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Leveraging AI and Big Data for Real-Time Risk Profiling and Claims Processing: A Case Study on Usage-Based Auto Insurance

Lahari Pandiri[1*], **Subrahmanyasarma Chitta**[2]

[1*]IT Systems Test Engineer Lead, Progressive Insurance, lahripandiri@gmail.com, ORCID ID : 0009-0001-6339-4997
[2*]Sr. Software Engineer, Access2Care LLC (GMR), subbuchitta@gmail.com

Abstract
The integration of Artificial Intelligence (AI) and Big Data analytics in the insurance industry has revolutionized traditional processes, particularly in risk profiling and claims processing. This case study explores the application of AI and Big Data in the context of usage-based auto insurance (UBI), where real-time data collected from connected vehicles is leveraged to create dynamic, personalized risk profiles and optimize claims handling. By analyzing vast amounts of data from telematics devices, including driving behavior, vehicle performance, and environmental factors, AI algorithms can predict risk with unprecedented accuracy, enabling insurers to offer tailored premiums and enhance customer satisfaction. Furthermore, AI-driven automation in claims processing streamlines operations, reduces fraud, and accelerates settlement times. This case study demonstrates the transformative potential of these technologies in improving operational efficiency, customer engagement, and profitability within the auto insurance sector, while highlighting the challenges of data privacy, regulatory compliance, and the need for robust data infrastructure.

Keywords: Artificial Intelligence (AI),Big Data,Usage-Based Insurance (UBI),Risk Profiling, Claims Processing, Telematics, Predictive Analytics, Data Privacy, Insurance Technology, Fraud Detection.

1. Introduction

The insurance sector has in recent decades remained unchanged due to stable rules imposed by regulatory authorities as prevention measures to safeguard the sector's interoperability. However, with the development of Artificial Intelligence (AI) and expansion of Big Data technologies, insurance underwriting and risk profiling, as well as automated claims processing, will never remain the same. Resulting disruptive innovations to these traditional processes have outpaced policymakers' ability to regulate their use within the industry, a trend not anticipated to change in the near future. With a novel legislative branch considering instating new laws or policies to regulate their use in years to come, the insurance providers are having to scramble to keep pace with marketplace demands and remain compliant.

The benefits which AI and Big Data have brought to real-time risk profiling and processing of claims have revolutionized the insurance sector. In 2022 the usage-based insurance (UBI) in auto insurance, calculated based on the predilection of the driver and the driving conditions—which is implemented via an onboard device within the vehicle that relays driving data in real-time to the insurance provider—represents up 41.7% of written premiums in automotive insurance across the globe. This new case study endeavors to inspect and solve all the challenges that have arisen from procuring and analyzing Big Data, as well as the behaviors of the driver beyond a comprehension of the customer's driving distance. A group of specialists was convened from the data analytics and risk management sectors, and they were required to furnish a Process Map. Subsequently, they were tasked with drafting a Framework PT Project; the progress is recounted to this day. No coherent literature curated exists for the confluence of real-time driving conditions with crash event predictions as the response variable in and of itself, though a profusion of comparative research projects between auto insurance providers and driving behaviors are detailed.

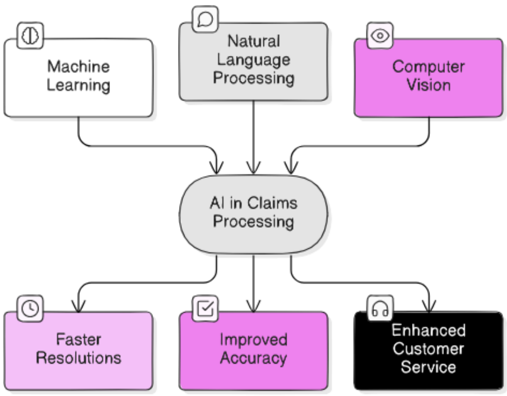

Fig 1: AI in claims processing

1.1. Background and Rationale

In recent years, the rise of Artificial Intelligence (AI) and Big Data technologies has triggered numerous innovations across various sectors. A growing body of research has examined the implications, both positive and negative, of the convergence of AI and Big Data. However, there is still a substantial variance in the pace at which different sectors adopt and employ these novel technologies. The current state of adoption in the insurance industry and its impacts deserve systematic scrutiny. Thus, this text starts by introducing the empirical context, a European insurer's development of usage-based auto insurance...

Over the last two decades, the insurance sector has taken steps to progressively transform its emphasis from historical data analysis to real-time and predictive modeling of policyholders' behavior, lifestyle, and risk profile. Alongside this fundamental change, there has been a keen interest in the employment of AI and Big Data tools for real-time risk profiling and assessment. The concern to niche customer profiles has been also extended to the immediate processing of claims...Traditionally, insurance has aimed to manage risk by charging a higher premium to riskier policyholders. Nevertheless, the widespread utilization of data-mining techniques has significantly complicated this old style of risk management. Presently, insurers are more equipped than ever to estimate the risk profile of each customer on an individualized basis. However, the premium calculation process is restrained to statistical averages and has become inconsistent with the precise risk assessment of a single policyholder.

