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The Integration of AI and Machine Learning in Transforming Underwriting and Risk Assessment Across Personal and Commercial Insurance Lines

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Abstract

Drawing on recent advancements in machine learning and artificial intelligence, there is a unique opportunity to fundamentally change how underwriting and risk assessment occurs across both personal and commercial insurance lines. Though these capabilities hold great promise for transforming the insurance industry and bringing long-term benefits to insurers and insureds alike, a broad range of ethical concerns may arise that need to be addressed before these technologies are deployed in practice.

Substantial advantages have been observed in using machine learning and AI for underwriting and risk assessment. Techniques such as gradient-boosted trees, deep learning, and natural language processing can, in many cases, yield models with predictive performance that surpasses that of traditional approaches . In work that focuses solely on homeowners insurance, evidence is provided of underwriting costs savings through the incorporation of high-dimensional satellite imagery and its associated spectral information. Meanwhile, in work that focuses on both auto and homeowners insurance, it is shown that the incorporation of high-dimensional demographic variables and advanced modelling methods could also yield substantial underwriting performance gains. In addition to homeowners insurance, the possibility of incorporating alternative data sources for underwriting automobile insurance is considered. It is shown that the degree to which vehicle image data could be incorporated into modeling is influenced by issues relating to data availability. While significant predictive performance improvements can be achieved, the increasingly prominent industry trend to take a "data-intensive approach" to underwriting and risk assessment through the incorporation of machine learning and AI forecasts a broad range of ethical concerns .

Prior to industry adoption, investigations into the broader ethical implications regarding the use of machine learning and AI should be conducted. Potential issues are multifaceted in nature, and there is the possibility of a variety of stakeholders experiencing harm. Focus is placed on two particularly concerning potential harms: unintentional bias resulting in disparate outcomes for different demographic groups, and non-transparency in the underlying data and modeling methods used.

Key words : AI, machine learning, underwriting, risk assessment, personal insurance, commercial insurance, automation, predictive analytics, data-driven decisions, fraud detection, claims processing, customer profiling, behavioral analysis, real-time data, telematics, NLP, image recognition, loss prediction, risk modeling, regulatory compliance, customized pricing, efficiency.

1. Introduction

This new article critically analyzes the integration of AI and machine learning in underwriting and risk assessment across personal and commercial insurance lines. In clear, concise terms, it discusses the current landscape, transformations, challenges, ethical and regulatory concerns, and future trends in the field. Research indicates that AI is not a new field for insurance, given its previous reliance on algorithm-based parametric insurance schemes. However, for the majority of existing schemes, both companies and clients are currently unaware of the insurance industry's propensity and capability to use ML for both long and short-tail insurance.

The effective implementation of AI would require the creation of Computer-aided Underwriting Methods relevant to data-driven risk assessment. Risk assessment metrics need to be both defensible and sound. The relative cost of ML should be lower compared to existing approved models. Most applications would require individuals with a hybrid background of Data Science and Actuarial Science/Mathematics, but these are scarce. However, the proliferation, versatility, democratization and acceptance of low-code solutions may obviate the need for data scientists in certain modelling niches. While ML has the potential to mitigate or replace broker negotiation or segmentation practices, long-tail personal and commercial lines will remain a bastion of human centricity for the foreseeable future.

Insurance groups that are relatively advanced in this domain have invested in organic or inorganic in-house data

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science departments, coupled with classic underwriting expertise. Others view underwriting as an operational cost that needs to be automated and replaced by indiscriminately rerouting it towards loss mitigation initiatives. Group arms-length broker channels and captive insurances have all offsighted much of their underwriting to 3rd party models or similar firms. Given the proximity and expertise of 3rd party models, insurance firms should consider new means of collaboration and material reciprocity such as Proxy-Models, CAUMs, partnership models or horizontally merged incumbency models.

2. Overview of Underwriting in Insurance

An insurance premium is an amount (usually in euros) to be paid at fixed intervals for providing cover for a plainly defined period of time against the insurer's expected costs of all claims by their policyholders in excess of a deductible agreed upon. A consumer's probability of filing a claim must be inferred, which is expected to differ for low-risk, medium-risk, and high-risk consumers. For low-risk consumers, the insurer decides that the consumer has a low expected claims cost. The insurer calculates a low premium for this group of consumers. The premium must cover the cost of claims and expenses, enabling the insurer to earn a profit. An AI system can be described as 'a machine-based system that infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions' . Traditional underwriting. Traditionally, both for personal and commercial insurance, insurers had a risk assessment department. After a consumer applied for insurance, the risk assessment department received the application. The application contained information with which consumers could be classified, such as the policyholder's age, value of insured object or person, and living environment. Aiming to predict insurance claims, the insurer determined general business assumptions such as 'young drivers are more accident-prone than older drivers'. For most classifications, simple and more complex models exist, which translate policyholders' characteristics (explanatory variables) into their expected claims (response variable).

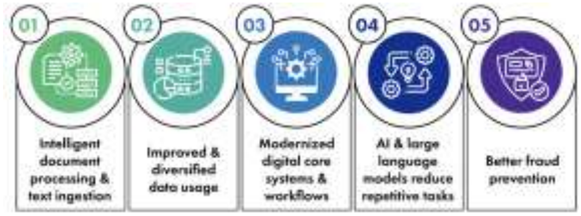

Fig 1 :5 Trends Shaping the Future of Underwriting in Insurance

A statistical model was fit with knowledge of the insurance sector, historical claims, and information in the application. Insurers defined predictive characteristics and argued about their relevance; actuaries calculated expected claims. Since a few years, insurers have increasingly started to use AI. What traditional underwriting automates is the actual pricing of policies for which calculations have already been made. AI systems can perform tasks that normally require human intelligence. They can execute similar tasks simultaneously for millions of (potential) policyholders and find correlations and insights within datasets comprising millions of rows and thousands of attributes, which humans cannot see. But to explain what these correlations and insights are is more complex; a so-called 'black box' problem arises.

3. Traditional Risk Assessment Methods

The goal of underwriting is to determine the risk associated with insuring a person, organisation, or property. This is usually done by determining the best fit between the consumer characteristics and a risk premium. The risk premium is defined by an expected claims cost. This expected claims cost is influenced by risk factors. Reserving is concerned with determining the expected cost associated with claims already incurred but not paid out yet ("claims reserves"). Rating is concerned with predicting expected claims costs when a new contract starts or when altering an existing contract in order to charge an appropriate premium ("ratemaking"). This paper exclusively deals with rating. Traditionally, a person with characteristics a1 is determined to fall in class C1, a risk class that is charged a median premium. A risky based consumer might fall in a higher risk class. Traditionally, insurers manually determined risk classes based on experience and expertise. Since the manual assessment of a consumer's risk based on (sufficiently) many variables is very difficult for a human, insurers relied on a handful variables that were thought to be most important. These variables were often categorical, easily interpretable index variables. Macro data was often combined with the data

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insurers already had. A rule-based model then implemented the decision process of selecting risk classes. The field of statistical learning now has many more data-driven and flexible modelling tools than rule-based models. These models may deal with many more variables, and many more variable types; categorical variables can be on values, counts, ordinal or text, but also images, graphs and more. They can also deal with missing data and outliers . With the growth of data being generated every second, affordable storage space, and quickly increasing computing power, the use of data driven machine learning models is rapidly growing. The way these models interpret risk might be very different from the traditional way. Unsupervised learning might uncover hidden structures in data, resulting into definitions of having risk that is very different from the basis model assumptions. Some commercially available models are "black-boxes", making it hard or impossible for insurers to interpret behaviour: this is often referred to model risk .

Equation 1 : Extended Risk Equation

$$R = \sum_{i=1}^{n} (P_i \times I_i \times W_i)$$

Where:

- **i** = Index of individual risks (from 1 to n)
- $\mathbf{P_i}$ = Probability of risk i
- $\mathbf{I_i}$ = Impact of risk i
- $\mathbf{W_i}$ = Weight or relevance of risk i to the system or project

4. The Rise of AI and Machine Learning

As the constant pressure builds upon property and casualty insurers to find new avenues of growth, streamline internal processes, and enhance retention, there has never been a greater demand for AI solutions across the insurance ecosystem. One of the key needs in the landscape is to transform the underwriting and risk assessment process, especially for personal insurance lines and small commercial lines . Unfortunately, while other areas in the insurance lifecycle have accelerated adoption and matured AI-fueled efficiencies, underwriting has lagged behind. Insurers can finally take advantage of AI and machine learning to meet the complexities of evolving market conditions and continue to delight insureds and agents alike.

