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AI and ML Applications in Dynamic Pricing for Auto and Property Insurance Markets

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Abstract

Abstract Dynamic pricing is one of the most disruptive trends in today's insurance market, causing great impacts on microeconomics and macroeconomics factors for multiple parties on both the supply side and demand side. In this research, we identify the existing gaps in the research and then provide a comprehensive literature review of the applications of AI and ML in dynamic pricing in both auto and property insurance markets, addressing the gaps and exploring the potential future research directions. We also analyze opened research problems related to ML-driven dynamic pricing, providing critical insights for both researchers and practitioners in this area. The rapid advance of AI and ML technology provides great opportunities and threatens traditional insurance pricing methods. We believe that the connection between ML and traditional pricing disciplines can shape the future pricing studies by deciding the pricing techniques used by the industry.
Dynamic pricing dynamically adjusts the price according to its customers' willingness to pay and reduces the demand excess. In auto insurance, the demand excess means a higher loss ratio, which disturbs the equilibrium of the company and affects its inherent value. In property insurance, the demand excess means that firms are highly exposed to more catastrophic losses. Reducing the demand excess can bring a win-win influence to both the insurance industry and buyers of insurance as AI and ML can scale the traditional pricing theory models by reducing the modeling cost and improving the modeling efficiency and accuracy. Advanced modeling can unfold inter-insurance correlations and reduce the aggressive pricing hazards and risk mispricing for the supply side. With more sensitive and targeted pricing schemes through ML, the demand side can obtain more reasonable pricing. Moreover, due to the outstanding data technique of ML, ML can also reveal the real-time pricing signal embedded in online offerings for complex products.

Keywords : AI, machine learning, dynamic pricing, insurance, auto insurance, property insurance, predictive analytics, risk assessment, customer segmentation, real-time pricing, underwriting, telematics, data modeling, behavior analysis, demand forecasting, pricing algorithms, policy optimization, claims prediction, competitive pricing, automation, big data, actuarial science, loss modeling, rate personalization, market trends, decision support systems, premium calculation, pricing strategy, AI-driven underwriting, intelligent systems, insurance analytics.

1. Introduction

Insurance is about uncertainty — uncertainty about future liabilities. Similarly, the primary focus of actuarial work is modeling the uncertainty of future liabilities. The expected values of future liabilities play an important role in pricing as well as in controlling adverse selection or insurance fraud. These serve as the foundation of the use of AI in the insurance industry. The use of Artificial Intelligence techniques and Machine Learning models, nevertheless, has recently gained major interest from both the research community and the insurance industry. The projections and guidance of future liabilities are often quite unstable, which creates a challenge for insurance companies and actuaries. This is especially true for the non-life or property and casualty insurance markets where the uncertain events occur typically based on extreme events such as catastrophes caused by natural or man-made disasters. Price or premium of insurance is primarily guided by actuaries using statistical models based on the class-based parameters such as current age, driving history, and credit scores for auto insurance and building density, living area, and distance to coast or flood area for property and home insurance. The actuaries define groups of individuals or classes of auto or property insurance from a risk-based approach perspective.
The method of pricing is called classification-based underwriting. The actuaries calculate the probability of an uncertain event or future loss of the insured assets for the different insurance classes based on Gini coefficient, maximum likelihood or more recently, boosted decision trees. These probabilities are ultimately used to determine the premiums of the insurance classes, which are further adjusted based on external influences in order to break even with the loss and the expense ratio or fronting fees for brokers and agents. Once a class of insurance is created, all the individuals in that class are charged the same price or premium, which is not sensible or subjected to criticism. Other theorists advocate the need for modelling the price or premium for each individual on a case-by-case approach. The introduction of digital scaling

has made it possible for the insurance industry to provide or assess “instant quotes” within seconds at a high level of granularity. These quotes usually fall into the model of predictive modelling or be an outlier detection model.

2. Understanding Dynamic Pricing

Dynamic pricing is defined as a decision-making process for determining the price of a product or service, through time and other factors, with the aim of maximizing a revenue function based on customer behavior and product/service characteristics. A characteristic of dynamic pricing is that the price of the service changes from instance to instance of its application which is different from the concept of frequent-price-changing in which the frequency of price change becomes so high that it becomes difficult for consumers to notice the changes.

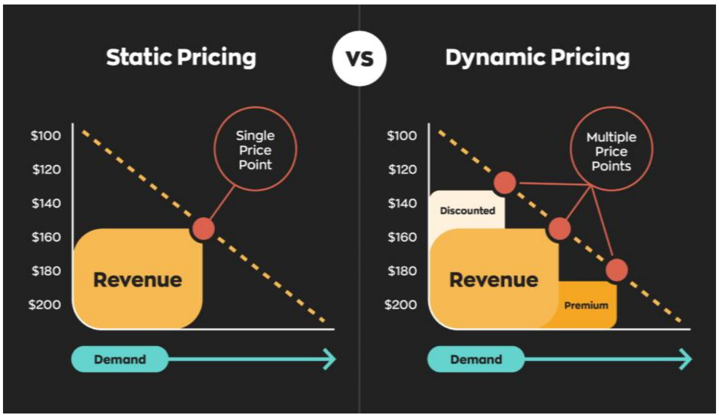

Fig 1 : Understanding Dynamic Pricing

Dynamic pricing is based on three basic pillars, which are product market characteristics, customer behavior, and revenue and pricing objectives. Starting with market characteristics, any product or service is characterized by various product lifecycle stages and demand patterns. Natural resources are usually characterized by a very inelastic demand, i.e., the shape of the demand remains almost constant irrespective of the price at the time of the day, month or year; however, the elasticity and pattern of demand differ over the specified time period. For example, the demand for services such as airlines, hotels, car rentals, and toll roads has a different elasticity and demand pattern with regard to the time compared to infra resources such as electricity and natural gas. When considering the customer aspect, customers or consumers seeking to buy the product have different preferences, and different behaviors such as elasticity with respect to time, group behavior, experience, and brand loyalty.