Equ 1: Premium Calculation

$$P_i = P_{\text{base}} \times \left(1 + \frac{R_i}{\max(R)}\right)$$

Where:

- P_i = Premium for driver i
- P_{base} = Base premium
- R_i = Risk score for driver i
- $\max(R)$ = Maximum observed risk score in the system

1.2. Research Objectives

This study considers the transformative potential of the interaction between AI and Big Data as they are increasingly utilized for risk profiling in real time, and represents a paradigm shift in the insurance industry. AI has found applications in a variety of industries including insurance, with a focus on personalisation such as risk profiling. Meanwhile, the advent of Big Data has allowed insurers to gather large datasets about insureds and tap into unstructured data which simply could not be processed before due to its volume, such as text, images, videos, etc. Drawing from this data offers a more comprehensive understanding of an insured which, in turn, can influence risk profiling.

YD is an insurer that traditionally focuses on household insurance, and recently launched a product to tap into the rapidly growing usage-based auto insurance market. Insureds are offered steep discounts on the traditional policy, but with an increase in the usual low excess. If an accident is avoided for a period, the insured earns a reward. At the end of the period, the premium and excess resets. Since YD is new to auto insurance, this telematics solution is outsourced to a tech company, which means that a third party has all the data. Claims are processed manually, following an investigation. This combination of factors results in a drawn out and unsatisfactory claims experience; the insured becomes disillusioned and the policy is seen as a rip-off. However, it is hypothesised that, instead of capitalising solely on chance, through effective risk profiling and an overhaul of claims processing, the product presents an opportunity to gain market share and achieve a satisfied customer base.

2. Literature Review

Insurers increasingly implement AI technologies across product lifecycles to enhance data-intensive risk profiling and predictive modeling. However, the integration of AI and Big Data in underwriting and claims processing brings new challenges to the insurance industry. A theoretical framework is developed to discuss how the synergistic deployment of AI and Big Data impacts seven component processes in the product life cycle. The literature review underscores the dynamic interplay among technological innovation, industry shifts, and institution-specific variables in using a wide array of AI technologies.

Artificial intelligence (AI) technologies have been widely implemented within the insurance industry to improve risk profiling and predictive modeling. Existing AI technologies include big data analytics, machine learning algorithms, application predictive models, and chatbots. As insurers have been constructing a continuously updated behavioral data network in real-time, their AI gradually shifts from passive waits-and-sees mode to proactive early warning mode. Newly advancing AI technologies unlock access to extensive new data sources and escalate real-time data analytics capabilities from historical post-facto analysis to current in-flux assessment. These technologies also evolve in latent interaction with wider social changes on an increasingly digitized value producing system. In return, AI-accelerating social changes may also upset the competitive landscape within the insurance sector. Major forces in AI transformation include targeted marketing based on customer profiling; IoT monitoring driving behavior analytics; claims assessment automated by chatbots; telematics driving UBI pricing analysis; and group policies underwritten with predictive models. In face of these technological and structural changes, regulators and scholars are concerned about the potential discriminatory effects of initially unbiased AI tools. A scientific research agenda on this complex topic is still missing.