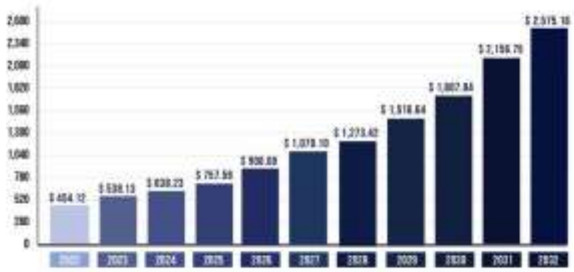

Fig : Top AI And Machine Learning Trends

Insurance underwriting is ripe for greater efficiency, accuracy, and speed, providing assurance to insurers and peace of mind for insureds. With the explosion of data sources that commercial insurers can curate, the importance of having sophisticated underwriting assistants to transform data into meaningful insights cannot be understated. From personal lines insurance to small commercial lines insurance, AI and machine learning research has been applied to the underwriting process to enable the qualification and quantification of risk in seconds. With AI-powered data extracts and predictive models, insurers formulate more predictors and models on more diverse datasets than before, leading to sharper insights. Automated inquiry responses and intelligent summary generation improve speed and accuracy of insurance agents and reps.

Financial services firms, including insurers and brokerages, face today's crippling talent shortage on several fronts: actuaries, underwriters, systems analysts, data scientists, and technology architects are increasingly difficult roles to fill. Firms are challenged to find people with knowledge of markets and products, but also the technology and data expertise that is quickly becoming critical in decision making tasks. Brokers and firms that cannot either reskill or replace will face challenges to keep up with competitors investing in new technology. Insurers are increasingly resorting to AI and machine learning to enhance underwriting and pricing decisions across their personal and commercial portfolios, and to deploy risk assessment tools to enable more granular segmentation targeting.

5. AI Technologies in Underwriting

In an ever-changing society, filled with uncertainty and a rapidly changing market, insurers have a newfound opportunity and necessity to rethink their business models. Captured by the snowballing amounts of data and the possible possibilities of artificial intelligence (AI), insurers' business models can be transformed radically, thereby

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enhancing efficiency, price-performance ratio, profitability, and growth. With obviously great impact on risk assessment and pricing, underwriting automation processes are coming to the fore. This process however, is influencing underwriting bias since all possible intelligence to cure bias is also considered, modeled, and anticipated by AI. To keep underwriting fair and compliant, new challenges arise As there is a multitude of applications, covering practically all areas as it comes to risk assessment in personal and commercial lines, the very basis of insurance has been altered. Exhaustive and in-depth risk assessment based on a multitude of external data sources, covering geospacial information and even (social) media, is now part of standard business. Engineered risk information is at the base of behavioral insurance products for motor vehicle and property, and for (almost) all personal lines, offering great opportunities but also challenges for regulation.

When talking about insurance, life insurance traditionally has a more profound underwriting process with a quantitative analysis of mortality. New data sources help insurers to adjust their actuarial basis considerably.

5.1. Natural Language Processing

Natural Language Processing (NLP) refers to the field where artificial intelligence is used to interpret unstructured text to extract information, classify, and generate it in different forms. Naturally, humans communicate using spoken or written language. An unstructured text could be newspaper articles, fraudulent claims against an applicant, email exchanges, contracts in a legal context, etc. The earlier working around text files was to derive features that would describe it in an interpretable way such as the number of certain keywords, Jaccard similarity, Late Stem Algorithm similarity. This working around has transformed drastically. In the last few years, the advancement of new architectures to learn representations of text and gain in performance with new techniques to manipulate large corpora of text, have blurred the boundaries of what is doable with text.

This raising NLP social movement is already present in the insurance. Several use cases have been derived from these new advances to manipulate text from multiple angles. From leveraging time-series to get out the deducted information of a claim's effect on financial dipping, to classification use cases aimed to randomize the allocation of claims files to adjusters. Text's manipulation resides in three main steps: Extraction — scaping texts from an unstructured format and translating it into data-friendly structured format, i.e., turning all email exchanges with a client into a pandas DataFrame that could then be used to build additional engineered features; Classification — preparing classification-based models which gives behaviors over a basket of policies; and Generation — generative models able to build text output based on some keyboard inputs.

5.2. Predictive Analytics

With the rapid digitization and proliferation of data, there are vast opportunities to innovate and levers to change existing processes through the introduction of Artificial Intelligence models. New and emerging technologies, if adopted with a clear strategic vision, can supplement and strengthen traditional methods to reduce underwriting expenses, improve efficiency, and relieve the administrative burden. Predictive analytics refers to model-based analysis aimed at predicting possible and likely future events, and includes AI-motivated processing schemes such as machine learning and deep learning. The input to the schemes can be time-stamped textual data, social media, internet history, other non-traditional digital footprints, and wide-ranging non-standardized datasets – the so-called big data.

As a result of the extensive deployment of online-enabled devices, a greater variety of personal behaviours leave behind a larger number of time-stamped sequences of data. To augment and upgrade existing physical underwriting plans, insurers can lever text mining, natural language processing (NLP), and time-to-event predictive analysis, where the duration within which an event happens is derived from temporal data, and broader use cases in product design, including policy wording analysis and Boolean keywords in search, are included . Insurers can also improve retail insurance portfolio and pricing, risk inspection automation, and process workflow across the whole underwriting cycle and policy life-cycle stage through machine vision, image recognition, and multivariate temporal evolution process modelling.

Research and practices in modelling coherent multivariate temporal data remain extremely sparse, especially in particular application areas such as insurance. A deep learning framework based on the additive hazard hazards regression model is proposed to better exploit complex time-dependent effects and non-standardized conventional digital footprints. It also investigates the potential of various data transformation and representation embedding schemes as predictors for broader time-to-event modelling and sets forth new ambitions to design a deep temporal

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information network. To accommodate a wide variety of time-stamped and unstructured data with different calibration schemes, mortality biomarker temporal HMMs were designed for behavioural or death risk segmentation. Simultaneously, a family of deep network embedded risk-aware graph neural networks was developed to infer with personalized representation integrals for real-world-heavy-tailed quantile estimation.

5.3. Computer Vision

Computer vision concerns the extraction of information from images or sets of images, which can include producing a descriptive summary of the images or classifying them into a predetermined number of classes. In insurance, the application of computer vision focuses mainly on the first problem and the processing of images taken prior to underwriting. For inspecting and ensuring the construction quality of various structures, including highway bridges or underground tunnels, it is common to have a human specialist examine each of these structures in detail. More recently, this process has been automated and inspected by a computer program. It is faster and cheaper while yielding the same result. Some insurers deal with risks that a human specialist absolutely cannot assess. For example, it is impossible to visit every one of the hundreds of millions of buildings worldwide. However, images obtained can be retrieved. Recent graph neural networks have even suggested that the entire task could also easily be automated and formalized in a probabilistic graphical model. This second stage can be achieved using similar approaches as those mentioned above.

Fig 3 :Top 15 Most Popular Computer Vision Tools

Two other analyzes on the distributions of risk variables can also be easily automated. The first involves the detection of changes, which can be the modification of the façade of insurance buildings. This can be done using pictures taken by drones remotely. The second involves architectural recognition, determining the architectural style of a building. This classification can yield two benefits. First, it could help identify the probable year in which the building was constructed, which generally affects the exposure to earthquake and fire. Second, it could be tied to the knowledge about how to group buildings into classes, which generally have similar properties, such as pricing. In general, it can be stated that the approach, which starts with complex non-vector data and results in interpretable and useful preprocessed data, is developing fast in most domains and is expected to progress in insurance.

6. Machine Learning Algorithms in Risk Assessment

Machine learning algorithms improve risk assessment in underwriting by allowing for rapid analysis of risk indicators from varied data sources. The algorithms, designed to learn and adapt as more data is analyzed, can be classified into three main categories based on the learning techniques they utilize. These are supervised, unsupervised and reinforcement learning. Supervised learning algorithms generally are used where existing data with known performance is available and can subsequently be used to build a predictive model. Unsupervised learning algorithms are used where data is abundant but not labelled and looking to identify patterns where no prior grouping of the data is available. Reinforcement learning models are a relatively new technique and utilize a training set, which changes with each additional transaction or data point. An example of the application of reinforcement learning is an algorithm that adjusts the quoted premium based on the accept/reject decision out of the portfolio of policies offered up for underwriting by an underwriter.