Dynamic pricing can be used to achieve different objectives. The first group of these objectives is related to the revenue function, which is the revenue obtained from the sale of the product during the specified time horizon. Typical examples of these pricing objectives are maximizing revenue collaterally, maximizing service profit, maximization of expected utility, desired revenue function, and realization of price discrimination. The second group of these objectives is related to the consumption levels achieved by customers. Examples of these types of objectives are improving productivity, maximizing social welfare, keeping a fair waiting time, consumption speed, and consumption risk.

3. The Role of AI and ML in Pricing Strategies

Dynamic pricing is an uncommon pricing strategy in auto and property insurance. However, predictive modeling has become the most important pricing strategy for auto property in insurance. It measures the risk of a potential policyholder applying for a quote or a current policyholder whose quote is about to be renewed. Good predictive models help develop underwriting and rating plans that achieve overall profitability while being competitive in terms of price. First generation predictive modeling uses decision trees, generalized linear models, splines, and development of substitutes predictive models in different regions by fitting the parts of the model to different target groups. The next generation predictive models needs to create an optimal hierarchy of predictive tree models using new pricing techniques and suitable data for modeling. Methods when judiciously used and operate on the right data sets will produce better predictive models for auto and property insurance dynamic pricing that help reduce costs.

Dynamic pricing is a rarity among the auto and property insurance products offered by companies in the markets, although the technology and tools for dynamic pricing are available. The issue is deciding the set of networks to use. Predictive modeling is increasingly becoming the most important dynamic pricing strategy in auto, homeowner’s, and commercial multiple peril insurance. Although insurance rates were historically established by using loss development factors from the past claims and then applied to the current exposures, the significance of underwriting and risk assessment increases.

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More vehicles are sold at higher price points, meaning higher insurance rates. Losses of larger size demand more from the insurance market in terms of premium income. Predictive modeling creates a more appropriate rating plan than mere modeling used earlier.

3.1. Machine Learning Algorithms
Due to the significant quantity of the data available from different sectors and the ability to analyze that data and extract useful information with the development of new and better algorithms, artificial intelligence (AI) and machine learning (ML) play an important role in shaping the research work and the theories established in different domains to make sense of the paradigm that connects technology and innovation. In the insurance market, data regarding customer topics, risk, and pricing strategies are available significantly. AI and ML techniques, especially predictive analytics, make sense of this available explosion of data. Researchers in the field of insurance are attracted to implementing AI and ML applications on these large datasets and analyzing the results.

Eqn 1 : Transformer (Attention Mechanism)

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

Where:

- Q, K, V: query, key, and value matrices
- d_k: dimension of the key vectors

While AI encompasses a wider range of technologies, ML deals primarily with systems that learn from data and allow a computer program to learn to associate the input data with the output data based on past examples and allow for inference on new data with unknown target variable. Various ML algorithms exist and various machine learning tasks are available. Popular ML models are the decision trees, support vector machines, naive Bayes, k-nearest neighbor, compositional model, ensemble model, neural network-based learning model, hidden true state models, convolutional deep learning networks, and recurrent deep reinforcement learning. The specific models used have advantages and disadvantages in terms of predictive performance, modeling capabilities, and required overhead, and help predict for the target variable from the feature variables. In insurance operations, the target variable could generally be claim occurrence, claim severity, or expense or claims cost presentation in the insurance market, and pricing estimation and pricing segmentation in the insurance market.

3.2. Data Analysis Techniques
The term "Data Analysis" encompasses a wide array of analytical tasks pertaining to data of various types, sizes, and structures. Specific goals of these tasks can be highly diverse when using different tools and algorithms, targeting diverse levels of abstraction. In principle, the goal of Data Analysis is to discover previously uncovered facts, information, and insights, or confirm existing hypotheses, based on a set of analytical methods chosen to fit a specific computing model, tool, or algorithm. Data Analysis techniques can be primarily distinguished by the following categories: Visualization, Descriptive Analytics, Explanatory Data Analysis, and Data Mining. Data Analysis has been around for decades, becoming increasingly popular with the emergence of Big Data. The historical roots can be traced to Statistical Inference, where Statistical Models were built based on the analysis of a small number of samples from a population, targeted at testing hypotheses regarding modeled parameter distributions of the population.

Data Analysis is primarily used in the initial stages of Research and Development (R&D), primarily for data exploration and Data Preparation, and cleaning Data. Although Data Analysis usually precedes predictive modeling, in practice prediction accuracy is often used to assess and compare results of various Data Analysis methods that output models predicting target variables, after they are validated. As with other Data Mining tasks, model performance metrics such as accuracy, F1 score, ROC curve, lift score, specificity, and sensitivity are used to assess and compare prediction accuracy from different types of models. In addition, data profiling is primarily used as a Data Quality Assessment tool to assess and profile its data content, quality, data type, and structure for each data table and their columns.

4. Market Analysis for Auto Insurance

Specialization in auto insurance traditionally allows for use of more data than for other lines of insurance. The ability to use telematics data or other behavioral data are being implemented in several markets. There are significant differences in price elasticities by demographic group as well as by price point for a quote. What's more important for incentive

alignment is that there are significant differences in conversion rates and purchase frequency. Are market leaders at risk of market shares losses as they haven't overreacted to the pandemic?
As stated above, price competition has increased as predictions are made for more property, plant, and equipment losses. Given that price competition is less than for other property & casualty lines, it is interesting to see that some companies were able to sell internet compare prices by providing additional policy features that the customer values, but that the competitor has failed to provide. In a very interesting move, another company has also recently announced its intention to sell commercial fleet auto insurance online. Its current market leader position in this segment seems to indicate some falling profit margins in the segment.

