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DISCUSSION
PAPER

AI AND THE OPPORTUNITIES AND CHALLENGES IT PRESENTS TO INSURABILITY

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CONTRIBUTORS

Artificial Intelligence and Data Science Working Group

JONAS HIRZ

ESKO KIVISAARI

PHILIPP MIEHE

CLAUDIO SENATORE

BOGDAN TAUTAN

FRANCESCO TORALDO

CONTENTS

1 INTRODUCTION

Insurability is heavily dependent on understanding the risks affecting those to be included in the insured pool. These risks are then shared by the participants in the insured pool: each participant pays a reasonable premium that corresponds to their risk, and the unlucky ones who go on to suffer insured losses will be compensated. But without good data and advanced modelling it is impossible to accurately ascertain the risk level and suitable pricing. If pricing is not set correctly the pool will potentially have either an inappropriate surplus (a problem that can certainly be corrected through lower pricing in future), or a shortfall that threatens its ability to compensate the insured events.

With the emergence of broadened opportunities offered by, for example, the availability of expanded data volumes, advanced prediction methodologies, and the use of artificial intelligence (AI) or machine learning, some have raised concerns that the concept of insurability is under threat. They perhaps envision a world where Laplace's demon has become a reality:

> *'We may regard the present state of the universe as the effect of its past and the cause of its future. An intellect which at any given moment knew all of the forces that animate nature and the mutual positions of the beings that compose it, if this intellect were vast enough to submit the data to analysis, could condense into a single formula the movement of the greatest bodies of the universe and that of the lightest atom; for such an intellect nothing could be uncertain and the future just like the past would be present before its eyes.'*[1]

More moderate considerations arising from misgivings about technological possibilities might include:

- that it becomes possible to classify risks so minutely that uncertainty disappears and the possibility of risk-sharing becomes obsolete, or

- that the expansion in the number of tools available tilts the information asymmetry (which has traditionally been to advantage of the insured party) too far in the opposite direction (i.e. that insurers have tools which make them a great deal better than the insured party at assessing risk), which could ultimately lead to discrimination and mean insurance becomes responsible for exacerbating social exclusion.

1 Pierre Simon Laplace – Essai Philosophique sur les probabiliés – 1814

An earlier study[2] suggests that the impact of artificial intelligence on society has so far been largely positive, reshaping the way financial institutions work and supporting the design of new products for the market. The research by M. Eling et. al. (2019) looks at various ways artificial intelligence is in use within the financial industry, focussing on data usage and process optimisation. The data is derived from case studies taken from 91 papers and 22 industry studies. They found that the most common applications of AI are in image detection, fraud detection, claims management, natural language processing and predictive analytics in the form of actuarial pricing models, as well as many other examples.

AI is set to help us understand, at least in an analytical way, the risks we face as a society and the risks insurance companies are willing to accept. To do this it requires vast volumes of data, and as such insurance associations, regulators, supervisors, insurers and actuaries should expect to be busy understanding and implementing the 'big data' concept, both internally through digitalisation and externally with respect to policyholders and stakeholders. Studies which deal with digitalisation within the sector, such as Bohnert et al. (2019)[3], have found that digitalisation is good for the business performance of financial institutions. The topic will certainly continue to be of interest, as it is probably one of the most important factors when considering a well-implemented AI landscape.

AI-powered products may lead to changes in risks, and these changes must be carefully examined when designing new products. The creation of data-ecosystems will ensure that data is not only highly accessible for different industries, but also shared between companies. With such expanded availability and access to data, insurers will be able to access and design new types of products that will ultimately challenge insurability criteria as they are currently defined. More efficient management will lead to lower costs; on-demand insurance will be more accessible – and will look different, as it will not be chosen from a static portfolio that carefully takes into account all elements of insurability criteria. New assets will be covered – personal belongings in connection to travel insurance, for example. As such, insurance of risks will change because policyholders will have the possibility to access low-severity risks for the time their asset / insured object is actually used and is at risk. Similarly, if societies develop a more risk-based approach, moral hazard may come into play, with individuals choosing the 'more likely moments' for their assets to be affected. If such a 'more likely moment' underlies a high-severity risk, the insurer's exposure could be higher, opening the possibility of challenge by moral hazard.

2 M. Eling et. al., 'The impact of artificial intelligence along the insurance value chain and on the insurability of risks', 2019, The Geneva Papers on Risk and Insurance - Issues and Practice

3 Bohnert, A., A. Fritzsche, and S. Gregor. 2019. Digital agendas in the insurance industry: The importance of comprehensive approaches. The Geneva Papers on Risk and Insurance—Issues and Practice

Generally, actuarial methods have been historically based on real-world actions and therefore data. Given that large volumes of such data have not been readily available in the past, actuarial methodology tends to use statistics, data accumulations, assumptions, and often simple proxies. There is always a need to challenge the data in terms of whether it is appropriate for a specific use-case, or is somewhat biased. In general, any data point requires some re-investigation – often called data validation or data quality assessment – as in insurance, data sets are the starting points for predictions which are sometimes crucial for the future. The current paper aims more at describing the theoretical background of AI and insurability. It is planned that there will be a later paper addressing the role of the actuary in this area.