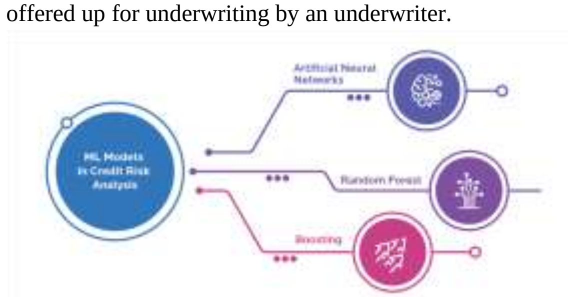

Fig 4 : AI, Machine Learning, and the Future of Credit Risk Management

There are a variety of supervised and unsupervised machine learning algorithms. Some examples of supervised learning algorithms that can be applied to underwriting and risk assessment are gradient boosted decision trees, logistic regression, decision trees and random forests. As these algorithms have a relatively straightforward nature it is advisable to try these first before attempting more complex algorithms. In general a gradient boosted decision tree outperformed all other algorithms. A gradient boosted decision tree is a robust algorithm that consists of multiple

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decision trees, with each tree improving upon the prior trees predictions. Although the algorithm requires some tuning it can be implemented quickly and easily in a variety of software packages with low code implementations available. Comparatively to other supervised learning algorithms the gradient boosted decision tree algorithm performs similarly well out of the box but performs advantageously on miss-specification tests .

6.1. Supervised Learning

Supervised learning can help insurance companies create accurate pricing, underwriting, and fraud detection systems. By using a large quantity of data about the insurance company, such as previous claims, it is possible to create complex models to predict future claim amounts. Many insurance companies have recently implemented pricing algorithms to automatically calculate and adjust the price of current products. These systems use forward- and backward-looking variables, such as the policyholder's perceived value, historical claims data, average customer acquisition costs (CACs), and other interactions with the insurance company, in ensemble approaches with boosted trees. Instead, these systems can also use a bag of pre-trained transformer architectures paired with transfer learning to achieve state-of-the-art performance on numerical prediction tasks. These are one of the main lines of insurance pricing by academic and industrial implementation.

Supervised learning is also used for underwriting automation. The transformation of entire industries by machine learning is based on graphics processing units (GPUs), open-source libraries, and large datasets. These techniques have proven successful in fraud detection, and American, English, and Central European companies use various computing tactics to predict fraudulent claims based on policyholder histories, partner behaviors, claim ratios, and social network-style features . Questions outside the underwriting process are beginning to be applied to the underwriting process in the insurance sector. It could be demonstrated that full automation of underwriting decision speed was safely achievable. At the same time, it showed that only limited automation of pricing decisions was safely achievable.

Besides pricing and underwriting, the possibility of fraud detection systems is flourishing. By focusing on personal and commercial auto insurance fraud detection, promising results could be achieved using techniques formulated in the open-source Deep4Fraud package to get indications of anomalies in transaction records as well as values of the policyholders' geolocations. While many applications leverage neural network architectures, there is ample room for contribution to the industry using tree-based approaches as well. Coincident with demand.

6.2. Unsupervised Learning

There is a growing thirst for data in the general insurance industry, as it gathers increasingly diverse types of data for use throughout the entire insurance process. However, for all of these forms of data, the existing ratemaking models typically used by actuaries were built without consideration for them. The data utilized in any given classic ratemaking process is often primarily quantitative, based on a few large unstructured data sources. In contrast to that philosophy, many emerging data sources may complement the traditional data, resulting in much better insights as to the future losses in an insurance contract.. However, the majority of this additional information sources is gathered in a form that is incompatible with conventional ratemaking models. Consequently, there is a fierce need for a unified framework allowing actuaries to incorporate these additional data in their existing ratemaking models.

Representation learning is a candidate framework in this regard. The goal in representation learning is to create representations of raw data. A useful representation will transform the original data into a dense vector space where a predictive task (in this case, the classic ones of insurance ratemaking) is simpler to model. The goal of the work is to: (1) convene and piece together a short overview of methods to transform non-vectorial data into vectorial representations, and provide compelling examples of what these methods can achieve in the actuarial science context.

Equation 2 : K-Means Clustering Equation

$$\arg\min_{C} \sum_{i=1}^{k} \sum_{x \in C_i} \|x - \mu_i\|^2$$

Where:

- C_i = Cluster i
- μ_i = Centroid of cluster i
- $\|x - \mu_i\|^2$ = Squared distance b
- Goal: Minimize intra-cluster variar

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The contents are organized in three sections respectively focusing on data transformation and vectorization techniques, use cases of such transformations in classic ratemaking, and honest and overall discussion of those techniques, in the insurance context. Most of the methods showcased in this paper fall under the scope of unsupervised learning. Focusing on data transformation techniques allows to present a broader set of promising methods while showcasing applications in several settings in insurance, not just in pure ratemaking.

6.3. Reinforcement Learning

Multi-Agent Reinforcement Learning (MARL) algorithms are employed to address the implications of competitive pricing. In this setting, one insurer's pricing behaviour has implications for the objectives of others, leading to the emergence of a range of strategic pricing behaviours in the environment. It is computationally infeasible to know the pricing behaviour (policies) of all other insurers within the same environment, a setting often referred to as “partially observable.” This section discusses how MARL architectures and algorithms allow agents to learn pricing behaviours based only on local or observed information about competitor’s prices. In addition, agents can concurrently train with prices from enormous competitors so that any agent can better exploit competitors that are far away in the action space. It is important to note that all of these studies focused on the “single-agent" pricing problem within a stationary environment. In contrast, the paper addresses a more challenging pricing problem in a competitive “multi-agent" environment. A high-dimensional discrete action space (more than 100k actions) is required to accommodate all combinations of price modifications for the multi-price setting. This significantly complicates the underlying learning problem, with issues such as vanishing reward signals and search space explosion that are often referred to as “high-dimensionality” .

In this setting, there are even more agents that are concurrently learning and adapting their strategies. The interaction between their behaviours leads to emergent environment transition dynamics that differ from the local transition dynamics of each agent. This may lead to agents facing a non-stationary environment, which is often regarded as one of the main challenges of MARL . Agents only implicitly observe the policy distributions of other agents via the complex emergent pricing behaviours within the environment, and they do not directly observe each other’s actions. This additional challenge is often referred to as “observation limitation” before the integration of additional observation nodes, making it infeasible to furnish local information regarding other agents’ actions for conditioning policy gradients.

7. Data Sources for AI in Insurance

The fusion of AI systems and datasets capable of supporting these systems' functions brings about the potential for significant progress in industries like insurance. Insurers possess vast amounts of data. If it could be exploited properly, it could substantially improve how risk is evaluated in insurance underwriting. To make these fascinating AI technologies useful in the P&C insurance industry, access to novel data sources is increasingly required. The increasing availability of various alternatives for novel sources of information creates promising opportunities but also daunting challenges.

Fig 5 : How AI is Transforming Credit Risk Management

More and more opportunities for novel data in the insurance process emerged in the last decade. These insurance data sources combine industry capacity to obtain large and heterogeneous datasets, the development of advanced computational techniques to leverage the data, and the emergence of novel data acquisition technologies making it cheaper to obtain data . Examples of novel data sources include a broad variety of data collection, processing, and insights extraction techniques. Textual information is harvested from online review sites, news articles, or passport application documentation and combined with network analysis techniques to detect fraud. Structural information about buildings, contents, bridges, or tunnels is inferred from images found in public databases along with structural simulation or computational fluid dynamics techniques. Information about driving habits is collected from GPS receivers embedded in cars or mobile phones and processed via classification algorithms to measure whether driving is smooth, aggressive, or incautious .

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Some of these emerging data sources can complement traditional data sources to provide better insights to predict the risk of future losses in a contract of insurance. For example, it may be possible to predict catastrophic flood claims better using flood susceptibility maps than using the geographic location of the concerned buildings alone. Although all these predicted models are motivated by the insight that there are other, possibly improved, ways to risk discovery than instructed algorithms acting on sparse traditional data, the mathematical sophistication and general applicability of the proposed models should be evaluated. Some of these emerging data sources have particular characteristics that make them more or less suitable than traditional data sources to assess insurance risk.

7.1. Big Data

Some leading commercial lines insurers' uses of creditworthiness data in underwriting and claims processes have raised significant regulatory, enforcement, and reputational risks. Similarly, more aggressively negative media coverage focusing on remote sensing of property characteristics, surreptitious gathering of information from social media, and/or monitoring of customers' effectively surveilled driving to infer the risk of future accidents should become a clearer possibility . Such scrutiny would naturally raise questions about whether insurers' use of those and similar inputs to the degree that would boost their predictive performance might violate federal or state consumer protection or anti-discrimination laws, or exceed what would be deemed acceptable even if few or no laws were violated.

In theory, the mathematical techniques and computing capabilities that allow for the application of Big Data analytics to insurance marketplaces lend themselves to hordes of practical insights regarding how input desirability varies with consumer characteristics. Emerging insights' possession of that powerful capacity for structural understanding raises the specter of a rise in "data darkness" or consumer disadvantage. For example, if gathering of ticket purchase data were to be paired with mathematical insights to enable assessment of willingness to pay, airlines could substantially increase revenues even in the face of great threat to passenger welfare. Such broad-based affordability or access challenges raise a host of hard-to-answer questions about the policy landscape necessary to encourage wondrous Big Data advances while limiting nefarious application.

