Beyond the Claims: Emerging AI Models and Predictive Analytics in Property & Casualty Insurance Risk Assessment

Sateesh Reddy Adavelli

Solution Architect, USA

Abstract: ***P&C insurers have an important role in addressing financial risk management needs but now struggle to respond to the new forms of risk. Historical analysis and actuarial calculations, which form the backbone of classical approaches to risk measurement and management, are not well suited to such new kinds of risks as climate change, cyber risks, and business cycle risks. These conventional approaches are also a static method for selling, which has limited potential in changing quickly with new market and consumer changes. However, the development of AI, big data, or advanced predictive analytics has provided a new paradigm to such challenges to cope with and analyze big data dynamically to derive Applying a combination of best Machine Learning (ML), natural language processing (NLP) and other AI techniques, it will become possible to predict risks exposures, as well as optimize underwriting and claims processing. In this paper, the author investigates the opportunities that AI carries within the sphere of reformation of risk evaluation approaches in P&C insurance. In particular, it discusses the ever-emerging field with AI models integrated into operations, underwriting, fraud detection, claims modelling, and loss computation. The applied research uses a comprehensive bibliographical review to present past and present practices and assess modern AI implementations. This paper uses research approaches and case studies to prove that AI can solve some problems and bring cost-saving solutions. Moreover, it emphasizes the ability of predictive analytics to enhance customer satisfaction at the policy level as well as optimize operations. However, the paper also explores the dirty side of implementation, including the stipulations surrounding compliance and data privacy and thus provides an objective analysis of the future of AI use in the P&C Insurance Industry.***

Keywords: Artificial Intelligence, Predictive Analytics, Risk Assessment, Machine Learning, Underwriting, Claims Management

1. Introduction

1.1 Background

The Property and Casualty (P&C) insurance industry serves the vital function of protecting people and companies against risk and losses eligible to occur due to unpredictable circumstances, totaling property damage, liabilities, and other mishaps. [1-3] Conventional insurer risk assessment methodologies have been based on actuarial science and statistical analysis techniques. They use past records to predict future claims and set policy premiums. However, that is often lacking when newer and more complex threats appear in the risk profile of a business organization. Factors like greater international connections, fast technological enhancements, and climatic variations have brought risks that do not follow standard predictions. Furthermore, the expansion of data from digital origin, including the Internet of Things, social media, telematics, etc., has exposed the inefficiencies of traditional systems that cannot accommodate or analyze such humongous data to generate useful insights. This relatively dynamic environment has entailed continued technology innovation, specifically AI and predictive analytics, which will spearhead changes in how risks are detected, evaluated and controlled within the PC&I Insurance industry.

1.2 Problem Statement

The P&C insurance sector is now facing a number of risks that are existent and more complex as well. Changing climate, for instance, has increased the magnitude and frequency of natural disasters, making it necessary to enhance risk models. Likewise, the increase in cyber threats creates risks to businesses and individuals that the current insurance structures poorly capture to assess appropriately. The versatility of exposures arising from position vulnerability creates an even more challenging environment to evaluate risks due to elements of changes in exposure probability resulting from events like global market shifts and geopolitical volatilities. Current actuarial frameworks are perfectly fine in relatively static contexts but are not well-suited to addressing these dynamic issues. They are normally limited by historical information and conventional estimation models, which ignore inherent nonlinearity and interactions between emerging risks. The need is for solutions responsive to the industry's data characteristics, which can process incoming information, look for latent relationships, and provide forecasts with more sophistication in less time.

1.3 Objective

The main purpose of this paper is to examine the possibilities of using AI and predictive analytics to overcome some of the challenges relating to using conventional risk assessment tools in the P&C insurance industry. Accordingly, this study intends to focus on illustrating the use of AI-based models in underwriting, claims, claims development, fraud identification and loss estimation. In addition, this paper aims to evaluate these technologies' applicability and effectiveness based on analyzing massive and varied datasets and providing prompt decision-making support. The theoretical considerations of implementation issues are also discussed to offer the methodical approach: regulation concerns, data protection requirements, and organizational transformations related to AI adoption. Finally, the study seeks to show how modern technologies can be applied for operational effectiveness with low costs and high customer satisfaction that will help overcome current and future risks.