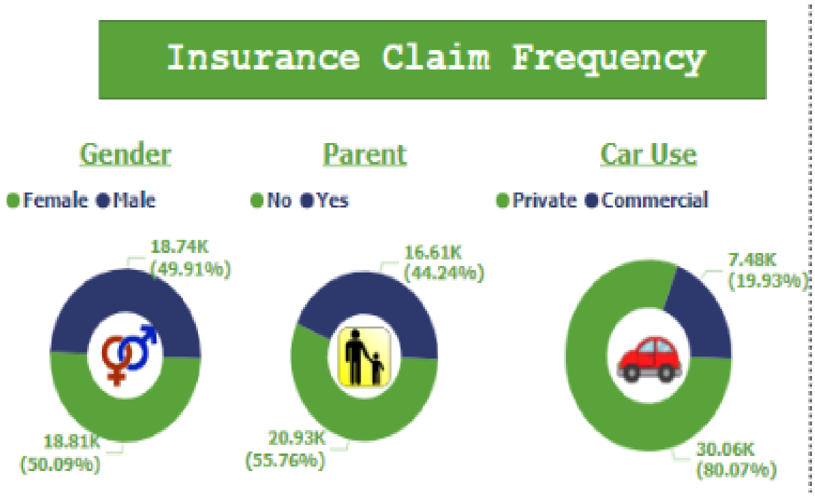

Fig 2 : Unveiling Insight

We have recently investigated online consumer behavior modeling for an auto insurance comparison quote website. We have captured surf session data and we have a match with actual auto insurance purchases. Using the statistical method of multiple imputation predictive regression, we generate predictions for the underlying purchase intent probabilities. Based on these estimates and traditional estimates, we show that the incentives for the comparison shopping website are aligned if it is owned by one of the comparison shopping websites. It makes sense to charge a higher price for the ad of a participating firm, however, only where the actual purchase probability is high enough.

4.1. Current Trends

The auto insurance industry has been facing volatility over the last decade as accident frequency and severity have significantly increased. Rising claims cost for insurers has been fueled by severe weather and supply chain disruption, heightened driver distraction in the form of mobile devices, reckless driving, and the ongoing surge in driving levels combined with other risk factors. Consumers have been gravitating toward digital-first insurers that offer a better enforcement experience leveraging technology. The consumer experiences offered by Insurtech carriers are completely rethinking the processes of buying and using car insurance, leading to growing consumer interest in purchasing coverage. A somewhat healthy demand environment, coupled with pricing, loss reserve, and reinsurance discipline in the past few years, has supported the auto insurance market's transition to profitability.

Considering all of the underlying trends, we expect continued auto insurance pricing discipline with the potential for some slight increases in the next several years as key loss drivers impact loss cost trends. Reflecting the industry-wide challenges, many companies have made headlines announcing significant auto insurance losses in recent quarters and accused of employing bad practices by making it difficult for customers to receive their claims. Within these searches for solutions, some state regulators have embraced a new proposal that breaks the accepted model of communication in property insurance, which requires an explanation for price increases in the form of communication between the insurer and insured, stating the necessity of price burns.

4.2. Consumer Behavior Insights

The relationship between insurance prices and customers' willingness to pay directly affects insurance companies' profitability. Increasing demand, high competition, and sensitive elasticities are major characteristics of P&C insurance. Demand is associated with price volatility because price differences across carriers affect the choice of insurer. Indeed, data have shown that about 50% of customers switch insurers each year. Ostensibly, these clicks seem to be driven by potential savings from seeking a lower price. Nevertheless, several other factors contribute to the click activity. This includes contracts that customers sign with their insurers. The insurer-customer relationship is characterized by the potential for friction, such as a discount paid in expectation of loyalty. With the aid of clickstream data, researchers show that in motor insurance, observed clicks are a robust predictor of impending policy lapses because customers anticipate their insurer's price quote. Another strategic decision is to leave the existing insurer and take up a new policy with a lower price.

Eqn 2 : Budget Constraint

$$P_x x + P_y y = I$$

Where:

- P_x, P_y: prices of goods x and y
- I: consumer's income

As part of strategy, some insurance companies make it a practice to regularly renew existing policies based on decreased prices, at the expense of new customers being offered a better deal. Data has shown how price discrimination policies are necessary to reduce churn on consumers with higher lifetime value. Indeed, data has shown that 50% of consumers who make a switch do so because they want to save on their policy premiums, and that 75% of those switching will do so for a premium savings of $250. This is one of the reasons that other carriers adjust their pricing every three months, in order to remain competitive. Price sensitivity is an important characteristic of policyholders. High frequency and switching consumers do not lapse only because of predicted savings, but also as a consequence of perceived inequity between the premium paid and the expected level of covered damages.

5. Market Analysis for Property Insurance

While consumer insurance products are less susceptible to external environment impact than enterprises business product, it behaves differently among different countries in loss connection with macroeconomic variables. For property insurance market, the demand is sensitive to economic fluctuations and the coverage shifts with property values, due to nearly-exhausted capacity. Demand for property insurance is insensitive to price cycles, and a near-exhausted capacity cannot command a large risk premium. Demand for property insurance is quite sensitive to changes in massive short-term natural disaster risk. Our empirical results for homeowners insurance, coupled with the comparative dynamic style analytic model with a mass-non-inertial response of net demand to massive short-term natural disaster risk, tell us that rent-seeking capacity, due to price-inelastic demand, is greater when insurance is precariously available, so is the incentive to under-price pre-existing hazard.

Insurers rely upon data analytics to gauge the risk of catastrophe so that they can more accurately price particular properties. Quantifying property risk allows insurers to set prices that truly reflect the likelihood of a natural disaster occurring in, or near, that area during the policy period (typically a year). If a house is very likely to flood, for example, the rate set for flood insurance would need to be sufficiently high so that the selling price complied with the basic actuarial principles upon which insurance pricing is based. If the house is not very likely to flood, the homeowner would want to buy flood insurance because the price would be less than the potential loss supported by the premium as well as reflect the probability of that potential loss occurring during the policy period. While the demand is insensitive to certain properties pricing, insurers are careful to avoid insuring a portfolio that is overly loaded with properties that are heavily exposed to identical hazards.