The combination of recent developments in data science and insurers' existing predictive analytics practices has the potential to catalyze incredible advances in efficiency and innovation, creating tangible benefits for consumers and providers alike. But it also poses substantial threats to consumer welfare in the context of insurance markets. Amalgamating so much information about consumers makes data breaches more consequential. Companies' uses of Big Data can violate anti-discrimination laws. Insurance markets possess certain characteristics that will cause insurers' embrace of Big Data analytics to threaten public interests. Competitive pressures and the increased availability of data will inevitably lead the industry to begin collecting and analyzing massive amounts of information about applicants' social and commercial behaviors.

7.2. IoT Data

Insurance companies are rapidly evolving technologies in response to the growing demand for effective, affordable, preventative, and tailored insurance products. As competition surges, Personal Lines (PL) insurers are integrating new data sources into their risk assessment processes with new technologies. One of the more recent data strategies involves tapping into the Internet of Things (IoT) ecosystem to enable the real-time collection of detailed risk information. IoT data may vary widely in form and source. As such, using IoT data requires new methodologies to refine and aggregate raw data into usable risk factors. In addition to the practical challenges posed by this emerging data strategy, IoT data mining poses a number of fundamental actuator challenges that need to be addressed to fully realize its potential value.

There are opportunities for insurers to better understand their policyholders by exploring the use of IoT data for risk assessment. That said, the kind of IoT data is diverse, while the data can be sparse in nature. Therefore, there are feasibility concerns regarding how to select and refine IoT data to maximize their predictive potential. The development of effective insurance pricing methodologies has always been seen as a challenging endeavor . One area previously overlooked yet is whatever a simple or complex model should be employed for each risk factor, especially for the precise representation of non-linear relationships. With the advent of various machine learning algorithms, models with uneven complexity can be used to capture heterogeneous consumer behaviors.

Such emerging methodologies bring new opportunities for actuaries to explore, yet many challenges arise from potential overfitting, model interpretability, dimensionality, computation burden, and competition. Another main challenge overlooked in the literature is how to make optimal use of newly collected IoT data to ensure a fair and

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affordable underwriting of consumers with a wide range of risk profiles . With the growing prospect of heterogeneous and multi-source data, actuaries shall establish better guidelines and criteria for data usage, while regulating agencies and data governance groups need to monitor the fair and accountable use of data.

7.3. Social Media Analytics

Social media data are generated by users across a variety of platforms and can take diverse information formats (i.e., videos, photos, texts). Social media analytics refer to the set of tools that facilitate the harvesting of this information. Insurance companies have experienced increasing interest in a wide array of emerging data, ambitious to provide additional signals to traditional data sources in order to predict future losses . Using data processing treatments in conjunction with predictive modelling tools, insurance companies have proven solid expertise in traditional data analytics, and recent research has demonstrated this methodology's success to analyse dynamic and time-dependent forms of information in the non-traditional context of social media. The increasing volume of information is a challenge for insurers and a well-structured process must maintain model tools' efficiency, performance, and robustness. Indeed, implementing data-stream analysis methodologies requires profound knowledge of data construction and properties within both the contextual and digital environments.

The scope of this pathway is to frame most existing tools and techniques of text and photo analysis available across social media and to outline a well-defined process at both the data engineering and modelling levels that can maintain performance and validity on such emerging data inputs. Data manufacturing should be carefully handled to restrain corruption, noise, and bias . An analysis model's architecture is the statistical choice that will ensure best performance, generalizability, and robustness. On social media platforms, the presentation of data could change along with new features on platforms, new frameworks of publication, or additional filters to content categorization. These changes, in turn, can modify data construction. A monitoring structure for performance tracking should therefore be put in place to preserve robustness and maintain up-to-date performance.

8. Benefits of AI and Machine Learning in Underwriting

The insurance industry is undergoing a digital transformation driven by technology. New technologies allow insurance companies to offer new and improved services to their customers. Advances in data science, AI, and machine learning lead to a deeper understanding of consumer behaviour and risk assessment. These technologies also allow companies to automate processes of gathering and processing large amounts of data. Businesses in all sectors can benefit by increasing revenue, efficiency, and improving customer satisfaction.

Fig 5 : Transforming Commercial Insurance Underwriting

. Cyber-crime is growing, and technology failures and data leaks are becoming more common. Incidents in companies that store personal data such as banks and insurers are common news stories, causing reputational damages and hefty fines from regulators. As a result of this "increased digital risk", companies look for improved risk mitigation strategies. In today's digital world, insurers see opportunities in providing "cyber-security" insurance, as well as a growing need in mitigation through risk assessment consultations .

Insurance companies have recently increased efforts in preventing insurance fraud. Because insurers require more personal data to assess the risk of accepting an insurance proposal, attempts to mislead the insurers increase accordingly. Data science and AI are increasingly used to analyse insurance proposals holistically and detect suspicious proposals before they are accepted. Automated generation of proposals' scores based on combined factors is also becoming more common. Many of the mentioned technological trends are already used in the personal insurance market, but only slowly in the commercial insurance market. Most of these require insurance knowledge, making adoption and productization more difficult. Nevertheless, some innovative companies have developed pilots for the commercial market using the aforementioned data science and AI innovations.

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8.1. Increased Efficiency

Because risk assessment has many adverse qualities in today's insurance market such as time, costs and subjectivity, a rapid development of AI in the insurance industry is gradually undertaken with breakthroughs in many problems such as underwriting, claims, fraud detection and compliance. The classic underwriting process usually consists of three steps including information gathering, exposure verification and acceptance decision, while the predicted probability of loss is evaluated on compiled information . However, due to the huge burden of manual underwriting process and compliance risks, fully automated underwriting is implemented by many insurance companies by deep learning and entity linking. In order to bridge the gap between loss prediction and the need for a structured pricing table, methods employing the ideas of Copula are raised to build the pricing table and generate premium for omitted risk exposures with promising results.

Meanwhile, a new paradigm shift of Risk Assessment 2.0 is under rapid development because of the booming sharing economy and non-insurance risk transfer technologies. A core of risk assessment 1.0 is underwriting in an insurance regime with collaborative incentives to accurately evaluate the risk exposure of clients with risky behaviors on shared axes, while risk assessment 2.0 expands risk assessment from underwriting to broader domains including risk prediction pricing algorithms for non-insurance risk transfer technologies such as comparative services. Risk assessment 1.0 is revisited with models for contact networks and risks, while some newly desired capabilities required for risk assessment 2.0 are also mentioned. Finally, internet-based companies with novel risk assessment and governance models are presented to demonstrate the new style risk assessment. Looking forward, some future development trends and important issues on effective assessment with valid and valuable community involvement are also discussed.

The process of underwriting has been evolving rapidly with the advance of Artificial Intelligence (AI) and big data. Around ten years ago, underwriting made use of early stage of AI algorithms to extract structured features. Moreover, insurance regulators of many countries imposed prudential regulations on data use. To tackle the challenges brought by these rules and regulations, the fundamental underwriting process needs to be redesigned as a closed and interpretable system. An interpretable variance-explaining tree (IVET) for risk assessment is introduced to uncover the existing dilemmas in the underwriting system and subsequently redesign it with more interpretable, robust, and human-centered AI/big data architecture.

The Redesign of the Underwriting System. The classical underwriting process involves three necessary steps of information gathering, exposure verification and acceptance decision. A client of a new application form submits to an insurance company via the internet. Then the insurance company gathers data and information for risk exposure verification from multiple external or internal sources using web crawling and API calls and sends queries to relevant departments.

8.2. Enhanced Accuracy

While machine learning has been a driving force behind influential innovations, it is still a challenge to achieve widespread utilization across the insurance industry's most critical areas. Implementing AI may require significant effort, extensive data enhancements, acquiring relevant expertise, and persuading key stakeholders to adopt AI-driven solutions. The technology will also need to progress to address changing available data and consumer preferences, as insurers have learned that value propositions based solely on avoiding harm will be challenged by alternative firms offering better arrangements. Measurement-based insurance products are likely to be more commonplace with opportunities in data-rich environments, but that will require creative thinking and AI development to effectively price risk.

Bias is a major concern in developing and using ML techniques. The necessity for ML algorithms to learn from data raises concerns regarding the contents of supplied data. Excluding variables used in traditional risk assessment algorithms from an ML process may be insufficient to ensure fairness. ML models should be continuously monitored and regularly updated to remain relevant and avoid sacrificing fairness for accuracy. New and inadvertent biases should be acknowledged and mitigated to the greatest extent possible. The use of geo-information, third-party data, or social media may pose challenges to fairness, while questions of model interpretability may arise in both supervised ML and natural language processing contexts. The insurance industry and regulators need to devise ways to ensure firm accountability without stifling innovation and ensuring scalability.