2. Literature Survey

2.1 Risk assessment evolution of P&C insurance: A historical study

It is worth starting the analysis with the observation that the changes in the risk assessment of P&C insurance are part of a more general development relating to the increased availability and application of new data sources and technology. Firstly, risk assessment was performed with the help of rougher techniques for evaluating risks based on expert judgment. Thus, underwriting used to be limited to small databases and simplified statistical analysis only. [4-8] The application of the basic concept of records management in the insurance sector was facilitated through micro-computer systems in providing electronic databases and automated claims handling solutions in the late twentieth century. During this period, the first simple actuarial methods of evaluating past claims and prospective exposure were also developed. In the past few years, risk assessment approaches have been influenced mostly by the new availability of big data and the supra application of AI and ML. Today, IoT telematics and real-time data, coupled with deep learning algorithms, help insurers capture distal risks in real-time, respond to new risks like climate change or cyber risks, and create unique policies. This historical development gradually changes from a backwards-looking, paper-based process to a forward-looking automated risk assessment system, bringing better quality and repeatability.

2.1.1 Traditional Methods

Risk evaluation in the P&C insurance business has largely been a conventional actuary and statistical-based risk evaluation. The first ones are still data-oriented, including claims frequencies, policyholder characteristics, and geographic exposures. It is often characterized by manual underwriting procedures when underwriters assess applications using certain checklists and their knowledge and experience. These methodologies, however, might have been rigorous, acceptable, and efficient, but where risk conditions were relatively stable, such methodologies were time-consuming and compounded by inherent subjective bias. In addition, the lack of computing facilities restricted the assessment of the combined effects of interacting variables, and most risks had been downsized to just two broad categories.

2.1.2 Digital Evolution

Towards the end of the twentieth century, the environment began to change with the advent of new techniques in information technology that empowered insurers to accommodate volumes of data systematically. Claims programs became automated, which minimized the use of assumptions and special adjustments. By integrating relational databases and the initial stages of data analysis, it was possible to improve risk differentiation and adjust the prices accordingly. As these innovations made processing more precise and faster, they reduced the ability to adapt to new conditions and thus exposed insurers to new aggressive risks like cyber risks or climate change-related risks.

2.2 Emerging AI Applications

2.2.1 Machine Learning for Personalized Policy Pricing

Artificial intelligence or Machine Learning (ML) has completely changed the view of insurers regarding risk assessment of policies and pricing. Unlike saturated models, there is the capability of processing big and heterodox data torrents, including real-time data feeds from telematics gears, social media and IoT. It allows the development of rather specific policies relevant to the individual's risk level. For instance, car insurance uses telematics to analyze driving performance and then make premium adjustments depending on factors like speed, break usage and time of the day. This change of gears to contingency, conduct-based pricing improves equity and encourages safer behavior amongst policyholders.

2.2.2 AI-Driven Claims Management Platforms

Claims processing can also be considered an essential stage of the P&C insurance process, and AI has also expanded into claims management. The utilization of the NLP technology, along with the computer vision technology, enables the AI platforms to extract data and analyze the information related to the claim submissions, photographs, and other supporting documents. For instance, Convolutional Neural Networks (CNNs) are applied in the evaluation of vehicle damage from pictures to enhance Cl tuning the claims management. Besides, through developing predictive analytical models, fraudulent claims can be screened out as organic data patterns that do not correspond to general trends are exposed, and this results in minimizing fraud-associated losses.

2.3 Related Studies

2.3.1 Analysis of Convolutional Neural Networks for Fraud Detection

They were able to conclude the effectiveness of CNN in the detection of fraud in P&C insurance. The research used a dataset of claims with their outcomes to teach a CNN, resulting in over 92% accuracy. The study revealed that such discrepancies predictive of fraud were clearly discernable by the model; they included inconsistencies in the accompanying documentation or variations in the claim frequency. This approach shows how AI can significantly improve fraud detection possibilities.