5.1. Risk Assessment Models

Various pricing models facilitate the development of and adjustments to a product's pricing over time. The pricing of insurance against catastrophes is typically done on a per-asset basis. Since each asset is only a small part of the insurer's overall portfolio, it is possible to accurately assess the probability of an insured loss on the asset due to certain events, and thus, to set a price that should not deviate significantly from long-term expected values. Commercial systems for decision support by the insurance industry have been developed to predict the probability and severity of insured events. Exposure and catastrophe models are increasingly relied upon, along with asset renewal cycle models, to support high-quality decision making in the property insurance sector.

Fig 3 : The evolution of model risk management

Dynamic models linking insurance premium rates to reinsurance premiums paid also forecast how insurance premiums might evolve. Predictions made by any model depend on certain assumptions, such as whether catastrophe models used include demand forecasts as well as predictions for risk-adjusted discretional budgets, variations in price elasticity, and the availability of capacity at price increases. The models, while quantitatively defensible, do not provide more than ad hoc estimates of the general features and likely time paths of premium growth for different distributions of discretionary capacity for income elasticity of demand. These models, however, assume a perfect market, without volatility in the cycles, the availability of capacity for the widespread transfer of catastrophe risk via reinsurance, or the probable participation of capital markets with assumptions that underlie the model design.

5.2. Impact of Natural Disasters

The last two decades have witnessed an increasingly observable rise in the frequency and magnitude of natural disasters worldwide, especially extreme weather events. The four warmest years of modern temperature records have been the last four, immediately followed by a cooler but still unnaturally warm year. Climatologists track both global surface temperatures and global average land-ocean temperature for the purpose of reporting and anticipating global climate change. The rise in global average surface temperature has been puzzling scientists for ages. This, coupled with the high risk of fire, fire losses, and subsequent insurance related issues in the US West Coast states like California during the just-concluded pandemic year, raised a few eyebrows.

Eqn 3 : Insurance Loss Modeling

$$E[L] = \sum_{i=1}^{n} P_i \cdot L_i$$

Where:

- P_i: Probability of disaster scenario i
- L_i: Associated loss in scenario i

Interestingly enough, whilst the pandemic delivered an economic shock of almost unprecedented proportions, natural disasters like wildfires and hurricanes ruptured through, wreaking physical havoc across regions, leading to countless deaths, mass evacuations, and destruction of habitat and human property. There have been strong indications towards the negative impacts of climate change, especially accelerated sea level rise, on the health of a number of regions across the globe. Sea level rise is increasingly perceived as a paramount long-term planning issue for the country. Additionally, recent years have been marked by the increasing frequency of impressive medium to large earthquakes in historically low seismic activity regions of the world. Given the short-term and structural market impacts of natural disasters on property insurance pricing, as well as the growing implications of climate change on the occurrence and intensity of natural disasters, it is no surprise that our research also highlights the importance of natural disasters in the context of insurance pricing and business strategy.

6. AI-Powered Risk Assessment

AI and ML applications for risk assessment, which include predictive analytics and fraud detection, have been long in use in the insurance field in a traditional format. In the past, actuaries carefully selected a set of predictive characteristics

to explain loss cost variations and adjusted loss cost models based on those characteristics; however, with the rapid development of AI technologies and methods, such as deep learning algorithms, these tasks can be performed with little human intervention. In a typical AI/ML predictive analytic process, a raw database is generated from various underwriting, financial, policy management, and actuarial systems. Using big data processing technologies, a model database is created. With the help of existing software tools/platforms, the AI model is built to predict the model database based on raw features of the data and validate the model.
Because most of the risk assessment in the insurance field is related to the estimating of future uncertain events, the purpose of predictive analytics is to build the ML algorithms/models to project the expected outputs of the uncertainty involved based on the input features. These predictive analytics can be scaled from the policy to the insurance portfolio. Important aspects include the volume of the data, whether they are balanced (equal number of positive outcomes – for example, fraud claims – and negative outcomes), and the predictive features.

6.1. Predictive Analytics
As we just noted, a typical distribution system in an insurance market seller of a variety of products – such as automobiles, houses, owner-occupied or rental housing, and contents coverage – develops a set of risk predictions about the insured properties, based on historical claims data associated with "predictor" variables that identify the condition of the properties underlying these policies. Using data from the portfolio of business written in the past three to five years, actuaries determine the risk factors associated with various lines of coverage. Policyholders typically require that insurance companies offer coverage at the lowest possible premium. However, price is usually determined using a combination of a market survey, determination of the requisite loss ratio, and securing approval from the state-based insurance regulatory agency. These methods are not predictive of loss payments; they are, instead, retrospective, because they are based on historical data from a limited market survey and, in particular, on specific classes of approved losses.
Predictive analytics are actuarial techniques that allow insurance companies to determine what a policy premium must be, as a function of properties' historic damage characteristics, to achieve the requisite adjusted profitable losses. Since, by definition, the best predictor of future insurance loss is a prior loss, predictive analytics employing supervised machine learning help accelerate the insurer's acquisition of subjective insurance risk. Models that predict property losses, typically built using generalized linear models, logistic regression, or gradient boosting machines trained on historical loss severity data as a function of predictive variables, include the probability of an actual loss, the dollar amount of loss, and the damage characteristics of prior losses. These models are used to identify hurricane exposure, for example, or the probability of loss by damage group during hailstorms.

6.2. Fraud Detection
Insurance fraud causes significant revenue losses for insurers. Fraudulent claims increase the premium amounts that all insured customers pay. Small insurers can become insolvent when facing fraudulent claim payments that are much greater than average. While all insurers utilize expert adjustors to identify and investigate suspiciously fraudulent claims, they also need to identify these types of claims using statistical models and indicate which of the claims to prioritize for further investigation, to optimize the effectiveness of their resources. ML techniques can be utilized to identify, validate, and investigate suspicious claims. An unsupervised Gaussian-Mixture Model with Hidden Markov Model was applied using 2 years of accident history to flag unanticipated claim amounts for further investigation. A supervised Random Forest model was applied to identify second injury claims involving the same accident description from multiple injury claims submitted by the same claimant.

