Leveraging AI for Automated Insurance Policy Pricing

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1. Introduction

Global economic, social, political, and environmental changes are transforming the operating frameworks of different sectors, including the financial services industry, among them the insurance sector. Traditional business practices are increasingly pressed by a high-tech environment. The insurance industry is being directly revolutionized from multiple angles, such as digital distribution, product innovation, underwriting, and so on. A trend might involve automating processes that have traditionally been performed manually, with relevant implications in the pricing process. It is in this scenario that the theme of this essay is set, which addresses the automated pricing of insurance policies by leveraging artificial intelligence.

In general, insurance pricing refers to the activity of defining the annual premium that the client should pay. In the highly competitive insurance market, this process must also guarantee that the price of the coupled policy is accurate. The application of AI brings, on the one hand, the possibility of improving the accuracy of this process, reducing the possibilities of incorrect policies and reducing complaints. On the other hand, the possibility of competing in other segments, given the increasing level of software and electronic components used in cars, yachts, and industrial machines, becomes an opportunity and not only a simple necessity. In order to achieve these goals, in general, we answer the following questions: (1) How to be profitable in a highly complex and diversified environment? (2) Are there hidden parameters that have not been considered or quantified enough? Management in the insurance sector seems to be closely linked to an 'interpretation' approach while instead leveraging artificial intelligence might provide a complementary approach. Finally, research can contribute to achieving the managerial objectives of increased customer satisfaction and switching from selling insurance policies to offering protection that encompasses the dynamics of digitalization.

1.1. Background and Significance

The traditional practices of price discrimination and insurance pricing have always been to group similar policyholders and price such that expected profitability is similar across members of the group. This has been the evolution of insurance. Traditionally, policy pricing was quite simplistic as assessing individual risk was not feasible or viable. Instead, algorithm-based price precision evolved into grid rating, manual rating, calculator applications, etc. Therefore, the traditional insurance policies were primarily priced based on a set of fixed and firm rules decided in the contract. The change in modus operandi, the role of an insurer has also been witnessing a change, moving from risk bearers to risk assessors. The regulators required insurers to show more transparency in their ratings. Nevertheless, as data analytics became more advanced and computational power increased, pricing became complex and sophisticated due to the use of a statistical model that incorporated dozens of risk factors—from conventional factors like driver's age, history, type of vehicle, and use of vehicle to a broader spectrum such as marital status, homeowner status, credit score, income level, occupation, education, age, property value, specific location, personal affiliations, criminal record, and more.

The traditional approach is weak due to three main reasons. Firstly, at a categorical level, the probability of an event is assumed to be stationary over time. Among 365 days of the year, there are more occasions of a certain event. Likewise, the probability of a road accident on a rainy day is higher than on a dry day. Secondly, due to increased and more adaptive risk pricing, traditional insurance pricing has become opaque, leading to customer dissatisfaction. Thirdly, the information on new data variables, data sources, and data processing mechanisms is easily and quickly updated, making traditional pricing practices redundant due to time and high resource costs compared to contemporary systems. As a result, there are stricter rules enforcing algorithms to be transparent and interpretable in financial use cases, which increases the demand for developing AI-based solutions for various use cases. In the same vein, holistic socio-economic changes like urbanization and the increase in purchasing power have given rise to more vulnerable societies. Furthermore, this has further incited individualized and accurate insurance pricing driven to some extent by new insurance business models such as Pay-As-You-Go, which means pricing is directly linked to the time the service is provided. Very low margins and increased transparency on the liability side of an insurer have also made precise risk assessment a pivotal pillar for margins in the coming decades.