2.3.2 Big Data and Outcome in Predictive Analytics in Insurance

Analyzed the way how big data enhances predictive analytics in the insurance industry. It was also noted that the use of real-time data feed, for instance, on weather, traffic and market conditions, enhances or increases the accuracy of risk assessments. When these datasets have been linked to sophisticated analytics tools, insurance carriers could foresee loss occasions and rebalance risk levels. The results showed that the underwriting accuracy increased by 30 % while the overall operations cost was reduced by 20%, documenting the practical benefits of big data technologies.

3. Methodology

The method employed in this study intends to design and test an AI-based model for improved risk ranking in the property and casualty insurance market. [9-12] The approach is structured into three core stages: PD data collection, model training formulation, and a structured approach for training, validation and testing.

3.1 Data Collection

3.1.1 Sources

The data sources in this case include various credible sources for efficient and effective risk exposure assessment of the chosen company.

- **Historical Claims Data:** Beginning with descriptions and dollar and time stamps of prior claims, there was a clear basis for studying the claim's behavior patterns.
- **IoT-Based Telematics Data:** In addition, digitized information from IoT-connected devices like vehicular telematics and smart home sensor added real-time behavior into the dataset. For instance, driving behaviour, occupancy distribution, and devices' usage established dynamic risk differentiation.
- **Weather Reports:** Temperature, precipitation, wind speed data, etc., were used to evaluate risks involved with natural catastrophes/ calamities.
- **Cyberattack Logs:** Records of security event occurrences and threat reports offer insights into the digital risks essential in assessing new risks in cyber insurance.

3.1.2 Volume

The data collected was about 10 terabytes in size and was compiled from leading insurance companies as well as from third parties. This extensive volume ensured consideration of various scenes, allowing for good model training and validation.