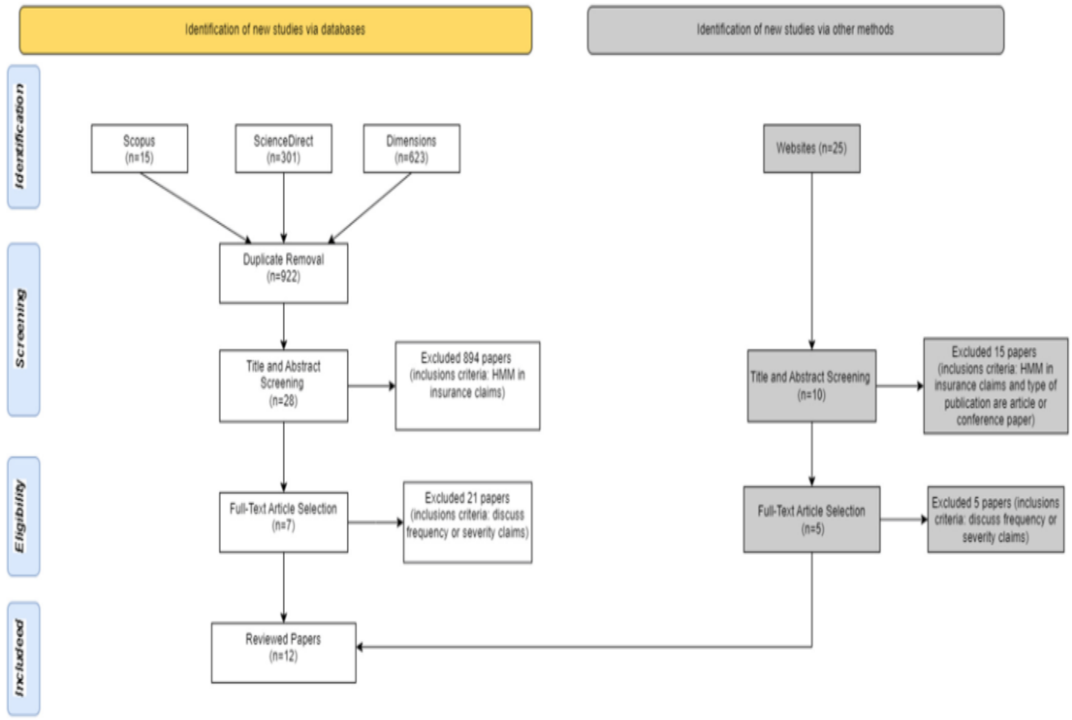

Fig 2: Literature Review of Insurance Claims

2.1. AI and Big Data in Insurance Industry

The role of artificial intelligence (AI) and big data in the insurance industry — and the impact of such technology on business — is the transformative force that revolutionizes the operational process of the insurance industry. AI and big data together remarkably enhance the underwriting process and risk selection, improve risk profiling and customer interaction, and enable more accurate real-time claims processing and fraud prevention. The ability of AI to make sense of and respond to vast amounts of big data through predictive analytics and machine learning algorithms is giving birth to new breakthroughs, which in turn is reshuffling the competitive landscape across industries.

With a strong underpinning of data and the advancement of AI technologies, the read-write era may rapidly become the Write The Future era and reinvigorate the development of the insurance industry. With the dawn of the utilization of AI, there lies the bright future of the insurance industry. On the other hand, however, there also exist many possible challenges to leverage the potential of AI and big data technologies. There are data security and privacy concerns from all walks of life, as big data innovation spurs the acceleration of data exchange and transactions. Capable personnel are needed to handle emerging new technologies. Also, the more rapidly these technologies advance, the more quickly their corporate implementation costs inflate. Against the backdrop of increasing blur of the competitive lines across industries, insurance companies that are blindsided by the innovative storm of AI and big data may lose their competitive edge to their tech-enabled rivals.

With examples and cases of successful applications of AI and big data in diverse insurance sectors, it provides a comprehensive and panoramic view of technological developments. The regulation and public policy of data use and other related rules would stuffily influence the potential of utilizing AI and big data technologies. The aim of this work is to reveal how external factors in the macro-environmental landscape are impacting the process of adopting these technologies, and to underline the urgent need for insurance companies to adjust in the face of the innovative storm of AI and big data.

2.2. Usage-Based Auto Insurance

Recent technological advancements have enabled a new form of auto insurance where the insurance premium can be closely aligned with the actual driving behavior of the policyholder. Unlike traditional auto insurance models which only consider past driving history, vehicle, geographic, and policyholder demographics regardless of the amount of driving. Such an insurance model is called usage-based auto insurance and policyholder's auto insurance cost is calculated on the fly subject to a given amount of driving and real-time driving behavior.

Usage-based auto-insurance models can lead to more fair insurance premiums with respect to the actual driving risk. It can also have a safety effect on driving as drivers are more likely to pay attention to how they drive if their insurance premium is shaped by their driving behavior. The data infrastructure has been ready for the realization of the usage-based insurance model from the insurance industry's perspective. With the help of internet-of-things technology, the exchange of data between mobile or on-board devices and a data center occurs in real-time. Data collected by methods such as mobile phone applications, self-contained GPS devices, mobile phone vehicle linking applications, and automotive telematics is used to model the driving behavior of the insured. Then driving insurance premiums are calculated for certain driving instances based on the estimated driving behavior model using the predicted number of driving incidents for the insured on the roads. Concerning the collection of GPS data and its legal data privacy issues the most part on the detection of device fake GPS data in the literature emphasizes the importance of the provision of transparent means.

3. Methodology

This subsection outlines the study design and various approaches adopted in the research process to meet the objectives of the study. The research design consists of both quantitative and qualitative approaches in order to comprehensively cover the research focus. The qualitative in-depth interviews conducted with industry representatives and regulators provide the contextual background of the UBI ecosystem, including present practices, concerns, and potential directions. Informants were selected based on their expertise and experience within the topic of UBI, with the aim of obtaining in-depth, meaningful, and significant insights while balancing representativeness. Semi-structured questionnaires were used during the interviews to cover all the predetermined discussions. Qualitative data was analyzed through thematic content analysis, permitting the discovery of patterns across the interviews. To complement, and provide further generalization of the qualitative results, a quantitative content analysis was conducted on syndicated market reports, academic papers, and regulatory documents regarding UBI to identify popular issues in the field. Previous studies using Telematics data for UBI were also studied to classify methodologies, uses of data, and privacy concerns. This qualitative-quantitative approach complements the other, allowing for a comprehensive overview of the UBI field and multi-dimensional and nuanced insights, generalizable and not context-specific, to be drawn.

