine learning. Developments in actuarial science build trust between stakeholders through control, regulatory adherence, and reasoning. However, the most successful machine learning models often excel because of their complexity or vast features, which may lead to 'black box' scenarios that cannot be easily understood or even explained. Amid growing privacy and ethical concerns about the use of personal data in machine learning models, the practical use of these models is even more scrutinized, raising additional questions for insurance companies. There are growing calls for clear regulatory frameworks to govern the ethical use of machine learning in the practice area of underwriting. It is clear that actuaries must navigate this evolving landscape with ongoing education and training to ensure understanding, proper use, and compliance with current standards.

Fig 5: Challenges in Data Analytics Implementation

5.1. Interpretability and Explainability Model transparency and interpretability are increasingly important topics under machine learning methods, especially in the field of actuarial science. It is particularly challenging in some cases to interpret the outputs of machine learning models, especially when they are based on more complex algorithms. Uncertainty and precaution for decisions to be taken can be increased by the lack of understanding and recognition of information generated from these. Knowledge-extraction tools can help model interpretation, but the most relevant ones are not free. Since using a box-stacking method enriches the main model and uses a leave-pair-out approach to estimate the effects of the enriched forms, the model retrain on the full set of variables every time a possibly enriched model is present reduces accuracy. There can be no solution that is suitable in all circumstances when it comes to balancing the opacity against the stability and accuracy of the model. Therefore, it is nevertheless necessary to pay particular attention to the following aspects: the model used is kept as simple as possible and the interpretation of the model variables is meaningful, decisions taken on the basis of black-box models are properly understood and justified, additional sophisticated methods supporting the interpretation of the model outputs are applied. To further enhance actuarial predictive analysis models used by machine learning, insurance actuaries are increasingly interested in the field of model interpretability. The increasing popularity of advanced machine learning methods, such as boosting algorithms and forests of random trees which are generally considered black box models, has brought an upsurge in statistical research on model interpretability. Complex and non-linear models are widely used here to optimize the policy. At the same time, from an actuarial point of view, it is crucial to be able to understand and justify proposed changes. A trusted model is a transparent model, as both stakeholders and regulators can precisely observe and so judge the fairness and the accuracy of it. It is possible to bring increased restrictions, and perhaps a growing expectation of transparency on the models that insurers fit to their data. Defensive decisions can call for straight forward models which are thus easy to argue as they scrutinize and communicate the sources of their predictive power. It is rightly asked that models be understandable to their user. An independent expert, whether an auditor or inspector, will normally examine the reasoning behind a decision. It is necessary to also explain how a computer model makes a decision. Model transparency is all the more important, as it is getting crucial to verify that outside actions against a mathematical model are consistent and, in the absence of explicit explanation for a decision, that same mathematical model is believed. This paper emphasizes the importance of a well-perceived trusted model in a world where data-based decisions are made with black-box algorithms. Moreover, a literature review on the issue of the interpretability and transparency of models, as well as some applications related to life and health insurance underwriting of such models have been displayed.

5.2. Data Privacy and Ethical Concerns Life and health insurers have begun to utilize talented in-house data scientists as well as partnerships with insurtechs to capitalize on the data-driven benefits of ML technologies. Meeting the statistical reliability standard involves accurately predicting mortality, morbidity, and health care utilization using credible actuarial methodologies. The first part provides a summary of the analytics toolbox for modern underwriting and policy pricing, demonstrating that actuarial science is swiftly evolving into a machine learning realm. This development enables both the pricing of life and health insurance policies for high-mortality-risk individuals and the underwriting of such policies in selected cases, as these ML models are theoretically compliant with statistical reliability standards. A second discussion on ML interpretation defines the scope of statistical decision theory in the interpretation of predictive models and relates it to the concept of model trust in a consumer-driven context. Smaller insurers may lose competitive data advantages to other insurers and integrators. Successful collaborations should be built on appropriate principles, and ethical concerns and guidelines should be developed.

However, an important aspect of these new ML applications in the insurance context is under-investigated, that is, the sufficient economic and actuarial review, with an ethical perspective, of what new EU policies on data collection, storage and processing practices of consumer-related personal data by life and health insurers should be. This evidence is provided by this article. This article is divided into two main sections.

Equ 3: Support Vector Machine for Risk Classification

$$f(X) = w^T X + b$$

$$\hat{y} = \text{sign}(f(X))$$

Where:

- X is the feature vector.
- w is the weight vector.
- b is the bias term.
- $\hat{y}$ is the predicted class label (e.g., low risk, high risk).

6. Conclusion

The impact of machine learning (ML) in actuarial science to underwriting and policy pricing is discussed. With the growing use of machine learning methods and the boost of the available data, actuaries can achieve the ultimate goal of the insurance industry: make correct decisions when evaluating the associated risks and based on this decide the relevant policy prices to ensure its sustainability. After setting the context where traditional actuarial methods evolve towards more and more complex ML, the improvement offered in underwriting and policy pricing are presented. A fast expansion, over the last few years, of ML applications in the evaluation of risks and the definition of tariffs involving both the life and health insurance businesses is observed. When these applications target risks with significant amounts of data to analyze (e.g., personal and macro-economic features for health risks), insured lives can benefit from improved accuracy and fairer decisions for applications between insured with similar observable risks. Decision-making processes of insurers and reinsurers become more efficient, allowing them to handle the understaffing of resources in their underwriting departments with increased activity and naïve analyses done at the cost of simple rule-based engines softened by the ability of sophisticated analytics to handle a wider range of non-traditional features. Commercial solutions based on fingerprint recognition to manage potential fraudulent claims are engaged with information entirely unrelated to the aspects of the claim that would traditionally be analyzed. Still, other applications in the health business seek the detection of instances never previously observed, such as rare diseases or new medical products.

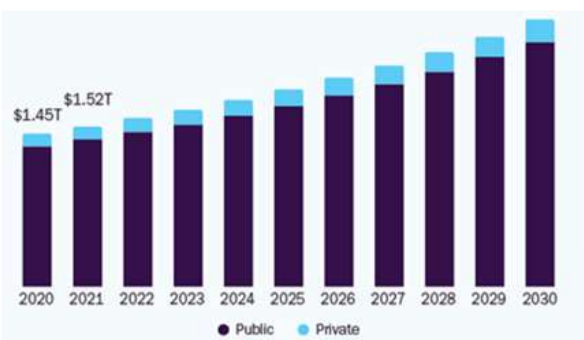

Fig : AI for Insurance Underwriting Market Trends

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