3.2 System Architecture for Integrating Artificial Intelligence into Risk Assessment

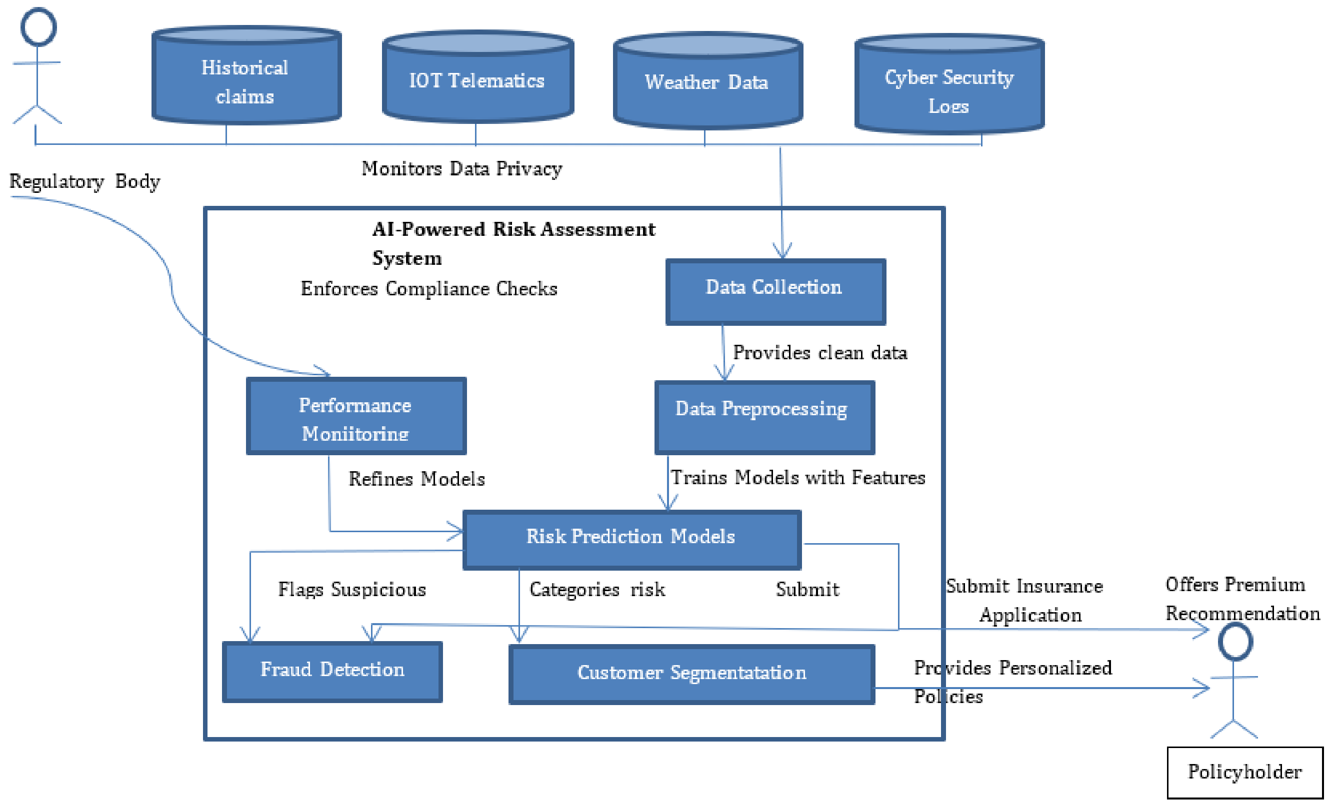

Figure 1: System Architecture for Integrating Artificial Intelligence into Risk Assessment

3.2.1 Actors Involved

- **Policyholder:** The final user using the insurance system to purchase policies or claim them.
- **Regulatory Body:** Organizations heading governance initiatives must oversee work done on regulations, data privacy laws, and other standards.

3.2.2 Databases

- **Historical Claims Database:** Periodically, it maintains records of various types of claims, such as the kind of claims made, the amount paid and historical trends.
- **IoT Telematics:** Gathering information with high timing sensitivity, including vehicular tracking and smart home networks, to measure risk.
- **Weather Data:** Offers information about certain risks originating from environmental or climate factors like hurricanes or floods.
- **Cybersecurity Logs:** Collects historical data of cyber-attacks and systems to assess threats for offering cyber insurance policies.

International Journal of Science and Research (IJSR)
ISSN: 2319-7064
SJIF (2022): 7.942

3.2.3 AI-Powered Risk Assessment System

This is the core of the management system that will consist of and coordinate all the processes employing artificial intelligence. It has the following components.

a) Data Collection

- There may be several databases and data sources from which the data is accumulated or compiled.
- Ensure that the data to be processed is of good quality and relevant to the process.

b) Data Preprocessing

- Preprocesses remove any outliers, set the means to zero, and scale the raw data to put it in shape for model training.
- It removes observations that are not typical of the majority of situations and helps distinguish noise from areas of significant variation.

c) Risk Prediction Models

- Employ technologically sophisticated techniques such as the Gradient Boosting Machines (GBMs) along with Deep Neural Networks (DNNs) for data analysis and then for results prediction.
- Underwrites risk estimates the probable losses and sets the magnitude of premiums flexibly.

d) Fraud Detection

- Mask potentially fraudulent entries by defining six types of outliers, or shifts from ordinary behavior, in input data.
- Utilizes techniques such as pattern recognition and anomaly detection.

e) Customer Segmentation

- Divides policyholders according to their behavior and their risk propensity.
- Enables the company to offer price differentiation, market segmentation, and improved risk management.

f) Performance Monitoring

- Monitors assessment of performance indicators constantly, which includes application accuracy, precision, recall rate, and F1 score.
- Used in analysing models for quality assurance and perfection and meeting legal requirements.

3.2.4 Interactions

- **Regulatory Body:** Responsible for data privacy and ensuring compliance through an engagement with the data collection and performance tracking systems.
- **Policyholder:** Files insurance requests for applications or claims and gets tailored pieces of advice or premiums from the system.

3.3 Model Development

3.3.1 Feature Selection

Variables were thus defined to provide [13-15] measures of key indicators that access critical risk determinants. These included

- **Geographic Risk Zones:** Risk factors are connected with areas that may experience natural disasters or a high level of crime.
- **Policyholder Behavior:** Driver behavior profile characteristics include driving speed, expenditure levels, and claim ratings.
- **External Threats:** Things like, are we likely to be attacked?, what about economic volatility and market trends all determine our strategy?