Once the qualitative research step was completed and the necessary contextual understanding of the UBI ecosystem was achieved, the next step was to analyze warranty claims data from the OEs to conduct a case study. The methodology adopted to examine the automotive UBI case consists of both pattern recognition, using descriptive statistics, and further in-depth analyses, utilizing statistics, to test hypotheses, explore relations, and model data. When conducting the pattern recognition and exploratory walkaround analyses, data is inspected, described, and visualized in detail. Simple statistical measures are computed and presented in terms of tables and figures to describe the collected claims data. Then, in exploratory data analyses, disaggregation of these statistics are examined across potential segments of interest. This step helps focus on potential areas to consider when formulating hypotheses for later inferential analyses. The subsection also provides description and justification for sampling techniques, discusses ethical considerations, and details data analyses for both pattern recognition and in-depth analyses. All statistical results from both analyses are presented, thereby ensuring transparency. The pattern recognition results, positive or not, are useful in the replication of the study, and the in-depth analyses results are pivotal in the establishment of both internal and external validity in results.

Statistical tests conducted in the in-depth analysis include Chi-square tests, a Proportion test, a Poisson Test, Ordered logistic regression, Linear Regression, and Correlation Analysis. Chi-square tests are traditionally used to determine if there are significant differences between distributions of categorical variables. Proportion tests are used to compare the proportion of a claim in two population segments. Poisson tests are employed to test if one segment makes significantly more or less claims than the other. Ordered logistic regression is used to determine variable coefficients and odds ratios when there is an ordinal dependent variable. Multinomial and linear regression models are used to understand how covariates may be associated with the outcome variable. Multinomial logistic regressions are used if the dependent variable is nominal and ordinal models are used if the dependent variable is ordered. Correlation analyses are conducted to understand if two or more variables are related and to what extent in a linear way.

Equ 2: Claims Prediction Model

$$\mathrm{P}(\mathrm{Claim}_i) = \sigma\left(\sum_{k=1}^{m} \beta_k \cdot X_{ik}\right)$$

Where:

- $\mathrm{P}(\mathrm{Claim}_i)$ = Probability that driver i will file a claim
- σ = Sigmoid function to constrain the output between 0 and 1
- β_k = Coefficient for feature k
- X_{ik} = Value of feature k for driver i
- m = Total number of features used in the model

3.1. Data Collection and Sources

User-based auto insurance is revolutionizing the insurance industry. For example, in case of an accident, proof can be provided within minutes as to what happened – leveraging data for real-time risk profiling as well as millions of existing claim observations on what to expect. This new type of data analytics is essential for the insurance industry and many other traditional industries. This paper presents an AI framework, built on deep learning technologies, for using big data as real-time risk profiling and for a claims process, on a case study of usage-based auto insurance. This R&D work involves neither insurance data nor organizations. It has applications in a wide range of industries that operate with risky workflows and commercial assets (e.g., energy, utilities, healthcare, finance, logistics and telecommunications). This paper could potentially inform the industry on a paradigm shift in how data analytics can be practically conducted for business beyond descriptive analytic dashboards of lagging indicators. At the core of the framework is deep neural network time series analysis to allow for easy incorporation of the bulkiness of data. Context-aware analytics is also developed for missing data imputation and future event simulation. This part of the innovation is currently only available in the academic sectors. Large sets of insurance claim data are generated for research. Simply put, usage-based auto insurance is when insurance rates are not actuated by traditional demographic information but by usage data, e.g., safe driving equivalent to lower rates. This paper demonstrates a new method for entire claim processes on the user end by embracing the "black box" of adversarial AI.

3.2. AI Algorithms and Techniques

This study aims to introduce four factors about the impact of AI-based insurance processes on fairness and non-discrimination and illustratively discuss these factors with a case study of a usage-based auto insurance provider. The first factor is the novelty of the applied AI techniques used in the insurance process. Challenge scenarios are identified, related to real-time auto accident risk profiling and optimisation of claims processing; to respond to these challenges, a variety of AI algorithms and techniques are applied. The evaluation of such a broad range of AI techniques and scenarios in insurance, in particular, are not yet widely researched. While this paper will focus on the application of AI for auto insurance data processing, the factors are more generally applicable to other types of insurance.