Despite these challenges, AI adoption has huge implications. Insurance companies usually rely on table-based approaches to generate premiums based on characteristics such as the insured person's age, car type, and driving zone, to name a few. Typically, a table for each one of the characteristics is obtained, and they are combined using statistical methods. The pricing process is

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often transparent, and a reverse engineering is possible by assisted model interpretability methods. Making a table for all the characteristics involved is complicated, and insurers often resort to a machine-learning algorithm. These algorithms provide an accurate risk prediction, but they often lack transparency and interpretability. The decisions made using these algorithms can be hard to explain, and correctness can be complicated to verify.

8.3. Cost Reduction

Many older documentation-based risk assessments datasets and their expert knowledge would remain powerful and vital to aiding models learn to recognize risk from newer, more integrated databases. Moreover, owing to historical discrimination against women in credit affairs, there are now statistically observable differences in risk between men and women. Relying on open data, insurance could reduce overall claim frequency means (refusing tablet-based apps or smartphone data by some customers could worsen the data pool). Both the 27-member states of the EU and the states of the USA have enacted modes of regulating AI to prevent the discrimination and unfair differentiation uncovered here. Furthermore, it could analyze transaction streams instead of charge sequences, thereby developing multicard risk profiles (each customer with a different risk pool). The same data-mining could help domestic insurers develop re-insurance models for all type building inspections as well as fire, flood, storm surge, etc. bluesky risks. Lastly, instead of forcing a proof of non-peeking at privacy-sensitive data, consumer sensitivity dimension scores listed 0-Feelings 9-Worse 10-Data Lawsuit could replace actual data. This could produce aggregate privacy scores guiding fairer policies re buckets and budget life chances (e.g., insurance premiums, rent increases, syndromic repairs) . Government policies could de-bucketing per industry above a limit (except if weighing new data sources is justified on grounds of safety, scarcity, suddenness, consumer need for choice or long-term affordability). Any discriminative bucket must always be explained, and consumers could have a say re their entry and exit there from in front of a neutral board. This could cut municipalities financed entry to data markets to change a privacy score. Differentiation could then become cheap enough to keep digital environments accessible under smart, organic, data mining picking off extreme prediction-fewest bits possible uptake.

9. Challenges in Implementing AI in Insurance

There's much interest in AI in the insurance industry. Much is expected of it, as with other industries, including significant efficiencies, greater risk understanding, and more tailored offerings to consumers. This notion is in line with economic theory: A better understanding of risk should reduce the cost and availability of risk mitigation, even in contexts where risk and risk pricing are affected by moral hazard and adverse selection. The COVID-19 crisis increased acceptance of AI in the insurance industry. But at the same time, there’s much wariness. This may come from bad experiences from the past or be associated with equity and ethics concerns, such as allegations of racial discrimination. In the present research agenda, starting from a broader theory of AI systems, recent developments around the use of AI in the insurance industry are mapped, including AI-related denials of claims and premium calculation and pricing, along with both discriminatory concerns and explanations. Rights approaches, including prohibitions against unjustified discrimination, data protection law, insurance law, and new legislation related to AI are discussed, and informed research questions are defined.

Equation 3 : Risk-Weighted Challenge Score

$$CAI_{score} = \sum_{i=1}^{n} (F_i \times I_i \times P_i)$$

Where:

- F_i = Challenge factor i
- I_i = Impact of factor i
- P_i = Probability of occurrence
- This helps insurers score and rank challenges based on severity and likelihood.

During the COVID-19 crisis, or perhaps better since COVID-19, much has been written on the digitization of societies, including in healthcare and education, retail, manpower and hiring platforms, customer relations, and the like. Amid this broader interest, there’s also much interest in AI in the insurance industry. In line with other industries, as around AI in health tech, the notion is that much is to be expected of AI, including significant efficiencies and therefore at a smaller cost for a better understanding of risk and even more tailored offerings to consumers. Such notions resonate with economic thinking. By better understanding risk, even in contexts where risk and risk pricing are affected by moral hazard and adverse selection, it should be possible to lower costs and increase breadth in the offering of risk mitigation.

This optimistic narrative is not solely based on the expectation of new technologies. Deeper societal changes

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are involved and already observable. COVID-19 encourages online offerings. Young adults and rent seekers are increasingly difficult to start. Mandatory disclosures are legislatively defined . There's an increased sensitivity to risks, including the long- and short-term consequences of climate risks and the spread of risking in a digital society, etc. From other sectors and sciences, the notion is that tighter regulations also come. At the same time, there's much wariness. This may come from bad experiences from the past or elsewhere or be related to equity and ethical concerns, such as allegations of racial discrimination. The current research agenda aims to start from a broader theory of AI systems and, from this, map recent developments around the use of AI systems, and the like, in the insurance industry, including around AI-related denials of claims and AI-related premium calculation and pricing.

9.1. Data Privacy Concerns

The combination of recent developments in data science, including machine learning (ML), and insurers' existing predictive analytics practices has the potential to catalyze incredible advances in efficiency and innovation, creating tangible benefits for consumers and providers alike. But it also poses substantial threats to consumer welfare . These issues assume greater significance in the context of insurance markets. Amalgamating so much information about consumers makes data breaches more consequential. Firms' uses of Big Data can violate anti-discrimination laws. Insurance markets possess certain characteristics that will cause insurers' embrace of Big Data analytics to threaten public interests. Competitive pressures and the increased availability of data will inevitably lead the industry to begin collecting and analyzing massive amounts of information about applicants' social and commercial behaviors.

Even if misuse or a security breach is revealed to the consumer, they cannot change their health information like they can change their bank account details to protect their privacy . Therefore, sharing this health information causes privacy concerns. These privacy concerns can be a key predictor of using health services online. Privacy concerns can be divided into perceived privacy control and perceived privacy risks. Perceived privacy control can include confidentiality, secrecy and anonymity. Perceived privacy risks can include the sensitivity of the information and the level of regulation. Using AI in healthcare insurance can reduce the perceived information control and increase the perceived risk. The lack of understanding of the role of AI in this context, the unpredictability of AI, the low transparency on the algorithms, the lack of humanness and the unclear ethics may increase the concerns over personal information privacy. Furthermore, AI is part of an ecosystem of technologies such as big data that enhance each other's capabilities and pervasiveness. When a consumer enters their personal information during the process of acquiring health insurance, they may be thinking about how this personal information could be used against them in the future. An example of this is the privacy paradox where consumers still give their personal information despite their concerns. Therefore, it is necessary to identify all the relevant factors and model their relationship. The literature review identified two enablers and two barriers to the use of AI in insurance from the consumer's perspective. As the consumer will be explicitly informed about their interaction with AI, this may influence their attitude and raise the barriers of insufficient trust and information privacy concerns.

9.2. Regulatory Compliance

Managing and addressing challenges in regulatory compliance, with the shifting landscape of the digital economy, requires a firm understanding of the regulatory environment across the entire organization with respect to country and regional jurisdiction. First, insurance firms are required to gain access to a clean and comprehensive set of risk and market data. In collaborating with third-party data providers, care should be exercised to address concerns surrounding data quality, completeness, inherent bias, and fairness before integration into underwriting and risk assessment models. It is essential to document the use-cases in deeply technical and business-friendly ways to avoid potential non-compliance issues surrounding data sources. The incorporation of business rules pertaining to the use of AI/ML in the recommendations/calibration of underwriting policies/rules, as opposed to only supporting an underwriting decision, addresses many of these issues since they provide maximum transparency into the working between Variables and Recognized Rules or Business Logic. This is accompanied by the use of an Underwriting Governance Framework to assess the consequences of rule changes and discover unintended consequences downstream from the AI/ML decision recommendation.

Further, regulatory compliance at the country-level adds another layer of complexity to the above. At levels of regulation, from Principals to Policy, the laws and regulations controlling how explosions can be discovered and triggered across companies/individuals/agents are different in every single country. It is therefore important that the entire underwriting process is thoroughly understood and that an encyclopedia of rules is prepared for new products. Compliance is aided by understanding the statutory and regulatory environment surrounding

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prohibition vs. regulation, including the immediacy and visibility of disasters caused by violations of the law that underpin local AI regulation focus. Understanding the regulatory risk across the life-cycle of products across geographies is especially important in cases of quick and radical product change and sudden appearance of new information. Such a codification process could lie at the heart of setting up a compliance team to manage the risk of this burden through the ingestion of natural language. Also, industry knowledge can be captured through the representation of business rules together with a direct pipeline from raw documents to discovery tasks.