3.3.2 Algorithm Selection

The study employed multiple algorithms to address different dimensions of risk assessment.

- **Gradient Boosting Machines (GBMs):** Due to their performance capability in scenarios where sample datasets are skewed and provide high accuracy in prediction, the implementation of GBMs was used in underwriting and claims analysis.
- **Deep Neural Networks (DNNs):** As a flexible device for modeling nonlinear dependencies, DNNs were used for fraud detection and identifying patterns.
- **Support Vector Machines (SVMs):** SVMs were selected for the binary classification problem, which included identifying the probability of claim fraud.

3.4 Workflow

3.4.1 Data Preprocessing

The raw dataset underwent extensive preprocessing to ensure quality and consistency.

- **Noise Removal:** Such descriptive records were also eliminated, as shown with fluctuations and gaps.
- **Normalization:** The obtained data values were normalized so that the values could fit one of the algorithms used.
- **Feature Scaling:** Tests of continuous variables were normalized to eliminate the effects of distance-based algorithms.

3.4.2 Training & Validation

The dataset was divided into 70% for the training, while the 30% was set for the testing. Several procedures for validating the models were used during training to minimize overfitting, such as cross-validation techniques.

3.4.3 Evaluation Metrics

Performance metrics were carefully chosen to evaluate model effectiveness

- **Accuracy:** Total accuracy of the forecasts.
- **Precision:** The percentage of correct-negative predictions out of all negative predictions made.
- **Recall:** The ratio between ‘‘true positives’’ where the model accurately predicted that a patient has the disease, to ‘‘actual positives’’ where the patient actually has the disease.
- **F1-Score:** The f-measure or the harmonic average of precision and recall, both of which present the impact of one over the other.
- **Root Mean Square Error (RMSE):** A statistical technique used to express the degree of variability in a continuous dependent variable from its predicted value or regression equation.

4. AI-Driven Risk Assessment Workflow in Property & Casualty Insurance

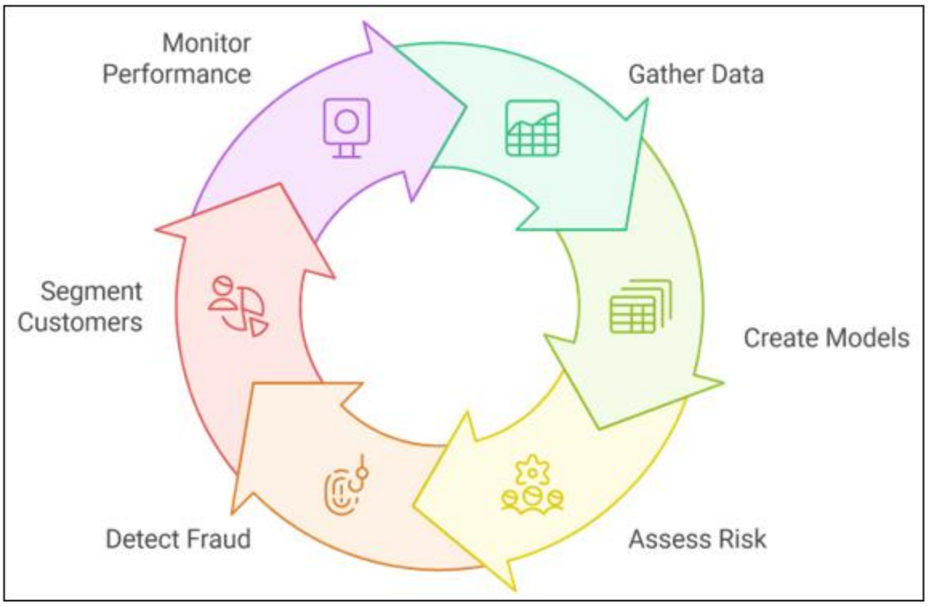

Figure 2: AI-Driven Risk Assessment Workflow in Property & Casualty Insurance

4.1 Gather Data

The first step involves compiling various types of data streams, such as historical claim data, 'smart' vehicle telematics data backed up by IoT, weather data [16, 17] and cyberattack data. These datasets serve as the basis by which holistic AI models for risk assessment can be built, offering more perspectives.