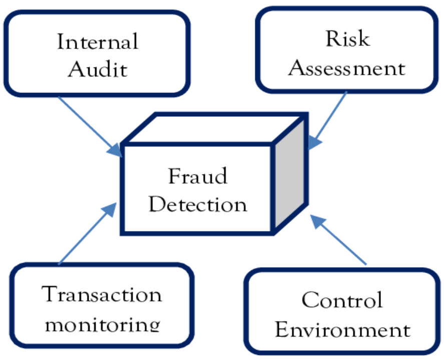

Fig 4 : Fraud detection tools

An integrated fraud detection model was created that combines predictive modelling and an anomaly detection model. A two-step process was proposed that develops the prediction model without any fraud cases. This model is then used to focus on investigating only high risk customers for fraud in the inventory. In the second part of the two-step process, an anomaly detection model identifies the remaining fraudulent applicants in the investigated customer inventory with fraud cases manageable to be investigated further. There are many other application areas in insurance pertaining to the prevention and detection of fraud that can benefit from AI techniques.

7. Dynamic Pricing Models

Insurers have utilized procedures extensively developed in the pricing daemon of software installed on retail or casino tables. Presetting of acceptance levels actuated by rating, risk type, and request analysis functions allows a wide variety of variable gains to react autonomously to bending demand along a predicted risk and price gradient. Tables may significantly present a peer or market gradient by possessing loss characteristics inherent to risk position. Finally, tables may maintain own unique profitability characteristics by being self-contained with loss exposure limits inherent to the balance sheet structure of the risk holder. Dynamic pricing is less about policyholder characteristics than it is about adapting prices to demand fluctuations. A last-minute trip and a last-minute flight are rich in demand concentration, where demand these both to the left and to the right is heavy-tailed.
Dynamic pricing is more characterized by market properties than by particular segmentation of risk and risk user. This may yield market risk factor estimates with relative short regard to the resampling risk. The rapidity of concentration alone disaccommodates a factor dependent on a long forecaster horizon. As a matter of fact, pricing is not related to the probability of an occurrence. The objective of a pricing decision is to find out whether at a certain time an occurrence should be accepted or rejected in order to optimize the instant profit or optimize the expected return during a timeframe.

7.1. Real-Time Pricing Adjustments

Insurance is traditionally sold at a fixed rate with efforts focused on return and fraud detection. As technology is increasingly used to automate and eliminate long-standing frictional costs throughout the insurance industry, the roles of actuary and underwriter at the front end of the business become increasingly obsolete. Insurance is a loss-contingent financial service. Every other producer of financial services poses the relevant risk factor and, through transactions of sale, transfers that risk to the community and makes a profit in the process. For example, banks set varying interest rates they charge for credit upon analysis of risk in terms of default probabilities and then make a profit on the transaction. Likewise, integrating machine learning with predictive analytics implements the same structure for insurers in real time. Machine learning provides the service that demonstrates how risk varies for contention factors presented in a potential transaction in such a format that actuary, underwriting, and business management can easily act upon for their intended purpose.

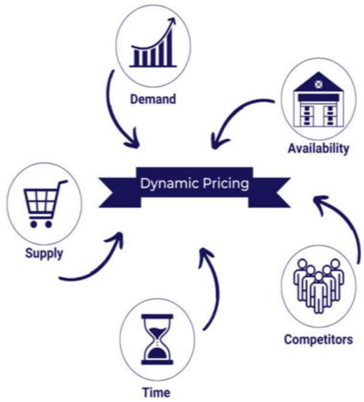

Fig 5 : How to Use Dynamic Pricing Strategy to Stay Ahead of Competitors

Dynamic, or real-time, pricing recognizes that anticipated loss, sales, and service costs evolve every minute, every hour, every day and make a portfolio of insurance different from what it was when the treaty bound. Social media constantly provides information both about loss contention factors and about short-term reputation changes pertinent to service and sales. Detection engines pass this information to the predictive analytics team for rapid evaluation in terms of the models of behavior the team has implemented. Predictive models evolve in response to big sets of data both in terms of new information provided by sensor-tagged data and in terms of new covariate factors in combination and interaction with loss, sales, and service experiences. Consequently, the probability distribution, characteristics, and moment functions used to price insurance products evolve quickly and dynamically.

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7.2. Customer Segmentation Strategies

In the industrial economics, the well-known theory of price discrimination states that insurance buyers are heterogeneous in relation to their vertical preference, and that price differentiation according to the type or class of the customers should be done in order to maximize profits. This is usually achieved through customer segmentation strategies, which consist of differentiating the products or services offered to each customer type at different prices according to their relative willingness to pay. An explicit requirement from the insurance regulators is that insurance companies need to show demonstrable benefits to customers from the use of price optimization systems. Such model-driven strategies are usually based on the following factors: the purchase and retention dates, the product lines; the margins and claims histories; the discount and upsell histories; and the purchase seasonality.

In previous chapters we have discussed some specific limitations of the application of multicriteria pricing models in the insurance business, in relation to the very nature of the problem itself. In developed insurance markets, the price of insurance services is determined based on a set of fixed attributes, which do not vary in the short run. Under these conditions, the price-elasticities of demand are sensitive to product designs. In such a situation, it may be difficult to base a parametric attribute-elasticity model on just a very small sample of demands without relying heavily on a few firm-level structural assumptions about the nature of elasticities across customers and tests of the validity of price elasticity models across collaterally inferred demands. Hence it is appropriate to condition the design of customer segmentations by taking into account a set of ancillary models, prior to the actual elasticity design stage itself.

8. Regulatory Considerations

The growing use of AI and ML techniques for pricing auto and property insurance has raised numerous regulatory concerns. Regulators are increasingly focusing on the questions of compliance and ethical implications when these complex and frequently unknown models are being used for delivering important decisions. For example, how does the usage of large neural networks for capturing the complexity of local demand movements in a given interval comply with the principles of transparency and explainability of the decision-making process? What are the guidelines concerning the conduct of external validation of the predictions from the model, for example, during the model training phase? What should be the warranty about the safety of the prediction from these models? In terms of liability, should the insurance company be completely responsible if the prediction from the model concerning the expected value of loss is far-off from the expected value of loss realized over the period, or should the provider for the model be held responsible, if the prediction model is based on machine learning input from the model provider? How should these issues be resolved is still in a state of flux.