Use-cases for the employment of ML/AI in Insurance illustrate their very diverse statistically in nature. The serious structural changes being undertaken across businesses necessitate a factory/hub model of service provision to better recognize and enculturate new ways of working and enable necessary skills and tool transfer. Automation targeting key processes is driving significant models.

9.3. Bias and Fairness

The deployment of AI made possibilities for providing decisions based on data and automated processing. Use of ML algorithms, from a set of data important features are considered, excluding irrelevant or redundant ones. Data may contain sensitive variables such as race of applicant, which should be excluded in compliance with regulations. However, the automatic assessment come with risks. Automated decisions may result in unequal treatment of groups i.e. protected by law, resulting in biased substantive decision outcomes. Therefore, explanations of algorithmic decision outcomes become a pressing need. Multi-metric alternative methods are needed. It is possible to mitigate the bias by alterations made in the feature assessment procedure. A constrained modelling task can be used approach with protected variable ensured that only equitable decisions are taken concerning the applicant groups, therefore, data on groups can be analysed in a different way: minimization of discrimination in subgroup outcomes ..

Bias towards factors related to income may have neutral outcome in respect to population means, but some clear protection of groups, i.e. with unfavoured factors, needed. E.g., unfair treatment of overall outcome leading to loss of a group of applicants with a preference in the acceptance rates. Otherwise, a group with a preference treated sharply equally can be punished. In practice, however, many secondary economic factors apply: equally treated loss leading to a higher risk missed. Also, a consumer will try to move from unfair treatment to mitigate circumstances in case of detection . AI is increasingly integrated into various business and policy domains, revolutionizing processes in the context of big data. Institutions specializing in insurance are no exception to the growing trend of data-intensive underwriting. As a result, they are victims and perpetrators of unfair differentiation in automated settings. This includes the advantages of levying personalized premiums in line with the risk of clients, as well as the possibility of monitoring behavior and being “nudged” in unhealthy or risky patterns. A better understanding of the mechanistic intertwining between insurance and AI is needed.

10. Case Studies of AI in Personal Insurance

While the insurance industry has been slow to adapt to new technologies compared to other fields, AI now shows great promise in enhancing the speed and precision of risk assessment and price calculation. Given the vast sources of information and the eagerness of consumers to share it for incentives, insurers can now fully serve the most needs of the insured. More and more insurers use AI to analyze data, leading to automated decision-making in underwriting, price calculation, and claims handling. However, this brings scrutiny regarding fairness and discrimination in assessment and policy.

In the effort of deploying AI in pricing, insurers currently mainly focus on automating and enhancing models of data already used. A further step could be to develop and implement other innovative models for new types of data. Better exploitation of new data sources could change the industry. Insurers could obtain even more advantages by exploring undeveloped types of data and developing models to exploit them. Using privacy-sensitive sources, like social media profiling, requires beautiful balancing between lower risk assessment and more privacy intrusion [2]. In this regard, it remains to be seen whether and how the already quite pervasive processing of new data is furthered by using AI in insurance.

While the use of AI in risk assessment is still in its infancy, adverse effects have already occurred. There have been some accounts of discriminatory or unfair practices of newly developed algorithms that were suspected of sacrificing fairness for prediction improvement. However, many statutory and NSM duties come with the use of these technologies, which may mandate the assessment of such questions according to fairness criteria, partly specified in

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law. It can be expected that uncertainty regarding the assessment of newly introduced technologies looms in more extensive studies; however, insidious effects of the new technology have also been described that do not or may not primarily pertain to illegitimate discrimination in contravention of laws. Still, they may cause big trouble.

10.1. Homeowners Insurance

Homeowner insurance (HOI) coverage helps provide financial protection to homeowners for expenses arising from loss to their properties and injuries to other people. HOI products are provided as packages, which guarantee against default, so a bank won't refuse to process into mortgages, as long as payments are made. With the integration of machine learning and AI in HOI underwriting, existing technologies and data may yield new insights to improve risk classification for more accurate premium pricing. In addition, explanations of these systems will be more credible due to their foreseeable, albeit defeatist, inevitability.

The HOI underwriting process may utilize the following data layers: (1) forecasted natural hazard data on wildfire, earthquake, and flood based on scientific models that describe conditions resulting in these hazards; (2) simulated financial data with insured structures being settled or repaired with validation of aggregate claim amounts against official financial statistics; (3) historical masked claim data proven non-refutable and essential for empowering parameterized models of HOIs; and (4) other historical data on loss-causing agents including water heaters, types of insurance policies, soil types, and HOA (Homeowners' association) constraints [8].

A classification tree is established through Monte Carlo simulations making reasonable assumptions on all four data layers. HOI underwriting classifications are fitted into the classification tree, which is analyzed to derive HOI underwriting charging functions. A state is classified into one of the classes of natural hazards, for example, state = (earthquake, none, wildfire, none, flood/other continental…); classification indices of those hazards already known are filled in, with the other with the highest possibly CO standing still to be classified.

10.2. Auto Insurance

Auto insurers have become quite progressive in adopting AI (or ML) underwriting, providing bets in better pricing, more accurate risk assessment, improved risk management & prevention, personalized coverage terms, better loss avoidance measures, and strong fraud detection mechanisms. Insurers are increasingly seeking to tighten the intellect engine upon which their underwriting is built. MVP has been inundated with a surge of inquiries from leading auto insurers globally seeking to integrate advanced machine learning and artificial intelligence capabilities for underwriting automation, risk classification improvement, claim cost estimation, inspection automation, and telematics. Insurers have begun adopting better modeling and analysis approaches for understanding risks coming from new data and enhancing underwriting decisions. They are either seeking to build their machine learning and artificial intelligence models, processes, and platforms from scratch or achieving the same through partnerships with leading insurtechs. There is a huge variety in the scope of underwriting requirements and capabilities. Yet, a well-defined process evolution roadmap and defined milestones on that road can help minimize failures in AI-model setting, deployment, and performance enhancement.

The boundaries identified for the application of deep learning enhancements affect the capability to implement a well-defined AI process roadmap, and auto reinsurers and insurers are working on the same broad issues across various regions. The scope of AI enhancements can vary significantly between reinsurance and insurance organizations within the same line of business. Planning well-defined approaches for each part of the AI process, which are based on the success criteria developed for each task, can help in maximizing the value extracted from AI. On the other hand, the evaluation success of other process parts can be more effectively benchmarked through comparisons against like enemies. Trying to do too much at once or being too broad could overwhelm the implementation, thus risking failure. In a rapidly changing environment, rapid iteration of enhancements can be more beneficial than a lengthy design effort with far-reaching deployment timelines. Fellowships need to be taken across the board but need not be tackled in one step [2].

11. Case Studies of AI in Commercial Insurance

AIG has developed several Artificial Intelligence (AI) platforms designed to streamline the underwriting process for various kinds of business insurance. Risk Insight, for instance, allows an underwriter to check a company's risk and exposure with just a few clicks. The platform is capable of analyzing thousands of external data sources to find relevant information using natural language processing and machine learning algorithms. AI and machine learning can help insurance companies with risk selection by

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creating a first-cut underwriting decision using various data sources. However, younger firms providing on-demand insurance offerings at low prices might be considering the implications of how and when to implement underwriting robots because such technology requires extensive back-end integration.

Greater transparency in machine-driven decisions is required for data privacy and discrimination model regulation to mitigate risks. Underwriting fitness is yet to be validated in any case, and having more risk factors may increase adoption challenges further. Reading the Underwriting Algorithm (RUA) of machine learning-underwritten policies could allow underwriting firms to check the risk comparison factors employed by a given model. The algorithm does not provide an overall picture of how risk is compared and rather focuses on evidence-based documentation highlighting risk inconsideration. However, such public documentation is in its infancy, and the underwriters and firms may require everything checked to trust a potential shifting rate.

RegTech AI And The ROI Target The pace at which insurance companies were digitizing was estimated to have shortened even before a global pandemic accelerated the transition. By July 2020, many firms had lost market share by even missing FY20 ROI targets. In line with this trend, insurers have begun to invest in and examine AI and fintech systems to enhance revenues. These firms are adopting online channels and gradual strategy transitions to combat every type of risk faster. Insurers have continuously supported manpower reduction and process speed optimization in every insurance market to achieve the desired improvement in ROIs. Significant deviation from this exponential trend stems from countries and companies with less than adequate resources.

11.1. Property Insurance

A considerable portion of the general insurance market is made of property lines that cover physical assets, buildings, and goods, such as homeowner, auto, and commercial property insurance. Consequently, property insurers cover economic impacts that arise from scarce events, such as catastrophes, accidents, and thefts. To account for incoming risk in the underwriting process, property insurers usually inspect risk locations and characteristics using historical data and supplementary reserves. Moreover, they tend to spread risk portfolios geographically, avoid catastrophic zones, accept collateral insurance letters, support mitigating measures, and be anchored with diversifying lines [1]. Underwriting has been a challenging task of trial and error for property insurers until modern tools of data science and artificial intelligence (AI) have emerged.