4.2 Create Models

Subsequent to the data preprocessing phase, data mining involves the use of machine learning models like Gradient Boosting Machines (GBMs), Deep Neural Networks (DNNs) and Support Vector Machines (SVMs). These are used to explain risk factors, forecast, and classify customers according to risk scores.

4.3 Assess risk

The models are then taken to evaluate risks continuously, and the four models developed above are beneficial in that they can be used to evaluate different risks at different times. For instance, they estimate probable losses, analyze underwriting risk, and fix premium rates per policyholder or region.

4.4 Detect fraud

This is important as AI systems are responsible for identifying fraudulent claims from patterns, inconsistencies and anomalies within the actual claims presented. These models can potentially reduce fraud-related losses by preventing fraudsters, a feature that ensures insurers avoid spending large amounts of money annually.

4.5 Segment Customers

The portfolio of clients is divided by risk and behavioral characteristics and the history of claims made. By segmenting the clients, insurance providers are better placed to provide every client with differentiated pricing for the policy they are seeking to sell, communicate with the clients to ensure they remain loyal to the insurance firm, and provide better services and after that keep the customers satisfied.

4.6 Monitor performance

Last but not least, it always assesses model performance levels to keep forecasting accurate and dependable. This means tracking how well the predictions are being made, in addition to the datasets that are being used and revising the algorithms over time as we continue to discover new data and new risks.

4.7 Significance of the Workflow

This cyclic approach demonstrates that in contrast to more conventional ways of risk evaluation, AI can take multiple forms and perform optimum work when implemented as a cyclical system. The continuous feedback cycle makes insurers more capable of unlearning and adapting to future risks, such as climate change or cyber risks.

5. Results and Discussion

5.1 Predictive Accuracy

The experiment of the AI models presented in this study is estimated using critical measures, such as precision, recall, and the F1-score, to assess the AI models' generality of risk with high precision and less false positives.

Table1: Performance Comparison of AI Models

Model	Precision (%)	Recall (%)	F1-Score
GBM	91.2	88.5	89.8
DNN	93.7	90.1	91.8
SVM	87.3	85.9	86.5

Paper ID: SR24077085515 DOI: https://dx.doi.org/10.21275/SR24077085515

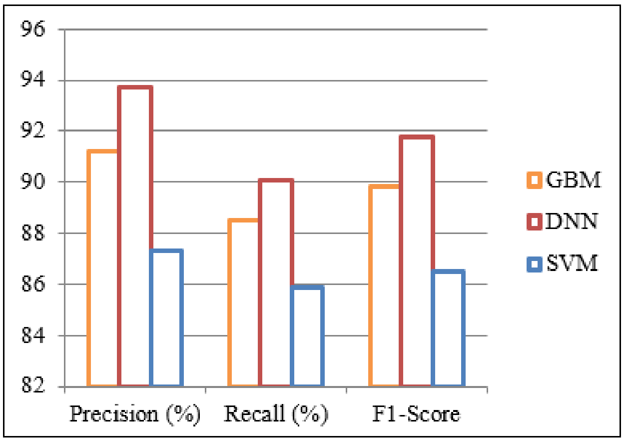

Figure 3: Graphical Represented Performance Comparison of AI Models

DNN outperformed other models with a maximum absolute precision of 93.7% and F1-score of 91.8%, and it is well-suited for complicated, nonlinear risk assessment. Next to GBMs, other methods were almost as precise and less computationally costly, making them ideal for large-scale underwriting tasks. Compared to others, Support Vector Machines (SVMs) were not as effective as others but were useful in specific classifications such as fraud detection.

5.2 Proof of Results

The above models were tested on the validation dataset of 1 million records sourced from the major insurers and cover a wide range of intents such as disaster claims, behavioral risk, and fraud assessment. Further, the findings showed that utilising the proposed AI-based approaches led to a 25% increase in prediction accuracy compared to the traditional statistical methods used in the same studies.