From modern machine learning and AI research, we know that prediction models utilizing technology from deep learning can be extremely accurate in many circumstances. Research in the last several years have provided answers to questions related to the ability to provide an explanation for specific predictions from any machine learning model and verifiably guaranteeing a lower bound on the accuracy of these predictions in terms of some validation set that can be built from the specific data features being used. While some of the regulatory questions may be how the models comply with the various regulatory requirements, fulfilling the ethical implications for the use of these techniques in risk selection and pricing for insurance is something that the insurtech technology developers and practitioners have to grapple with directly.

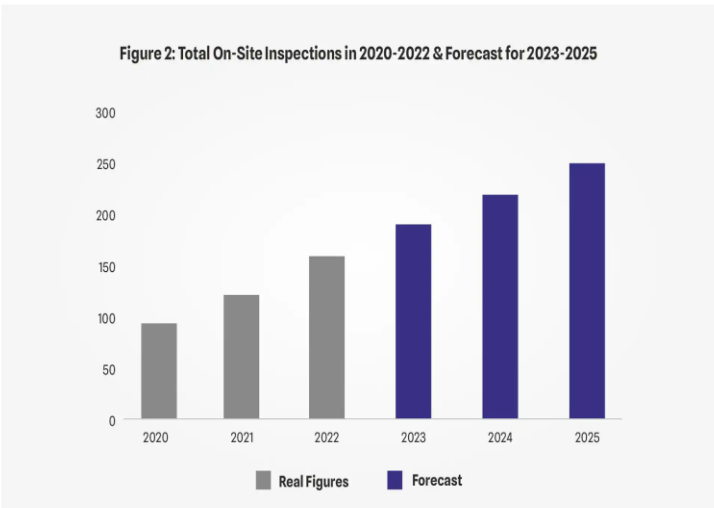

Fig : Regulation Data in the Spotlight

8.1. Compliance Challenges

This chapter addresses compliance challenges associated with speed of AI and machine learning (ML) adoption in dynamic pricing for auto and property insurance markets. These challenges arise in assessing high-dimensional mixing of AI/ML elements with other factors affecting pricing, imbedding validation and backtesting processes that are aligned with regulatory expectations.

Informed consumer choice is enshrined in property and casualty (P&C) insurance regulation through requirements for policy information that is clear, unambiguous, and timely. It is also achieved relationally through periodic examination and certification of insurer rates, practices, and disclosures. In P&C insurance, stated requirements put insurers under a compliance "burden" to document that policy rates are not excessive, inadequate, or discriminatory within the context of their policyholder obligations. These stated and behavioral mandates grant the Marketplace with direct power to influence policyholder microselection and insurer macroselection.

While dynamic pricing and use of AI/ML-driven consumer choice prediction of price elasticity and error optimization of estimation are not new, their regulatory implications in a P&C insurance context are heightened by speed and breadth of growing industry adoption. This requires assessment of the regulatory compliance framework, without which consumer disclosure, notice, and knowledge may become barriers to, rather than facilitators of, research, development, and deployment.

Most relevant to this chapter, the Regulatory Subgroup is, among other things, tasked with considering regulatory issues; including guidance on the use of behavioral scoring, big data analytics, and predictive modeling to assist with ensuring that coverage is in line with statutorily established caption.

8.2. Ethical Implications

In 2020, the Society for Professional Economists argued that "citizens have the right to be able to see how the decisions that affect their lives are made. In many cases, algorithmic decision-making leads to better public policy and greater public benefit than traditional methods. In some cases, it is an unalterable or essential part of data-sharing or policy implementation. But the design, implementation or use of algorithmic processes should not be hidden from public scrutiny and should be subject to the same checks and balances as all public policy processes." While in this statement the point about transparency is related specifically to submitting a method to public scrutiny, a different point about the objectivity of decision-making processes ought also to be made. The use of an algorithm entails recording the knowledge and beliefs that fed into the algorithm in a stable form, and this offers the possibility of subjecting that knowledge to review, argument and criticism more generally than otherwise and of displaying it in a way that makes it more publicly accessible than decision-making processes that do not use algorithms.

The point relating to stability and scope for public scrutiny is common to any predictive process that is based on a structured representation of knowledge. But what is different when a process is algorithmically implemented is that the output is produced automatically and the method is applied as a general rule. Moreover, algorithmic methods have the capacity to deliver predictions for all available initial conditions in a given forecast period. In so doing, the prediction process is automated in the sense of making it unmediated. There is no subjective judgment involved in employing the algorithm for prediction. The citizen obtains insight into the forecast by the transparency of the algorithmic method used and the advantage lies in the fact that algorithms can be far more complex than rules that can be followed by human forecasters.

9. Case Studies

Dynamic pricing has long offered significant benefits to the Auto and Property Insurance industries. Our research has uncovered many successful applications of dynamic pricing in the insurance sector. Applications range from financial trading firms to insurance carriers. Other companies applying ML to dynamic pricing include various insurance technology firms. In this section, we summarize the dynamics of some of those implementations on the market.

A significant percentage of U.S.-based insurance companies use dynamic pricing algorithms to help with rate optimality. Various data solutions take into consideration a multitude of factors that have been observed to have an influence on insurance demand in a given region and at a given time; such uses AI/ML tools promptly suggested for implementation into your company's core systems. Some companies have commercialized 'usage-based insurance', more commonly known as telematics. One company is attempting to corner the market on usage-based insurance based on being the first ever to offer a pay-per-mile auto insurance policy. Telematics dynamically prices for you based on detection of how fast the policyholder's car is traveling. The telematics device informs your insurance carrier of events; ensuring the policyholder does not take seemingly unaccounted risk exposure.