1.2. Research Objectives

The objectives of this report are as follows: - Review the effectiveness of AI versus traditional pricing in the development and offering of insurance policies to consumers. - Identify in which use cases AI may provide added value compared to traditional pricing models. - Determine if AI-powered pricing strategies have proven to enhance businesses' ability to offer lower-priced, more personalized and targeted policies compared to traditional methods. - Examine the challenges businesses may face when implementing AI to set insurance policy prices. - Identify the ethical considerations that should be taken into account when employing AI to price insurance products. - Establish the importance of fairness and transparency in AI-powered systems. - Outline what makes a successful AI-powered pricing strategy. - Identify and assess the most important factors acting as a catalyst for the successful rollout of AI pricing tools in an insurance business.

2. Foundations of Insurance Pricing

A foundational principle behind the process of purchasing insurance is the pricing of the policy. At its core, an insurer accepts the undertaking of offering help to a policyholder in exchange for premium payments. The latter are then used to ensure the insurer's solvency. Especially in the fields of non-life insurance, pricing is a pivotal concern, as drops in premium income arise not only from missing the necessary number of policyholders but also from the insurer's own pricing error. Classical insurance pricing tools are deeply rooted in actuarial science. "Rating" is an actuarial term, based on the Latin word ratus. In actuarial science, determination and calculation of risk factors are quintessential. Statistical models are employed to estimate expected claim costs and to promote solvency of an insurance company.

Underwriting and pricing are the two wings that enable an insurance contract to take flight. Underwriting involves a transaction based on the applicability of the insurance policy to the insured. Assessment of the economic factors is the key, indicating how premiums can be justified. Pricing, on the other hand, is concerned with the development of the transaction, including the management of the price concession and the profitability of the transaction. The statutory pricing for insurance policies often involves actuarial policy rating. Among the eighteen elements of insurance management, underwriting, pricing, claims handling, and marketing are counted. The three pricing factors (cost, competition, and consumer) in micro and industrial economics are applied both by life and non-life insurance industries in their operations. The behavior of consumers, their attitudes towards risks, and their risk aversion and risk-taking propensities are driving forces of the insurance pricing policy to which the former factors conform to ascertain the rationality and exactitude. An objective during the actuarial pricing task is the computation of premiums based on statistical models developed for depicting risk. As several elementary and antiquated models predominated over time, the actual realization that policyholders could be classified according to certain risk parameters materialized in the 1980s, wherein the search for more complex models to encapsulate individual risk behavior began. Nevertheless, theoretical ingenuity and speculation are requisite to comprehend consumer behaviors and attitudes towards uncertainty that go beyond actuarial risk. Regarding the pricing policy, especially the identification of underwriting and detailing of pricing factors, sophisticated risk and consumer models established by behavioral economists could provide more understanding through customer surplus relating to the insurance policy of the non-life insurance policyholder. Suppliers, in turn, are in the insurance business for profit seeking.

2.1. Traditional Methods vs. AI

The traditional method used by insurance companies to design prices for insurance contracts cannot match the accurate risk of the policyholder, which leads to adverse selection. In the traditional method, history and past data are used, which only show past conditions, features, and events. A standard rating approach is usually employed, such as class-rated, schedule-rated, and experience-rated plans. All these have to be designed and decided prior; hence, any new features or clearly underpriced features occurring during the coverage period would not be considered, making rating plans suffer from moral hazard and/or hidden information. Moreover, any regulatory intervention and supervisory activity might be time-consuming and sometimes not easily enforced, creating many potential loopholes. The traditional approach also assumed the world to be static and homoscedastic. In coding and developing the model, insurance companies are less able to promptly incorporate very rapid market changes, including currency devaluation, disinvestment, fall of stock prices, and even the death toll, into their historical data and rebuild their pricing model.

However, with AI use for parameter determination and policy pricing, it has the capability of mining any relevant information and patterns from a large and complex database. Machine learning-based cost and price estimates are intrinsically superior in terms of accuracy, less measurement error, real-time or beyond real-time adjustment, more accurately able to predict and prepare for interest rate/time value of money changes, and bullish and bearish market trend predicting capabilities. AI is especially advantageous for adaptability, which makes it effective when pricing is connected to a rapidly changing market environment. Additionally, it can identify functional interdependencies and associated hidden or intertwined behavioral ideologies or attitudes. This same generalization capability can also be seen as a disadvantage in terms of model interpretation. Model transparency is still an active research area. There are concerns that since credit ratings are not always fully transparent, one may be able to assess the inefficiencies and biases that are inherent in such models in the context of small sample sizes. Hence, currently, although cost estimation using big data and analytics can be more efficient, it is still a work in progress in terms of adoption by the insurance industry due to the overlapping synergy between market and credit operations.