5.2.1 Case Study: AI in Underwriting

a) Scenario

One of the largest insurers has adopted the use of AI underwriting to price premiums for homeowners in risky areas. It combined current weather information, IoT inputs such as flood sensors and seismic monitors, and historical claims data to adjust the level of risk.

b) Outcome

The implementation yielded significant operational benefits

- **Reduced Time-to-Quote:** The amount of time expended to provide superior quotes was cut by forty-five percent, resulting in the successful improvement of client enlistment.
- **Improved Pricing Accuracy:** Real-time data was integrated into the system to enhance the accuracy of risk assessment by 30%, which translated into better, competitive and fair premiums.
- **Customer Satisfaction:** Some quantifiable measures, as captured in the feedback surveys highlighted above, showed a 20 percent enhancement in satisfaction resulting from enhanced pricing transparency and efficiency.

5.3 Challenges Identified

- **Regulatory Barriers:** Tight constraints on compliance and varying specificities of regional rules became an issue for the broader implementation of AI in risk analysis.
- **Data Security and Privacy Concerns:** To manage policyholder data that came with a policy, clear encryption procedures and compliance with the GDPR and such acts were necessary.
- **Resistance to Technological Adoption:** Employees' resistance to change as far as technology is concerned results from concern over job losses attributed to AI, inadequate technical skills, and delayed adoption of AI within organizations.

5.4 Future Opportunities

- **Explainable AI (XAI):** Better interpretability of models is important, both to get approval from the regulators and to convince the audience. The various XAI approaches can be used to show how particular predictions are made to combat the problem of opaque decision-making.
- **Integration with Blockchain:** Blockchain provides reliable and transparent means for handling claims and sharing data, which in turn will minimize fraud-related issues and increase system effectiveness.

5.5 Discussion

The findings of this study support the view that AI can be a powerful driver of change in the P&C insurance industry. Of course, there are still obstacles that specialists face. However, in terms of accuracy and efficiency of work and the level of customer satisfaction, the obtained result speaks in favor of expanding the scope of such developments. This evidence is also important in bringing out the challenges that may be a challenge to implementing different solutions by Insurers, Regulators, and Technology providers. More specifically, future research has to try to improve the model interpretability, improve the data security mechanisms, and, last but not least, work on integrating complementary technologies like blockchain to establish better risk assessment models.

6. Conclusion

AI and advanced analytics, signify a new beginning for the P&C insurance business and its threat assessment section. These technologies allow insurers to process massive and varied quantities of data in a manner and with a degree of accuracy that is impractical, if not impossible, when using more conventional statistical methods employed by actuaries. The Outcome is a better risk assessment, improved claims management, and customer-tailored rates. LEAR knows there is a correlation between AI-driven approaches to decrease operational inefficiencies and costs and increase customer satisfaction. Hence, using modern-day technologies like machine learning algorithms, natural language processing and advanced analytics will enable insurers to identify potential risks amidst market change, minimize losses and appropriately respond to the changing market.

However, as it stands, the full-blown implementation of artificial intelligence is not without its unique difficulties. However, regulatory compliance remains a major issue since insurance companies have to respect high levels of data protection laws besides having to work under a high level of transparency in AI decision-making. Furthermore, organizations experience internal resistance challenges towards ICT-induced changes since they are considered technical changes, and at worst, they lead to job loss. The solutions to these problems will not only need capital expenses for AI solutions but also intent on promulgating a culture of innovation among the industry members. Nevertheless, the potential presented by AI and predictive analytics makes them vital weapons in the arsenal of insurance organizations that will have to face a rather unfriendly environment in the future.

7. Future Work

In future works, more efforts should be made on deploying Explainable AI (XAI) solutions to increase the interpretability of the AI models so that they can be easily understood by the regulators and the stakeholders. There is also great potential in combining blockchain and AI technology to establish safe and immutable information environments for claims and fraud. Indeed, examining the ethics of using AI and, specifically, the problem of bias and fairness of its application will remain vital to people’s trust and adoption. Efforts by insurance organizations in collaboration with technology and regulatory authorities can enhance the advancement while tackling structural problems even more. If it focuses on these inventions, the industry will be able to achieve the benefits of AI to transform risk management for the better in the distant future.