9.1. Successful Implementations in Auto Insurance

In the insurance industry, predictive modeling has incorporated algorithmic developments both in determining automobile loss costs and in modeling its loss reserves. In the connected world, such models extrapolate real-time activity through telematics. The party who pays the premium has a massive information advantage over the insurer, who must find a meaningful way of documenting the price-gap dissimilarity. As a result, the risk of financially damaging adverse selection is real. The advent of AI and ML methods is especially timely as the dimensionality and size of the data are growing too large for traditional methods to answer the need for fast automated analysis. In using AI and ML for their dynamic pricing needs, auto insurance companies have realized two types of implementation, often working in tandem. The first changes the price of the quote based on information in the customer's profile. The second alters the algorithmic rate-making fat-tailed loss distribution or, in combination with the first, the virtual loss distribution whose derivative determines the booked reserves. In other words, the change in pricing is done through modifying the liability represented on the balance sheet. In working with its brokerage network, partner company both changes its distribution of risk and the pricing underlying its exposure. It is reported that partner has had productivity and profitability enhancements of 10 to 15 percent thanks to the deployment of AI-ML. As noted above, customers are increasingly price-agnostic, forcing partners to convince policyholders to seek out lower-than-usual premiums by shifting various aspects of behavior. To get those customers to shift, partner gives policyholders lower rates based on compliance, which has the additional upside of enhancing the policyholder's own safety on the road.

9.2. Successful Implementations in Property Insurance

In the past decade or so, AI and ML technology has been more difficult to demonstrate in Property Insurance pricing than it has in other applications, like underwriting quantification. The corporate-investment challenge is that in Property Insurance, a significant majority of the traditional actuary pricing algorithms are working quite well. Complication comes from the fact that homeowners and commercial liability insurance have so little interaction, every single person earlier based on a handful of census attributes who enlisted a digital ML approach, tended to get kicked out here and led straight back to traditional pricing. Because of that fact, actuary practice is hard to dislodge. Add that Home Insurance prices change once a year, and commercial liability even less frequently, and the effort involved in developing and continuing to optimize bespoke company ML and AI pricing algorithms could otherwise bankrupt an unprepared startup company. Nevertheless, there have been experiments in the last few years indicating ML, AI, and QRPA tools developed primarily for mundane Auto Insurance tasks can be helpful.

A team at a Canadian digital direct brokerage company, along with a Toronto-based AI landlord, created a digital prototype for mid-market commercial properties in Canada, shredding policies of insureds for the last 15 years within statutory bodies, also decisions and outlier pricing rules made by insurance companies' actuaries had made on coverages & limits in the last five years. Input features incorporated the tenant-paid % of the property, replacement-value recommendations, including skyrocketing construction-adjuster liability rates of nearby areas, flavour of business being operated, aggregate rates paid on clients' portfolios, and high-cost claims. Incorporated into a DNN were the 25 words on a commercial risk submitted by an agent, and the max policy price set by actuary board members, working at insurance companies giving preliminary rating indications.

10. Challenges and Limitations

The advantages of using AI/ML for dynamic pricing discussed in previous sections mostly apply to the internal needs of insurance firms. On the other hand, consumers have external needs and they see some disadvantages of AI/ML which create a conflict with the needs of firms. Responding to the fact that consumers are equally interested in the prediction of optimal price and the related input features, we discuss the challenges of firms using AI/ML based demand modeling and optimization for dynamic pricing. In particular, we explore the issues of data privacy and algorithmic bias. Along with impact on consumers, they also create challenges and limitations for insurers in using AI/ML based methods for dynamic pricing.

Advances in AI/ML require large volumes of data for model building, monitoring, and maintenance. This raises concerns in consumers regarding privacy and security of data. PII collected by insurance companies during the life cycle of a customer, while being essential to create personalized product and service offers, has become a source of considerable worry. The PII includes information about an individual's identification, contact, and financial-related details. Both internal and external threats could affect the security of consumer data. A study projects that the global budget spending on cybersecurity for protection against cyber-crime during 2021–2025 will reach a significant amount. Insurance has the unique property of being able to pool risk. Having sufficient number of claims, insurers have the capability to evaluate the risk exposure of customers for the purpose of predicting pricing. While the industry as a whole can insulate itself from cybersecurity threats, lack of proper protections could negatively impact the individual company. This, in turn, would compromise the privacy of consumers thus leading to a mistrust among them. Mistrust would deter these individuals from purchasing insurance products and prevent insurers from collecting the information necessary for improved predictive capability.

10.1. Data Privacy Concerns

Policymakers have implemented many regulations to protect consumers' private life information. There are limitations on the types of data insurance companies can collect to underwrite specific risk groups for pricing. Some pricing features, such as credit score and insurance lapse, have been removed in a few states. Insurance pricing models may be limited based on some features and demand predictors which are private information. If insurance companies use external data and methods to construct pricing models, they may violate fair marketing act regulations. This concern has also been raised in a few recent studies on applying machine learning in predictive analytics for insurance demand modeling. Our study is mostly policy based. The usage of incentive and non-incentive price discounts in rewards and the ethical pricing philosophy is left for the future study based on the public feeling.
The dictionary definition of privacy is "the quality or state of being apart from company or observation". Because insurance is a data collection-intensive business, privacy concerns are worded in a legal, data, security, and public schema. The legal schema is what is permitted, what consumers and public entities are responsible for, and what is forbidden. The data schema is what type of data can be collected and for what purpose, and what type cannot. The public schema is what is considered public or private data, publicizable or non-publicizable data, and what has to be disclosed and what does not have to be. The security schema is how to safeguard secure and secretive data and how to respond to security and data breach incidents. These schemas can be interchangeable or overlapping, but they are distinct and provide unique facets of privacy concerns. Security concerns are distinct but overlapping with privacy.