The rapid combinatorial growth of underwriting data has completely transformed underwriting into a subbranch of data science and AI. On the one hand, property insurers now scramble to gather and load nascent and emerging structured, semi-structured, and raw data onto databases or cloud storage. These datasets may include digitized public documents, regulatory filings, inspection reports, aerial images, satellite shots, social media animations, IoT feeds, and various environmental remote data. Generating dynamic physical digital twins of portfolio risks is a realistic expectation by consolidating these datasets [2]. On the other hand, data science and AI have substantially overcome data hurdles, developed sophisticated algorithms, deep learning structures, and GPU computing techniques capable of mining unstructured chain data, images, and videos since 2010. Predictive AI and automated decision-making AI models have transformed data pools into automated risk assessment, pricing, approval, and monitoring tools invisible to insurers. Similarly, AI-driven underwriters can derive customer profiles and assess insurance portfolios and business balance sheets for firm-level risk assessments.

11.2. Liability Insurance

The fast-developing AI technologies could enhance the efficiency and quality of products and services. With the increasing deployment of AI-based products in daily life, even though the economic benefit brought by the AI technologies is booming, there exists a lack of corresponding liability insurance to enhance the integration of AI into life. On the other hand, in the new historical situation, AI technologies, as an emerging phenomena, have demonstrated their unique and unprecedented features, resulting in an emerging moral hazard of AI technologies and the unprecedented development risks guaranteed by highly specialized systems [9]. These novel features of AI technologies lead to non-convenience of traditional liability insurance to guarantee their underwriting needs. They necessitate re-exploration of loss models, risk assessment, and pricing methods. To enable self-protection against the growing harm risks in the foreseeable future, it is imperative to invent a new market mechanism, AI liability insurance market.

The fundamental goal of AI liability insurance is to promote compliant behaviors in the design, development, and deployment of AI technologies. Insuring AI technologies as real-world assets with possibilities of indemnifying the loss caused by their functioning provides

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an incentive for parties involved in the AI industries to take necessary measures to avoid the occurrence of adverse events. Those compliant parties of insurance could obtain greater economic benefits than non-compliant parties. Therefore, insurance can effectively hamper the continuous proliferation of collateral damage of AI.

AI liability insurance can also serve as a certificate of peer quality assurance system. Peer insurers must take peer impacts into consideration when applying the Q&A policies to either reward or penalize clients. This mechanism will cultivate long-term mutual trust between peer parties and guarantee collective benefits. If an AI product cannot pass the insurance test, it is untouchable. The inability to pass the certification opens the door for rival competitors and potentially invites litigations from the harmed parties. As intelligent agents, uninsured AI systems become difficult to be controlled. The market disintegration illustrates a call on the necessity of AI liability insurance to mitigate the competitive risk.

The ever-increasing premiums would motivate AI industry participants to perceive it as a warrant of lower loss risk and safeguard a competitive edge. AI liability insurance captures the dominant feature of evolving ambiguity in AI technology and elegantly reflects the historical premiums adjustment of AI systems in the real world.

12. Future Trends in AI and Machine Learning for Insurance

AI and Machine Learning are fundamentally changing how insurers and reinsurers assess and price risk across personal and commercial lines of insurance. In particular, there is a growing interest from reinsurers in AI and Machine Learning and their potential application to underwriting. AI is a general-purpose technology that can change the structure and performance of entire industries. Machine Learning is an algorithm that can enhance pattern recognition from a dataset, commonly used in supervised classification and regression problems, with the potential for unstructured data utilising Natural Language Processing algorithms. In addition, AI and Machine Learning is actively being integrated into predictive modelling and risk assessment algorithms, which directly serve the underwriting function, and will have a transformational impact on underwriting and risk assessment.

In commercial lines, there is an increasing focus on risk analytics and AI applications in treaty portfolio construction, risk aggregation modelling, and catastrophe loss modelling. AI models are now just as interpretable and transparent as GLMs, but find “unconventional signals” directly related to risk through various AI applications. The rise of non-traditional data sources will drive change in the field of machine learning methodology, with the significant potential tailored data services for insurance.

In summary, in the next decade, insurance will become more customized, flexible, and accurate, with insurers honing the understanding of risk and developing engineered instrumented solutions. How can the insurance ecosystem leverage digital threads across life stages in the context of digital transformation? Having vested investments in ecosystems across verticals may yield exponential growth in insights and revenues. What win-win conditions will stabilize shifting insurance ecosystems? Concern around loss of consumer trust remains a critical commercial risk, and regulating and normative intervention even during cases of duplicit fiduciary expectations may allow for markers of trust calibration to evolve across the insurance ecosystem.

13. The Role of Human Underwriters in an AI World

Research indicates that human underwriters possess unique skills and knowledge that computers cannot replicate, nor can they be easily compressed into code. Research has revealed that their training and education focus on coding rules regarding policy wording and risk assessment. This gives human underwriters the upper hand in courts; their repudiation of liability triggers the “on the burden of proof” rule, meaning it will be up to the other party to prove they should be liable [2]. Despite the growing role of computers in underwriting, however, human underwriters are still required. Writing underwriting guidelines is a complicated process that involves subjective judgments about wording, exclusions and coverage. Coding these policies and the exceptions is an especially time-intensive task. In addition, the human-underwriting review of complex cases is not easily evaluated. By involving human underwriters in cases, paper trails are left of their reasons for decisions; when computers are at the helm, there is no record of how a decision was reached. This makes for a difficult, if not impossible, burden of proof scenario. Language versatility is another area where human underwriters stand to win. In conducting the underwriting review, human underwriters might rely on non-standardised information or supplementary documentation, which is difficult for computers to process. Even for standardised input streams, texts can be ambiguous; for instance, the word “salmon” may refer to either a fish or a shade of pink. Thus, the

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advantages of automated underwriting may not apply equally across the board. The human underwriter market will prosper in markets where coverage-decision processing is complicated and language input streams are heterogeneous, niche and complex.

14. Ethical Considerations in AI and Insurance

By identifying individuals' risk characteristics and price sensitivity, underwriting will task artificial intelligence companies with predicting whether an individual will take up an offer, and if so, how to construct an optimal offer without losing money. To achieve this, firms will need to identify, quantify, and express more complex factors as attributes, which will require further automating risk assessment [12]. However, there are ethical considerations surrounding the application of AI/ML to these tasks. With respect to human autonomy, this technology will enable firms to leverage 'big data,' feeding information about individuals into well-established predictive models of behavior that decide what risk characteristics to accept and at what prices. This raises the issue of whether such practices are a fair treatment of customers, especially concerning the fairness of the data used in the algorithms, transparency in the decision-making process, the interpretation of results, and the degree of human monitoring of the decision-making process and output. The firms will need to regard their customers as subjects of surveillance rather than merely as objects of business transactions or risk. With respect to the actions and perceived purpose of insurance firms, there are ethical concerns regarding their fairness, purpose, proportionality and impact on human autonomy.

Current practice in auto insurance offers some salient examples. Commercial and regulatory practice over coverage, price, and marketing means that most insurers have shared customer portfolios. AI/ML is generally leveraged on the price elasticity of demand, not on risk per se. Insurers leverage the potential behavioral and productivity dimensions of AI for competitive advantage. Pricing intelligence technology will estimate how loss ratios and profits vary with price changes. It will provide a richer understanding of individual customers and allow strategies to optimize price changes for maximum profit. On the enforcement side, firms can maximize profits by ensuring insurer compliance with filed rates. There are operational effects since the time and effort required from employees and management typically drop by orders of magnitude.

15. Regulatory Frameworks for AI in Insurance

Successful regulation of the new technology requires new regulations at the national, regional, and international levels that keep pace with the developments in technology. Cybersecurity solutions are required that effectively address the latest cyber risks, including the integration of AI and ML in cyber insurance. As insurance is a global industry, rapidly developing international regulatory standards must be complied with and implemented. Insurance regulation must also keep pace with the new generation of companies called InsurTechs and their solutions, which can potentially compete with incumbents. For example, requiring traditional insurers that heavily rely on data and quantification models to provide insurance that pays in accordance with restored credit ratings may constrain the development of new business models. Regulators may be inspired to emulate personal identification code systems to consider, for example, whether such a system would be effective with respect to AI-driven or risk assessment-free pricing [12].