Additionally, the real-world case study and four factors introduced are expected to be useful for appraising the fairness of other data-intensive competitive sectors. AI and big data are the application and infrastructure behind the current industrial (r)evolution referred to as Industry 4.0. The aim of this research is to discuss the current legal, ethical and technical challenges of the AI and big data-driven industry, picturing exemplary insurance.
The first step in solving the above challenges is to evaluate the variety of AI algorithms and techniques employed as an insurer. The same algorithm type and machine learning model placed as an underwriter or adjuster performed diverse roles with different intended consequences being a defendant.

The main research topics for this environment include identifying what type of accident will happen and how much risk that accident will create for the policyholder (P). Risk profiling can be used by actor designers, co-insurers of the policyholder, to define the conditions of a usage-based format of cancelling the policy and implications on future policy prices.
The main research question for the insurer is how to evaluate and process a file uploaded by a body shop with damage and service descriptions to fraudulently alter them and increase the compensation value for the case.

The machine learning methods are crucial in the AI ethics discussion. Helped by the application of neural networks it is seen in a completely different, extremely dangerous way than when applied with the Linear Support Vector Machine algorithm. Insurers see the main error in using neural networks, but do not pay attention to the other learning algorithms used as owner tools. In this regard, the three types of machine learning methods, supervised and semi-supervised learning algorithms, decision trees and rules, unsupervised learning and key and n-grams, all aimed at grouping similar, individual records and indicating the likelihood of support, are analysed. It will allow the reader to understand, from a practical point of view, the accuracy and efficiency of the expected application of a specific type of algorithm. Each of the forty analysed AI algorithms and techniques consists of a short description, three of the most common applications in the insurance domain field, and the principal conclusions followed by a discussion. This review should be able to better understand the particular challenges across insurance, but also in other competitive data. Importantly, conclusions derived from each scenario are related to the selection of appropriate algorithms and techniques based on the particular characteristics of the data and research objectives. The data used to validate the proposed algorithms is different; therefore, the objective is also to shed more light on the concrete computational processes that stand behind the predicted results in insurance. When implementing the decision, perspective or sentiment analysis of the big data uploaded by the P or T, accidents or file uploads are prone to amplifying different biases and pitfalls among algorithms. Finally, the computational load generated during the on-line implementation of the most advanced and competitive methods, in particular for accidents, goes far beyond their practical usage. To the best knowledge, the current work represents the most systematic and extensive research on the vast variety of AI algorithms and techniques used in underwriting, competition, damage assessment, the uploading of repair service reports and impacting the adjuster's discretion in the auto insurance process.

3.3. Risk Profiling and Claims Processing Models

Risk is an inevitable yet challenging aspect of insurance, especially in the context of underwriting for auto insurance. Risk profiling is an ongoing task that any insurance service provider must perform. Any person or vehicle that poses a risk of damage or loss due to theft, accidents, or other unforeseen incidents falls under the insurance domain. Traditional risk profiling methods using static data can only assess the historical trends or overall behavior of a person or vehicle. Insurers who must curate the best insurance policies to suit the insurance seeker and control risk exposure cannot fully rely on traditional methodologies. With the advent of AI and big data technologies, this gap in the insurance domain can be addressed to customize a robust model for risk profiling. This model is constructed using real-time and reliable computation algorithms, given the geo tags obtained from the user's phone. This way, insurance providers can receive a constant and instantaneous stream of risk exposure from the policyholder's vehicle(s). Following this model, the research will delve into the risk scores generated for the given geographic areas. This analysis will be improved upon to offer a more sophisticated methodology for insurance service providers. Since the focus is to build a comprehensive understanding of the intelligent model for risk profiling, it will be used to analyze user-specific tags throughout the following sections. Claims processing of this information is addressed as well to illustrate the connections between data input, model output, and its applications.