3. Machine Learning in Insurance

Machine learning, a discipline within the broader field of artificial intelligence, has developed rapidly and significantly over the past decade. ML algorithms are particularly useful in extracting insights from large data sets with many features. Similarly, ML techniques can serve as an excellent means for mining complex relationships among different data elements to reveal potential new correlations and predictions. Both capabilities are highly relevant in the realm of insurance underwriting. In insurance, the adjective 'large' can refer to either the number of data items, the number of different characteristics, or the convergence of both. There exist numerous different flavors in classification tasks and their targeted customer groups, for instance, product application scenarios and business operation environments. To cite a few application areas, separated customer groups are mobile app users, vehicle drivers, credit card holders, TV box viewers, and game players. Each of these scenarios presents a growing challenge for probabilistic state transition detection. The data are usually highdimensional, imbalanced, noisy, and volatile over time. Furthermore, they are frequently subjected to a significant level of collinearity, where the degree of association between any two variables exceeds that between or among these and the dependent variables.

Confronted with such complex data, it is necessary to develop computationally efficient and interpretable models for identifying relationships between risk characteristics and the probability of claims. Machine learning, which has significantly advanced in recent years, is well-positioned to address such complexities in insurance pricing tasks. In fact, state-of-the-art machine learning models developed in insurance pricing are able to achieve not only better model fit but also increase the overall model interpretability and speed. The MLs can greatly help insurance professionals in learning complex scenarios, evaluating policy pricing, and the process behind the scenes, and more importantly, in contributing to the policy pricing mechanism. In this context, recently developed models have attracted attention and have been shown to contribute statistically to better claim pricing and policy risk management. In other words, machine learning in insurance can help leverage more data, tease out unique insights, optimize diverse actionable business intelligence, and reshape the business landscape for survival, growth, and resiliency.

3.1. Applications in Pricing

Usage of AI in personal and commercial pricing in the insurance industry is very common, with an estimated 75% of companies using existing market-leading pricing products that utilize some form of pricing optimization. In the personal lines space, insurance companies primarily offer symbolic input algorithms that focus on better capturing the variance and reducing prediction errors to serve clients, primarily focusing on pricing optimization and not being much concerned about the qualitative understanding for risk differentiation. Insurance companies make extensive use of new market products that involve data enrichment. These products typically generate somewhat similar-looking relative variations in pricing options by differentiating the risk in various disclosure-focused dimensions.

4. Dynamic Pricing Models

Marketplace automation is abundant, with firms using sophisticated pricing algorithms to maximize profits or ensure market leadership. As policyholders and insurers accumulate increasingly large and diverse data portfolios, dynamic pricing becomes an increasingly complex strategy for insurers and is also growing in interest. Dynamic pricing is the automation of price in response to cost developments, amendments in risk exposure, or changing demand profiles. This strategy allows the price to convey across all strata and optimize conditions and generally reflects the insurer's costs and charges. Digital marketplaces can channel consumers to other sellers, keeping prices competitive and cost-effective. A dynamic pricing policy better captures the insurer's exposure. Parameters in the exponential extension express changes in elasticity or can identify sectors of vulnerability specified by the insurer. This pricing extension tends to straddle a condition between a competitive pricing environment and consumer behavior. So, if a government body should see it necessary, they can politically safety-net it out if required. This would then give a prime mover in terms of being quicker than the rest, providing the regulator is satisfied with both the rules and the justifications of them. Using AI, dynamic pricing models deploy machine learning algorithms to adjust the premiums of potentially every policyholder that an insurer is catering to. The philosophy behind this learns emerging trends and portrays them within a price. This becomes an improved advanced vehicle capable of learning consumer behavior trends. The model learns consumers, the optimal combination, hence demanding more attractive premiums beyond the market average while channeling out others typing uneconomical prospects. This model is vitally like the predictive model, except the data profiles replicated would change into a premium bracket defined by the artificial intelligence machine. The operator learns new demand exposure trends and segments for the best net returns. In application, this does two things: it satisfies a trend and demand strata for return, but knowing policyholder trends can provide detailed interest data for corporate intelligence.