Regulatory measures that required disclosure and lateral growth of data networks among big insurance groups or supplementary data providers or even entry into the insurance market for big techs should thoroughly be considered before they are implemented. On a related note, digital innovation is reshaping the data and risk environment of the insurance industry. Cyber insurance and the upfront engagement of insureds are being implemented to improve security and address idiosyncratic risks, including aggregation risk. The sharing of agreed risk mitigation measures would likely become a key requirement of cyber insurance services rendered to large companies and public authorities. More broadly, risk transparency and risk communication have always been core services of insurers but have fundamentally changed in their purpose, form, and audience in the digital age. In any event, insurance regulation needs to respond with a sound regulatory framework to the profound challenges and opportunities presented by the AI-driven digital transformation of the insurance business model.

16. Global Perspectives on AI in Insurance

Advancements in AI and big data analytics have the potential to radically change the insurance underwriting and risk assessment function. The explosion of available data through IoT and associated services allows technology

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providers, insurers, and re-insurers to gain a fuller understanding of individual behaviour and relative risk. In this way, new data availability may serve as a springboard for transformational change in pricing and underwriting within an industry traditionally based upon a standardized, segmented risk approach. In turn, this transformation has the potential to affect the financial and operational results of firms in the insurance ecosystem. Such changes may lead to the increased advent of exclusion or disqualification for insurance coverage on the part of consumers with poor relative risk. Even when such consumers are granted access to insurance coverage, they may be quoted exorbitant pricing. Such a dramatic paradigm shift introduces a host of pressing ethical dilemmas. These dilemmas must be resolved posthaste if the benefits of recent technological advancements in pricing and underwriting are to be enjoyed, while also mitigating the societal risks. Given the rapid pace of recent developments, regulation and oversight remain woefully behind the curve. The now less than theoretical existential threats to many individuals and their families demand immediate, concrete, and decisive action from national governments and their international counterparts.

With the increasing sophistication of AI-enabled insurance systems, insurers may become far too adept at identifying and distinguishing between risk groups, hence increasing the potential for exclusion from coverage. In such cases, insurance policies or secondary data collection could even become so complex and esoteric, that formulation (let alone understanding and compliance) becomes impossible for the consumer [12]. With regards to proportionality – a household with a good fire safety history may be refused coverage, but they may incur higher premiums or only be offered insurance with significant excesses. Factors affecting coverage that are elided by insurance firms merely become latent controls, disproportionately affecting already disadvantaged groups. The wider financial industry possesses operational control over many aspects of the lives of both consumers and small businesses, and any feeds that transfer to insurers may be used to affect coverage, premiums, and terms and conditions. Insurers may then chase payment or deny claims in manner disproportionate to risk, damaging consumer autonomy.

17. Customer Experience and AI Integration

With the rapid rise of customer expectations in past decades, businesses face not only the rise in volumes of data, but a data imbalance. On one hand, they own an insane amount of data, stemming from numerous systems collecting data in crumbs, bytes and gigabytes. On the other hand, businesses are challenged by the rising customer expectations regarding tailored offerings, execution speed, ease of access, and user experience — the ideal customer experience. This discrepancy requires strong tools for partnerships with customers. Against this backdrop, AI can play an important, sometimes disruptive role, capable of improving each interaction by understanding human wants, needs, limits, behaviours, and further through advanced language processing, computer vision and knowledge graphing techniques — an integrated AI across touchpoints and experiences.

The implementation of AI in business is challenging; AI is multi-dimensional — a complex, social and adaptive system. Existing research predominantly view AI from a technical point of view. Recent calls, however, emphasise the need of a dynamic, contextualized, business view on AI. In this respect, AI practitioners intend to understand integrated AI's business transformation power and impact factors, given that timely and rightly understood, integrated AI offers immense value generation potential across a broad range of areas including customer experience (CX) enhancement, process transformation, improved operation and management efficiency, data-led insight generation, risk and compliance monitoring and focus on higher value-added tasks [2].

Given the wide variations in business understanding and implementation of AI, two practices can be identified — AI forwards and AI backwards. AI forwards practitioners work towards an integrated question and answer based AI across the frontends of service, sales, marketing, and human resources, focusing on CX. AI backwards practitioners in most cases started out automating certain work in a trial approach, holding RPA for business improvement and adoption — mostly lower order data types on the backends. To obtain a business view of integrated AI, the AI forwards underpinnings and ABC-model synthesis are presented, resulting in well-defined integrated AI concepts applicable in a context setting.

18. Training and Development for Underwriters

Although AI can replace much of the underwriting tasks today assigned to humans, underwriters' training and development will be crucial in the hybrid future. The underwriting and risk management function of insurers is highly multifaceted and thus is largely decomposable into many sub-tasks. Like their human peers today, AI systems

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in underwriting and risk management use large numbers of data received from several internal or external data sources to provide risk assessment [2]. A variety of algorithms, such as different types of machine learning techniques, from simple ones to more complex ones, can be employed to capture the relations between features and their prediction target(s) and then calculate a score for the risks related to the business being underwritten.

Just as humans are trained to implement better rules and procedures in their underwriting tasks, proper domain knowledge and understanding of the algorithmic modelling process, such as data cleaning and preparation, hyper-parameter tuning, and performance evaluation, are essential in training and developing these AI systems. It is noteworthy to point out that underwriters must be trained to correctly interpret the ambiguities of the machine learning models and their decisions in order to better cooperate with them and thus increase joint human-AI underwriting performance. In the meanwhile, the presence of non-interpretability and information asymmetries of AI systems may lead to a lack of cooperation and trust in their predictions by underwriters. In particular, post-fictive approaches aim to extract and visualize succinct representations of the complex black-box AI models so that the end-users, including underwriters, understand how their decisions are derived. However, existing model-agnostic interpretability methods struggle to deal with the intricacy of modern deep ensembles or tree-based AI systems, limiting their applicability to specific models only.

19. Impact of AI on Insurance Pricing Models

Never before have the underwriting and risk assessment processes of (re)insurers been subject to such drastic changes from a technological perspective. While there are still operational bottlenecks and automation efforts largely limited to “low hanging fruits” that have been the focus of earlier initiatives, many players are rethinking their entire underwriting approach from the ground up. Patterns for systematic changes are emerging. The widely held belief is that the productive, efficient, and widely scalable underwriting of 20th century property insurance is becoming increasingly impracticable. In time, it may even have been rendered impossible by the rapid emergence of data-driven, behaviour-based, and predictive underwriting and insurance protection systems that have the potential to converge the understanding of risk and how to guard against it in completely new ways. The combination of the rising availability of new types of data, increasing computing power, and the improvements in algorithms enables considerable advances in the quantification of (insurable) risks, which in many markets could counter growing inadequacies in the underwriting of established risks. Insurers that obtain a first-mover advantage in this newly possible understanding of risks and how to manage them are likely to outperform their competitors. At the same time, the consequences of the use of data could be extremely polarising for societies, economies, and companies if certain visible or invisible (latent) data become available to different competitive contexts and are scrutinised relentlessly based on more powerful machine learning tools and more expansive understandings of behavioural finance. Substantial attention must therefore be devoted to defining the boundaries when devising and evolving such systems.

20. Conclusion

AI and ML advances can help insurers across the globe economically. Emotionally, organizations or underwriting departments have the potential to be triggered. A significant lead was built that is difficult to breach. The show subsequently takes into account attention economy characteristics which drive the growth in revenue and consecutive belt-tightening. Data is at the heart of this exclusive club, which insurers are incentivized to exploit. More data is available, in which non-standard data can outperform traditional data. This result addresses insurers’ data needs by examining trends in other industries. This novel aspect will spur experimentation and new methods to experiment with go-to-market conditions and underwriting capabilities.

Conceptually, insurers do not face the data-nightmare that is postulated and the common ‘replacement’ model that by machine-learning-based algorithms need to match human decisions. With structuring, data integration and driving the implementation of policy definitions and claim scenarios, humans remain pivotal. Key takeaways or objectives eventually craft change. Operationally, more modeling rules will clarify and enhance standards. Insurers should have their own methodology with one integrated modeling tool driven by common processes. With challenges, insurers need to embrace a new software architecture to deal with more data as a starting point.

The insurance industry is quickly adopting AI technologies as part of efforts to digitally transform how they manage risk, serve their customers, and operate their businesses. As current economies globally are steering towards new realities, one prominent area of focus for the industry is underwriting, where many incumbent traditional players

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feel vulnerable. Forward-looking organizations are attempting to leverage innovative technologies to rethink and reinvent their underwriting capabilities, methodologies, and processes. The use of advanced technologies, such as AI and ML, allows for the potential transformation of underwriting beyond current manual, adversarial, and arithmetic practices. Skills and scope will shift from analysis and evaluation to one of novelty, insights, and creativity. Additionally, the use of AI and ML to aid, augment, and enhance human expertise will become salient. In a climate where competition is intensifying and challengers are proliferating, this seeks to convene experts and practitioners to analyze how AI and ML can transform underwriting processes, workflows, and profitability across commercial and personal lines.

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