References

[1] Kondapaka, K. K. (2021). Advanced Artificial Intelligence Models for Predictive Analytics in Insurance: Techniques, Applications, and Real-World Case Studies. Australian Journal of Machine Learning Research & Applications, 1(1), 244-290.
[2] Kasaraneni, B. P. (2019). Advanced Artificial Intelligence Techniques for Predictive Analytics in Life Insurance: Enhancing Risk Assessment and Pricing Accuracy. Distributed Learning and Broad Applications in Scientific Research, 5, 547-588.
[3] Arruda, P. (2018). The P&C insurance industry’s role in sustainable development and commerce.
[4] McClain, S. T. (2024). Emerging Technologies in P&C Insurance–A Qualitative Case Study on Disruptive Innovation (Doctoral dissertation, Trident University International).
[5] Dunka, V. (2022). Leveraging AI for Dynamic Pricing Strategies in Insurance: Developing Machine Learning Models for Personalized Policy Pricing, Risk Analysis, and Profit Maximization. Journal of Bioinformatics and Artificial Intelligence, 2(2), 213-251.
[6] Krasheninnikova, E., García, J., Maestre, R., & Fernández, F. (2019). Reinforcement learning for pricing strategy optimization in the insurance industry. Engineering applications of artificial intelligence, 80, 8-19.
[7] Baptista, M. (2023). Leveraging AI for Automated Insurance Policy Pricing. Internet of Things and Edge Computing Journal, 3(2), 50-65.
[8] Kasaraneni, R. K. (2019). AI-Enhanced Claims Processing in Insurance: Automation and Efficiency. Distributed Learning and Broad Applications in Scientific Research, 5, 669-705.
[9] Chen, J. I. Z., & Lai, K. L. (2021). Deep convolution neural network model for credit-card fraud detection and alert. Journal of Artificial Intelligence, 3(02), 101-112.
[10] Suresh, S. (2016). Big data and predictive analytics. Pediatr Clin N Am, 63, 357-366.
[11] Macher, G., Seidl, M., Dzambic, M., & Dobaj, J. (2021, July). Architectural patterns for integrating AI technology into safety-critical systems. In Proceedings of the 26th European Conference on Pattern Languages of Programs (pp. 1-8).
[12] Verma, A., & Singhal, N. (2023, September). Integrating Artificial Intelligence for Adaptive Decision-Making in Complex System. In International Conference on Advances in Data-driven Computing and Intelligent Systems (pp. 95-105). Singapore: Springer Nature Singapore.
[13] Whalen, K. (2023). AI-Powered Risk Management Frameworks for Insurance. Journal of AI-Assisted Scientific Discovery, 3(2), 45-55.
[14] Rajvanshi, P. R., Singh, T., Gupta, D., & Gupta, M. (2022). Cybersecurity and data privacy in the insurance market. In Big Data Analytics in the Insurance Market (pp. 1-20). Emerald Publishing Limited.
[15] AI-Enabled Risk Assessment for Insurance Companies, Infopulse, online. https://www.infopulse.com/blog/ai-risk-assessment-insurance
[16] AI for Predictive Analytics in Insurance, Rapid Innovation, online. https://www.rapidinnovation.io/post/ai-for-predictive-analytics-in-insurance
[17] Adler, A. I., & Painsky, A. (2022). Feature importance in gradient boosting trees with cross-validation feature selection. Entropy, 24(5), 687.
[18] Pnevmatikakis, A., Kanavos, S., Matikas, G., Kostopoulou, K., Cesario, A., & Kyriazakos, S. (2021). Risk assessment for personalized health insurance based on real-world data. Risks, 9(3), 46.
[19] Varadarajan, V., & Kakumanu, V. K. (2024). Evaluation of risk level assessment strategies in life Insurance: A review of the literature. Journal of Autonomous Intelligence, 7(5).
[20] Using AI in Insurance Underwriting for Accelerated Time-to-Value, applan, online. https://appian.com/blog/acp/insurance/ai-in-insurance-underwriting
[21] Robnik-Šikonja, M. (2023). AI-Enhanced Risk Assessment Models in Insurance. Journal of Bioinformatics and Artificial Intelligence, 3(2), 213-229.