4.1. Definition and Importance

Dynamic pricing, also referred to as individually calculated or deployed premiums, is characterized as a pricing strategy involving personalized, non-static insurance premiums. The novelty of dynamic pricing is the increased leverage placed on individual pricing through applying actual case data and additional analytics of individual insured to insurance premium making and adjusting this as risks or risk groups change. This general approach fosters an additional focus on real-time data analysis and results to decide on prices applied as well as the pace, frequency, and level of pricing adjustments. In essence, it is part of the larger development and strategy trend towards optimal customer relations and a customer-centric strategy. The importance of building and maintaining an up-to-date risk profile of policyholders is stressed. Real-time assessment of the policyholder's risk is seen as an even more dynamic and preventive means to adjust the premium level compared to the currently static insurance policies in use. This creates market agility and a quick response to current short-term risk changes and market events. Thus, the additional speed and potential augmentation of the competitive advantage of dynamic pricing over non-dynamic insurance pricing are mainly made possible by the collection, real-time use, and application of a wealth of individual policyholder data, which had previously not been taken into account as adequacy predictors. Dynamic pricing influences to a large extent the way risk can be managed by the insurer. The invocation of real-time data can allow providers to both create and predict the risk profile and behavior of their policyholder at a specific moment in time with extreme accuracy. Even when the protection concerns were addressed, a general issue is represented by the ethical implications and transparency for the policyholder about the dynamics of the price-setting decision. This is the reason why dynamic pricing must be considered as a spectrum, with rules and ethical considerations necessary in any insurance practice. Moreover, it must be considered whether customer hardship might be incurred by charging a personalized or differentiated premium even if it is proven to be balanced and sound.

5. Factors Influencing Insurance Pricing

The task of price determination for insurance products is fundamental to insurers. The essence of insurance is the pricing of risk, and the premium is the ultimate source of revenue. The key independent variables that drive risk assessment in the process of insurance pricing fall into two main categories: internal and external factors. The internal factors are the risk factors of the insured that can be influenced by internal adjustments but cannot be changed or eluded without additional costs, such as the utilization of vehicles or the nature of driving for auto insurance. The external factors are beyond the insured person's control, which involves risks on the insurer's side, such as the development of markets, competitors, government policies, and behaviors not directly related to the insured, like the external situation.

Naturally, policyholders can benefit from these favorable conditions through a reduction in premiums. Taken together, the individual premium is determined by the interaction between transforming the potential for harm (risk) and other competitive conditions, which is based on both actuarial estimates of risk and non-actuarial factors. The actuarial expenditures take into account the standard components of insurance expenditures, such as assumptions and fees in investment returns. Given the non-actuarial trends, insurance firms generally offer prospective rates that already weigh estimated prices that have not been quantified with the possibility of future unforeseen accidents. Therefore, insurers need to constantly monitor costs and risk factors to determine the final acceptable premium. Insurers price new insurance policies and check that the pricing strategy is inexorably influenced by factors conducive to both long-term and short-term insurance premium effects.

5.1. Risk Factors

When a customer applies for an insurance policy, insurance companies examine various risk factors that influence how much to charge in the form of premiums. These risk factors include characteristics of the person applying for the policy and may also include characteristics that pertain to the assets being insured. A risk profile can contain many different characteristics. For a car insurance policy, the risk profile might include the likelihood of getting into a car accident and getting injured, the car owner's driving history, and the repair cost of the car, regardless of whether the owner or driver is at fault for the accidents.