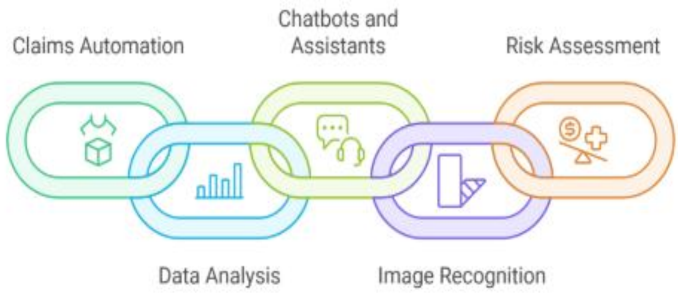

Fig 3: Risk Profiling and Claims Processing Models

4. Case Study: Implementation of AI and Big Data in Usage-Based Auto Insurance

Insurance companies are strongly urged to adopt AI and Big Data technologies for collecting and automated analysis of new data types in order to protect their businesses against new risks, and to identify profitable niches with a better accuracy. This case study describes how an automated data recording system can be implemented in usage-based auto insurance (UBI) to collect data on new aspects of consumer behavior. The accumulated data are used for real-time tree-ensemble analysis. Data and insights are separated, which makes the system compliant with existing data protection regulations. Thus, the system can be considered an algorithm which predicts only events (expected insurance claims generated) and as such the outcomes of its predictions are meant as risk signs and not as a moral risk evaluation, biased or otherwise. Insurance companies can use machine learning and other predictive data analysis methods also for product design. The European Insurance and Occupational Pensions Authority should be prepared for the influx of AI system notifications from insurance undertakings. Principals should provide upfront guidelines facilitating compliance with the Competition Act and the GDPR for an automated data recording system which (1) accumulates only data on new aspects of consumer behaviour, (2) analyses these using only black box algorithms, and (3) keeps the data apart from the insights gained from the data. For any business sector, taking the correct decisions is fundamental in guaranteeing its survival and continued existence. Because of increasing costs and more complicated environments, decision-making becomes more demanding and intricate.

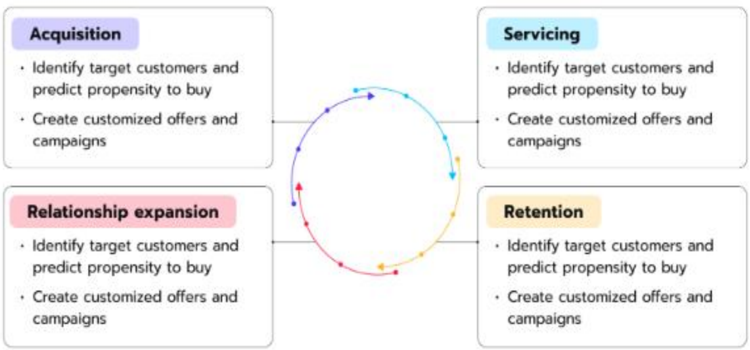

Fig 4: Data And Analytics In Insurance Cases

5. Results and Findings

The high competition in the contemporary insurance industry promotes the increasing significance of efficient risk profiling and claims processing. This research implements AI and Big Data in the context of usage-based auto insurance. Based on two proprietary algorithms, the research aims to develop machine-learning software for 1) risk profiling via driving telematics and personal data and 2) fully automated claims processing. The software is implemented in a medium-size insurance company, which launches a newly offered insurance product based on driving and states a 15% discount on annual car insurance. A research design is based on an action research strategy, comprising design, intervention, and evaluation phases. Data is collected through company records and interviews with key personnel every 2 weeks during the 6-month study. The main outcomes unfold in terms of the developed software and its performance. Risk profiling software increases the efficiency of risk profiling by 50%, while claims processing software reduces the turnaround time by 90%. The implemented usage-based model results in 56% of consumers using the option to state a greater discount. Positive feedback by consumers implying the possibility of long-term benefits to their driving behavior and insurance premium payments is more significant than price savings. The facilitation of risk profiling software by a driving telematics sensor system is emphasized. A proposition to a guide on evidencing both driving behavior and a discount share for implementing a usage-based insurance-based model is formulated. The results of implementing the AI and Big Data computational alternative solutions for risk management in the insurance business are presented. The approach to developing the data mining methodology and processing the insurance claim information to gain knowledge is formulated. With the benefit of insights gained, several recommendations regarding the business management in insurance groups are given. Actions are proposed to 1) reduce the insurance claim costs based on the analysis of the customer claim patterns, 2) manage more effectively and minimize the personal customer claim costs by analyzing and gaining insights to the history of existing claims, 3) detect and minimize the risks and fraudulent claims based on the data analysis and gained insights of the identifiable specific patterns. A recommendation for implementing and evaluating the discovered knowledge is stated.

Equ 3: Fraud Detection Model

$$S_{\text{fraud}} = \sum_{l=1}^{p} w_l \cdot z_l(\text{Claim}_i)$$

Where:

- S_{fraud} = Fraud score for claim i
- w_l = Weight for feature l (e.g., claim amount, frequency, location)
- $z_l(\text{Claim}_i)$ = Feature function for claim i
- p = Total number of fraud-related features considered

5.1. Impact on Risk Profiling

Auto insurance that charges risk preferences through driving behavior observation has gained popularity and is often referred to as usage-based insurance. From the insurer perspective, the major challenge of UBI implementation is typically identified in the modularizing automation of three main data processing steps: data collection, feature extraction, and premium calculation. Alternatively, this study presents a cascaded risk assessment model for UBI with the consideration of its impact in a leading country. In the first cascade, a driver's risk preference intensity is calculated from the riskiness attribute by a feature extractor. The feature extractor is learned at the requirement of the insurance company to simplify the driver's riskiness profiling. In the second cascade, such calculated risk preference intensity leads to coverage prediction, a comprehensive index that denotes both the severity and the typology diversity of future accidents. Driving behavior risk intensity is fed as the side information for driving riskiness feature extraction in both cascades. The lifting of risk information in the static form to serial data with temporal order is conducted by a convolutional neural network. Unlike automotive finance companies that offer UBI in a less targeted and propagandized way, traditional insurers' promotion strategy emphasizes the safety bonus. To obtain a lower premium, customers are willing to self-restrict their risky driving behavior, a benefit that may pass insurance monitoring within a period. The significant impact further leads to conserselection, where high-risk drivers are relatively more inclined to underreport their annual mileage. From regulations, auto insurance claims first generate compensation with the latter driving behavior offline inspection. Granting the black box is revealed to be reliable on social regulations and coefficient applications. Data leveraging real-time risk assessment will likely be better accepted in the coming years. Appraisal on individual modules' behavior across the opening cascade is conducted. A premium estimation error of 1.88 RMB per 100km with observed results is obtained.