10.2. Algorithmic Bias

AI's capacity for deploying large datasets has great potential to create a significant positive economic impact with estimates between \$3.5 – \$5.8 trillion per annum in the U.S. alone. Given the advances in computational capabilities, technology, and data management, a growing number of companies from a diverse set of industries have begun to employ algorithmic solutions. Sometimes this is done through direct deployment of their solutions, while being mindful of intended and unintended consequences, other firms wrongfully rely on algorithmic predictions and recommendations without carefully considering their limitations. In particular, recent research in the area of algorithmic bias in algorithmic solutions for social good, have demonstrated the potential pitfalls of blind reliance on algorithmic solutions for managing sensitive social issues of great importance such as health care access, housing security, criminal justice, labor shortage and sexual harassment. Here we define algorithmic bias to be a systematic and unfair distortion of results from algorithms. Estimates suggest that bias in AI solutions has a negative impact in terms of lost wages, and job opportunities. In recognition of the risk of discriminatory bias, there is growing skepticism towards the application of algorithms in important public areas including lending, insurance, college admissions, hiring, and policing. In particular, the use of algorithms in insurance premium pricing has been the subject of extensive debate, particularly in the domains of health and auto insurance. Concerns about algorithmic bias center around unequal treatment and disparate impact on protected classes. The unequal treatment perspective argues that certain algorithmically prescribed actions can cause more harm to certain groups relative to other groups. However, there are other instances where the algorithmic solution does not unfairly impact other groups, yet the false negative or false positive rate is unacceptably high. These considerations traditionally arise in the area of classification based algorithmic models.

11. Future Trends in Dynamic Pricing

Dynamic pricing is a continuously evolving concept. In this chapter, we elaborate on some of the crucial factors and put together how we see the important factors will shape the future of dynamic pricing. The emergence of AI and ML technology has opened up new horizons for dynamic pricing and given the insurance industry a new transformation destination. With the help of intelligent algorithms and a more in-depth understanding of customer behavior, insurance companies are ready to welcome the era of highly personalized and data-driven dynamic pricing. Algorithms developed by employing AI/machine learning models will be at the heart of dynamic pricing systems in the insurance industry. Insurance companies are expected to further invest in small artificial intelligent tools or frequently market-tested algorithm designs. The use of divisional and policyholder level strategies will also become commonplace.

Technology has become more available and affordable for insurance companies. Even small or many non-traditional companies can afford to develop and adopt advanced sophisticated technologies to support their operation and business in dynamic pricing. How well the current and future market players can collaborate with tech companies and technology providers are expected to define their positions in the market. The role of technology is especially critical in ensuring loyal customers switch to a new company or adopt new members. Although insurance products may not have limited price incentives in product offerings, services like a quotation, switching associations, seamless customer service, flexibility in payment policy, and others are expected to respective roles in determining the company's customer base and pricing strategy.

11.1. Technological Advancements

Dynamic pricing is an age-old practice employed across a variety of industries. However, the recent technological advancements in data pooling, data availability, and data analytics have changed the dynamics of dynamic pricing and taken this practice to a next level. The technological advancements in data analytics through artificial intelligence and machine learning enable companies to incorporate a breadth of readily available information in the form of big data and derive meaningful insights, which was not possible a decade ago. Every move made by the consumers is tracked and recorded by the online providers of services or products. Furthermore, the recent technological advancements have made tremendous cuts in the cost of technology development and implementation that were previously prohibitively expensive. The boom in online retailing has fueled the demand for companies to maintain a competitive edge and use technological developments to their advantage. The increasing underwriting loss ratios in the property and auto insurance industry have put pressure on these companies to make more effective use of technology implementation to actively manage the dynamic pricing model. The use of AI- and ML-based dynamic pricing will more correctly reflect demand and service delivery costs for insurance products and will protect against an increase of demand with a reduction in service levels but yet remain a profit-making enterprise. The requirements for implementing a data-driven dynamic pricing model remain unchanged: the ability to frequently update prices based on real-time insights gained through data analytics and the ability to personalize at scale for a vast number of consumers.

11.2. Market Predictions

Predicting the future of the dynamic pricing environment is a difficult endeavor. One perspective that may best represent the future journey for dynamic pricing states that across nearly all markets, we are either on the verge of, or going to experience, digital transformation. Key to this digital transformation is access to large amounts of data layers, data history, the ability to clean data, key data analysis, and skills to derive insights. From a business transformation perspective, businesses need to develop the right expertise, forge collaborative partnerships with other players, and undergo organizational restructuring of their internal departments. Essentially, the success of any digital transformation is the result of various factors coming together as a whole, not a single solution point.

A rough inference we can make about the role of big data dynamics and data science on developing pricing insights and pricing models is the countless innovations we have seen since the initial development of Economics 3.0. Those authors predicted a world where economists, computer scientists, and programmers would explore the world of large datasets to extract actionable insights for decision makers. This view was expounded on who advised economists to pay heed to data analytics and its power on decision-making in a world based on bytes and chips rather than pen and paper. Here we triangulate back to the virtue of developing core economic insights.

12. Conclusion

This paper explores the recent literature on how machine learning and artificial intelligence are reshaping automotive and property insurance. We highlight three areas where they have already made a significant impact on insurance pricing and other aspects of the underwriting process, and then focus on how AI and ML are changing the way that auto and homeowners insurance is priced and profitably marketed. We first describe the impact of AI and ML on pricing and underwriting in insurance markets generally. We then review and analyze selected empirical evidence regarding the role and impact of AI and ML-determined pricing within the insurance value chain. Lastly, we discuss the potential social costs and benefits associated with the widespread deployment of AI and ML in the auto and property insurance industries, as well as the important ethical issues raised – including algorithmic discrimination and the potential for adverse selection.

Pricing and underwriting are the foundation of every insurance company's business model. Prorata pricing allows insurers to efficiently hedge risk through highly correlated book collections, resulting in a portfolio-level insurance effect. When properly calibrated, the underwriting mechanism also has a signaling function that discourages high-risk individuals from purchasing insurance in the first place, as well as a screening function to identify, and either discount or deny coverage to high-risk policyholders among those who do apply for insurance protection. A significant recurrent question in the insurance economics literature has been what types of information insurers should use to achieve these dual goals optimally, in order to align incentives with low-risk policyholders, while discouraging gaming.

Smart pricing may also have collateral business implications; for example, pricing across multiple segments with different cost profiles may allow the carrier to bundle and cross-sell capabilities in a more attractive, profit-maximizing way. This may support efficient digital distribution partnerships with other players.

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