It can be relevant for deciding a premium to get fine-grained as the data allows on the characteristics of the insured individuals. Characteristics can have varying influences on the claim process. This is why insurance companies have policy supplements and penalties, and even prohibitions on insuring certain individuals. Currently, many insurance companies do not issue insurance policies with premiums based solely on average risk profiles, as it is common to segment the target market based on the insured's characteristics and historical years and market conditions. This is nominally to reduce the noise that is otherwise difficult to fit to models without any pre-segmenting or external factor constraining due to the scale of the customer base and attributes within these contained populations.

5.2. Market Conditions

The pricing of insurance policies is influenced by the state of the economy, in particular interest rates, inflation, unemployment rates, and business activity and capacity. On the supply side, operational and financial aspects of company management must be considered. Companies must buy assets to provide investment income and also to back policyholder reserve liabilities. The cost of these assets, with the accompanying interest rate and available interest rate durations and principal guarantees, significantly affects pricing decisions. Finally, an insurance company's management determines the pricing of insurance based on the competitive environment. Factors considered in setting price include current demand and supply conditions, the extent of competition, the legal and regulatory climate, and the availability of general industry data.

The extent of competition is a prime driver of premium rates. Large numbers of companies competing for the same business put pressure on the pricing. In a soft market, premium rates do not adequately cover losses, and companies may price either drastically, little more than enough to cover their costs, or merely to maintain or increase their average market share. Seasonal and regional differences may also affect pricing considerations. Insurance is usually not subject to as wide a variety as most consumer products, but variations in usage and certain low-frequency, but catastrophic losses, especially for property, are a major concern. Economic conditions are always changing. Regulation also affects the operation of the insurer, including the pricing of products. Regulators frequently influence the mix of products, level of guarantees, and the manner in which premium rates are managed by rules and regulations. They may stipulate requirements and set reserves or limits to pricing, depending on the type of insurance. Most states have an act that prohibits pricing based on color or race, but what is "reasonable pricing" is not specifically defined. The monitoring of competitive markets by insurers has also been highlighted as an important function directly affecting product pricing.

6. Challenges and Ethical Considerations in AI-based Pricing

Challenges in Implementing AI-Based Pricing

The application of AI in insurance raises societal challenges and ethical considerations that require careful consideration. In recent years, the AI rhetoric has shifted to focus primarily on algorithmic decision-making and its associated risks. Chief among these risks is the potential for AI to increase bias in the insurance pricing process. Indeed, if algorithms are only trained on "good" business, a "growing market is being told they're too risky." Another concern is that AI may systematically discriminate against certain demographics. In other words, AI may amplify the digital divide in the insurance sector. There is also a risk of AI-based pricing systems being gamed or, more specifically, in a competitive market setting, AI may incentivize customers to behave in particular, undesirable ways.

To address these issues, a certain degree of transparency will be required in AI-driven recommendation engines. Personal data, commercially sensitive information, and a number of third-party factors will deem a transparent model that meets regulatory requirements a necessity. This leads to questions of discrimination, explainability, and the accountability structure of AI systems. Ignoring present regulatory frameworks may lead to a minority of companies opting to generate compliant AI services in some cases. This approach could become a brand differentiator in itself. All of the above has given rise to the growing movement towards AI ethical and regulatory frameworks. In this regard, industry best practice may once again prove to be the best means of navigating potential ethical pitfalls. At the same time, these developments might exert considerable influence over new insurance opportunities. Customers may place a "data trust" in those vendors who make a concerted effort to act in an ethical manner. Thus, ethically produced AI-driven recommendation engines may ultimately translate to increased profit. Industry leaders must use inherent intuition to find an equilibrium between AI entertainment-based service innovation while appealing to the customer and their ethical viewpoint. Consequently, appointing somebody at the C-level to head this decision-making process is a must. Select elite stakeholders and data protection professionals should also participate in boardroom ethical key decision-making.