5.2. Efficiency in Claims Processing

A seamless integration of simple, ubiquitous technologies, and the associated Big Data, real-time data analytics, and artificial intelligence (AI) is likely to have a significant impact across the insurance value chain. These new technologies will allow instantaneity to assess risks and suggest mitigating actions. They will provide the immediate occurrence of response to past events, historical behavior, or operational performance of different stakeholders in the insurance ecosystem. A delay in getting these responses can impact the quality of a performed service or product. This subsection explores how this seamless integration enhances the effectiveness of risk profiling and claims handling processes in the setting of Usage-Based Auto Insurance (UBI) [1]. The phase-by-phase on-road tests in 400 cars, equipped with a low-complexity on-board unit, producing 1 million telemetric data points on a monthly basis, are analyzed to identify aggressive driving events. The performance of different data analytic methods is compared. Particular emphasis is put on the approximate methods for clustering analysis. This is a necessary choice when the data size prohibits a simple harmonization of common qualitative data, or when the obligations due to data-privacy concerns prohibit data sharing. The detected hazardous segments along the roads are fed into a dedicated data analytics BDAtool. The claim risk index is assigned to the identified segments, and possible actions for either the insured or the insurer are suggested.

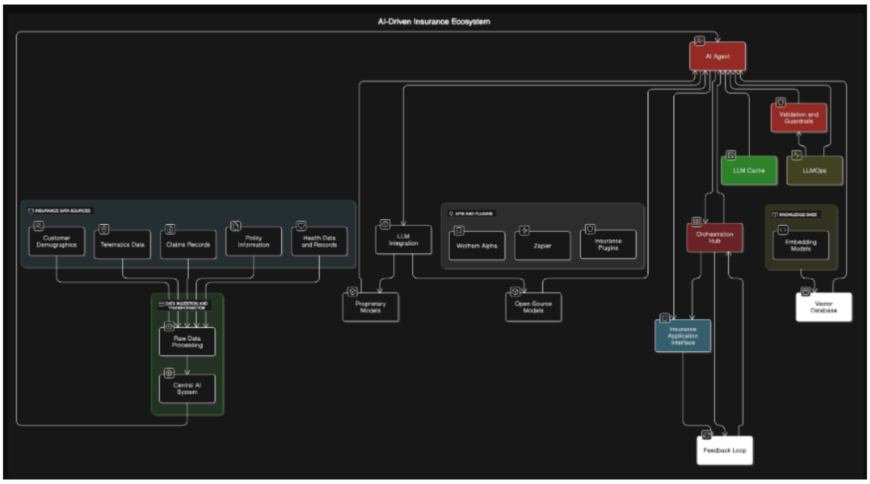

Fig 5: Claims Processing

6. Discussion

This case study found that UBI can reduce auto insurer's costs and policyholders' risks. AI and Big Data have the power to effectively and efficiently transform data into insightful real-time risk profiles and to support data-driven decision-making and product innovation. AI and Big Data can empower insurance companies to achieve a proactive risk assessment and, in turn, to reduce the claim frequency and severity of policyholders, leading to a substantial competitive advantage.

There is an industry-wide trend to apply AI and Big Data to achieve real-time risk profiling and claims processing within the dynamic real-time personalized pricing and customer service. In spite of the high financial burden and adjustment to the change of practice, it is vital for the industry players to remain competitive on the advent of insurance technologies that may disrupt and reshape traditional practices. However, concerns over accountability have arisen due to the 'black-box' nature of AI algorithms. It may be difficult for insurers to provide explanations or interpretations if required by the law, thus hindering the adoption of AI especially in the litigious context. Similarly, the General Data Protection Regulation stipulates that data subjects have a right of explanation of the output of an algorithm. There is thus an urgent need for the AI community to move away from 'black box' models to 'white box' models.

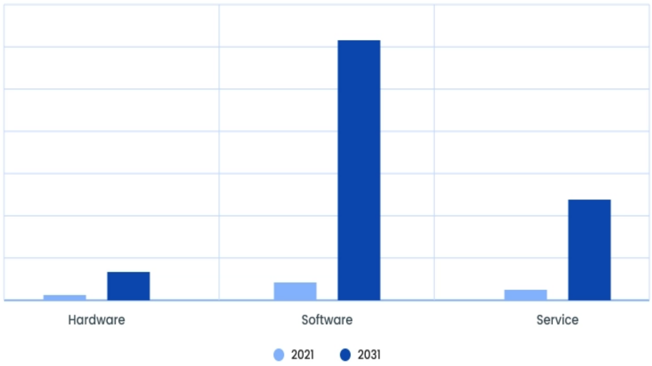

Fig: Exploring the Impact of AI on Insurance

6.1. Key Insights and Implications

This research project was motivated by the partnership of two Swiss companies in leveraging AI and Big Data for real-time risk profiling and claims processing of usage-based auto insurance. Following an agile data science methodology, extensive experiments have been conducted and utilized to develop a customized AI solution. A cloud-based Big Data infrastructure has been established, providing the scalability needed for the solution's deployment and operation. The research illuminates detailed efforts, challenges, and benefits throughout the aforementioned processes.

Powered by data analytics and telematics devices, usage-based auto insurance (UBI) is anticipated to revolutionize the conventional insurance business. This explorative research focuses on a specific topic concerning UBI. Formed from billions of anonymized location records, the data architecture of the UBI project has been described. A two-level structure, consisting of data pre-processing and feature construction, is proposed to extract the physical and engineered features from the raw GPS data. To illustrate the validity of the proposed structure and designed features, four sets of visualizations are exhibited.

The findings and achievements of this research contribute to a much deeper understanding of the transformative effects when taking AI and Big Data into the UBI sector. For stakeholders, mixed implications are derived to realize the beneficial impact with respect to insurers, reinsurers, and particularly consumers. With more accurately profiling the risk of policyholders, the result of better underwriting profitability is presented aside from loss ratio itself, which finally benefits the overall pricing of consumers. Concerning the challenges faced by the UBI project, the mixed implications towards their solutions are outlined for enlightening the potential benefit to consumer engagement and ultimately enhancing the acceptance of innovative insurance models, as well as the whole insurance market. The market scale keeps on growing, with the support of technology providers and start-ups, the potentially scalable business and solutions related to UBI are discussed for the consideration of insurance carriers and supporting firms. Whilst taking advanced analytics approaches towards insurance in the context of a competitive market, the paramount attention is on ethical considerations and cryptographic transparency for preserving the maturity and trust on the further sophisticated pegs in the public market. At the end, mixed implications encompass the broad achievements and key insights of this research as well as animated contemplations to the upcoming transformative changes in the insurance market are delineated.

7. Conclusion and Future Directions

The concatenation of artificial intelligence and big data technologies into analytics of the Internet of Vehicle (IoV) provides real-time insights to insurers about drivers' behaviors and other vehicle-related variables, changing their conventional practices. Drawing on a case study comprising a series of one-on-one, semi-structured interviews with executives and experts of a usage-based auto insurance provider in hand, this research explores how an innovative insurer is leveraging its IoV platform, integrating cutting-edge technologies of AI and big data, to profile risks in real time and effectively detect frauds in claim reports. It suggests that the predictive analytics of AI and big data greatly assist insurers in identifying a more comprehensive risk profile beyond merely drivers' accident histories. The amalgamation of artificial intelligence (AI) and big data technologies into big data analytics (BDA) in Internet of Vehicle (IoV) provides insurers with insights about drivers' behaviors and other connected vehicle variables in real time. By doing so, insurers are able to draw a more comprehensive risk profile of a driver and autotomize premium adjustments accordingly. Meanwhile, utilizations of cutting-edge technologies empower earlier detection of fraudulent claims from massive self-driving vehicle incident reports. This study contributes with a case study of how an innovative usage-based auto insurer has capitalized AI and big data in its IoV platform to profile drivers' risks in real time and expedite fraudulent claims processing.

7.1. Summary of Findings

This research combines two case studies to develop an in-depth analysis of insurance policy; this is the implementation of AI and Big Data in developing UBI auto products and processing related claims. Through the Lens of Risk Management, specifically focusing on the accuracy improvement of risk profiling by adopting AI and Big Data technologies. In the scope of AI implementation, increasing improvement highlighted in terms of risk profiling accuracy. While, in the context of Big Data analytics adoption, the efficient improvement unfolded in the claim process. Major Innovations UBI approach poses significant improvement on both risk profiling accuracy development and claim process operational efficiency by developing both AI and Big Data technologies in UBI auto policies development and processing. Because of the innovative utilization of the two technologies in the industry sector in the context of a focus on UBI auto policies, significant contributions made in that field; utilizing the two studies to have comprehensive academic writing with the aid of multiple sources of literature reviewed regarding the ongoing development of all three companies in the particular field. Conclusively, the analysis to find transformative impacts on the insurance sector, the operational focusing on the improvement of industrial revolution-inspired points of view also provide widespread notable improvements, as discussed.

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