6.1. Transparency and Fairness

In terms of price setting, the factors given most attention include transparency and fairness. Algorithmic transparency is frequently highlighted as a critical factor in engendering trust in an insurer's potential clients. Only those who better understand how prices are established will choose to study them further and engage with the insurer. Customer interest groups in some countries have gone a step further to demand competitive scrutiny over price and underwriting algorithms used in general insurance.

Insurance contract law and regulation demand that insurance prices must be non-discriminatory or at least justifiable. For both insurers and regulators developing legal and supervisory tests, the challenge remains how to ensure that prices based on the latest AI systems meet the degree of fairness demanded by the law. Measures of fostering fairness in the determination of insurance premiums also need to be balanced with the information gathering and underwriting requirements to offer price discrimination at an acceptable social level depending on applicable policy priorities. Failing to deal adequately with this transformation might lead to the concentration of insurance applicants by the insurance industry in new and widespread areas, while still light scrutiny of insurers' tariff setting would likely attract regulatory interest. It could ultimately be expected to diminish trust and damage their reputations, both disciplinary agents of insurance company behaviors. Anti-discrimination statements are increasingly appearing in the AI insurance policy and privacy statements.

Real-time transparency over which data and AI models are utilized offers significant advantages in terms of customer projected trust and explanations. Insurance providers have employed a variety of transparency methods in their AI approach from just-in-time consumer-generated explanations by combining several machine learning explainability tools, to listing all the inputs and arrangements in the use of algorithms, to offering high-level truths of the use of data, statistical modeling techniques, and reporting requirements. In their customer-facing transparency methods, they ignore a clarification about the use of price-relevant and risk data and automated decision-making in its car policy documentation, which by law must offer a data content creation instead of a pure data disclosure for the price data, the technology for which has not been created yet.

7. Case Studies and Best Practices

Description: Four specific case studies of organizations using or implementing AI in their insurance pricing to improve their ability to understand and price risk. These real-world examples outline the process, challenges, and outcomes. They include a discussion of how the respective insurers went about choosing the best price optimization model and the benefits that they hope to achieve. Several of these discussions include information on how these solutions improve their ability to underwrite risks and identify risks that might have otherwise been overlooked. Making the Business Case: Have you used or will you use a technology partner? What role will that technology partner play? What was or will be the outcome? Four examples of where AI and AI techniques have been applied to the pricing of insurance policies are presented. In each example, significant steps to improve the pricing process or to identify risk for acceptance or avoidance and select rating inputs have been made. Pricing is based on actuarial techniques or other industry practices that are in widespread use and are statistically valid in selecting combinations of price and conditions accepted by a large body of policyholders. The implementations are based substantially on data rather than judgmental processes.

7.1. Real-world Implementations

Next, we will highlight real-world implementations and use cases to describe how AI can be beneficial and practical for pricing in insurance. Examples can show the variety of applications as well as how AI can be used in various contexts.

7.1.1. Risk Assessment Automation
Several case studies can attest to the capabilities AI can bring to insurance pricing. For example, an American auto insurance company leverages machine learning methods to perform automated risk assessment in addition to automated damage assessment in processing car insurance claims. Adoption of the methods delivered a 44 percent increase in identifying fraud when compared to the traditional rule-based system and humans. The success of these systems provided the impetus for the company to develop a separate machine learning algorithm, which optimizes prices based on calculated risk assessment and the users' willingness to pay. Acceptance testing showed an uplift in revenue generation.

7.1.2. Personalizing Insurance
Some companies utilize customer choices to bring new insurance models to market through the development of contextual bandit price optimization methods and deep reinforcement learning to optimize price and conversion rate. These companies use a similar insurance model for home insurance. They compete against insurers not using machine learning methods, as the policies currently exist in the market based on predefined risk-centered categorizations. Pricing could also take time, months to optimize for safety during experimentation, given regulatory constraints. This pricing technique assumes consumers'

utility functions from their choices, offering a high degree of personalization and has shown to be 37% more accurate at predicting their insurance policy preferences than traditional methods. Other companies use a similar method to personalize pricing. The challenge when deploying contextual bandits, and in fact any AI-based pricing model, is to ensure alignment with business goals.

8. Future Direction

Ongoing research, applications, and trends may reconfigure the AI landscape in insurance pricing in the near future. One emerging area that is set to come forth in the next few years is the transfer of knowledge from one machine learning model to another on complex structured prediction tasks, enabling the development of more accurate pricing models. Another anticipated development is the algorithmic enhancement of technologies like gradient boosting and deep learning, allowing the implementation of bespoke machine learning algorithms that better capture the claim drivers in a given loss.

Increasingly, AI is being examined not as a purely predictive analytics tool, but instead as an integrated technology within larger solutions. Research is being conducted to determine the cost-effectiveness of replacing predictive analytics with a bespoke machine learning algorithm and to understand how AI can be combined with other technologies, like blockchain and the Internet of Things. Reflecting on the fluid nature of the pricing landscape and the potential for radically innovative pricing models of the future, including AI-driven data-sharing models based on blockchain technology or technologies that facilitate dynamic sharing of risks, it is clear that the sector must continuously evolve to adapt to emerging trends and changing expectations of market participants. It is relevant to note that pricing models may be influenced not only by technological advances but also by regulators' views concerning fundamental pricing parameters and viable AI solutions, including when to use AI and how to conduct fair pricing based on advanced analytics.

On the empirical level, ethics by design can take the form of specific directives, objectives, guidance, and principles within a company. Should serious challenges still limit policy pricing practices in the future, the informal value system of an individual may continue to play a crucial role in the final pricing. Ethics programs could also be implemented in future disruptive solutions, where policy pricing is fully executed via predictive, AI-based algorithms. In the long term, the ethical system will continue to foster an environment of trust and security in organizations, as these firms need to ensure that predictive algorithms and other metrics do not accidentally result in adverse selection or systematic discrimination of marginalized people; customers with a good functioning culture have more products while those who experience the algorithm as biased are expected to withdraw. AI-powered pricing will continue to evolve, and the industry should take steps over the years to adapt to these changes in real-time, which will necessitate competitors to be more innovative than they are today.

9. Conclusion

In conclusion, we have analyzed the effect and potential effect of AI on pricing strategies for insurance policies, focusing on the emerging trend towards automated pricing. We have observed that, because increasingly sophisticated and technically complex policies are being demanded by consumers taking advantage of the availability of big data, traditional simplistic pricing strategies are becoming less viable. This transformation has been facilitated by the advance of AI, especially techniques associated with machine learning, which are able to elicit the most important features with regard to pricing risk from non-linear data clusters. Subsequently, leveraging AI in insurance to make pricing decisions imparts multiple distinct benefits, including increased efficiency and the possibility of superior pricing accuracy. This heightened performance, in turn, makes it easier for insurance companies to later sell insurance policies using standardized, digitized methods because crafted sales are more susceptible to dealing prices. In addition, customers are more likely to achieve premiums that reflect their actual risk when out-of-the-box models are utilized to complement, replace, or develop human pricing techniques. However, there are also noteworthy areas of concern raised by AI involvement in policy pricing. These include, but are by no means limited to: the potential for unforeseen outcomes and regulatory inequalities, the requirement for transparent AI algorithm use, issues of moral personalization, and stakeholder collaboration. Thus, using AI for policy pricing, in concert with the sharpening of the techniques discussed, requires continuous learning and the collaboration of all stakeholders and regulators. Therefore, at this beginning stage of pricing innovation, we hope to start a new wave of research and encourage collaboration between data practitioners and non-data practitioners to advance current thinking in insurance pricing.

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