All such considerations and modelling have ethical, societal, moral and even behavioural aspects. The impact and effect of insurability can be a direct consequence of the effectiveness or failure of such data validation, or the accuracy of data quality assessments. Data perspectives affect societies, and societal behaviour affects data. It is clear that the issues here are closely connected to the topics of fairness and explainability. The aim in this paper is to concentrate on insurability and leave these other important topics to further consideration.

This paper intends to explore the topic by explaining insurability, taking a look at state-of-the-art tools and analysing the tensions between insurability and novel data-related technologies.

2 SHORT OVERVIEW OF THE CONCEPT OF INSURABILITY

An insurance transaction involves the insured party assuming a guaranteed and known, relatively small, loss in the form of a payment to the insurer; this is given in exchange for the insurer's promise to compensate the insured party in the event of a covered loss. The insured party receives a contract, called the insurance policy, which details the conditions and circumstances under which the insurer will compensate the insured party. The insurer may hedge its own risk, e.g. by taking out reinsurance, whereby another insurance company agrees to carry some of the risks.

The question of insurability does not apply only to private insurance transactions but also in some form to all ex-ante financial agreements made to prepare for a risk. That said, it is practical to frame the question in the language of private insurance. By private insurance here we mean voluntary B2C (Business to Consumer) and B2B (Business to Business) insurance transactions in the market, including also reinsurance. The ideas presented here can also be adapted to other settings fairly straightforwardly.

In some situations being insured is compulsory, such as with social insurance. In such compulsory settings, some criteria related to insurability can be substantially relaxed. That said, we nonetheless believe that the concepts developed here are even relevant in these settings, with some modifications.

For a risk to be insurable the following prerequisites must generally be in place:

- **Large number of similar exposure units**
- **Definite loss** at a known time, in a known place, and from a known cause
- **Accidental loss**
- **Large loss** from the perspective of the insured
- **Affordable premium** in relation to the amount of protection
- **Calculable loss** – it must be possible to estimate both the probability of loss and the cost of any loss that occurs
- **Limited risk of catastrophically large losses**

The above-mentioned prerequisites will be discussed in more depth in chapter 4.
While these general characteristics may qualify a risk as insurable, there are additional requirements that influence the situation and often create circumstances where insurability is threatened. The main issues in this area are:

- Control of **adverse selection**
- Control of **moral hazard**
- **Insurance fraud**
- The risk of **public support crowding out** private risk mutualisation

Another important application area for AI is related to the value chain of an insurance company. This refers to the process side of the business, which divides primary and secondary activities. From beginning to end the chain encompasses product development and selection, clients, sales and marketing, underwriting, administrative tasks, claims management, risk management and reporting. AI has become established mostly within the processes of customer interaction, product development, underwriting and claims management.

3 AI – WHAT DOES IT MEAN?

The High-Level Expert Group on Artificial Intelligence (the HLEG on AI) set up by the European Commission starts its paper[4] with the following definition of AI, originally proposed in the Communication by the European Commission on AI[5]:

> *'Artificial intelligence (AI) refers to systems that display intelligent behaviour by analysing their environment and taking actions – with some degree of autonomy – to achieve specific goals.*
>
> *AI-based systems can be purely software-based, acting in the virtual world (e.g. voice assistants, image analysis software, search engines, speech and face recognition systems) or AI can be embedded in hardware devices (e.g. advanced robots, autonomous cars, drones or Internet of Things applications).'*

The HLEG on AI expands this definition to clarify certain aspects of AI as a scientific discipline and as a technology, with the aim of avoiding misunderstandings, achieving a shared common knowledge of AI that can be fruitfully used also by non-AI experts, and providing useful details for inclusion in the discussion on both the AI ethics guidelines and the AI policies recommendations. Following these clarifications, the document proposes the following updated definition of AI:

> *'Artificial intelligence (AI) systems are software (and possibly also hardware) systems designed by humans that, given a complex goal, act in the physical or digital dimension by perceiving their environment through data acquisition, interpreting the collected structured or unstructured data, reasoning on the knowledge, or processing the information, derived from this data and deciding the best action(s) to take to achieve the given goal. AI systems can either use symbolic rules or learn a numeric model, and they can also adapt their behaviour by analysing how the environment is affected by their previous actions.*
>
> *As a scientific discipline, AI includes several approaches and techniques, such as machine learning (of which deep learning and reinforcement learning are specific examples), machine reasoning (which includes planning, scheduling, knowledge representation and reasoning, search, and optimization), and robotics (which includes control, perception, sensors and actuators, as well as the integration of all other techniques into cyber-physical systems).'*

4 A Definition of AI: Main Capabilities and Disciplines, https://ec.europa.eu/futurium/en/system/files/ged/ai_hleg_definition_of_ai_18_december_1.pdf

5 Communication from the Commission to the European Parliament, the European Council, the Council, the European Economic and Social Committee and the Committee of the Regions on Artificial Intelligence for Europe, Brussels, 25.4.2018 COM(2018) 237 final

A AI SYSTEMS

The term AI system is understood to mean any AI-based component, software and/or hardware. AI systems are usually embedded as components of larger systems, rather than standalone systems.

The term AI contains an explicit reference to the notion of intelligence. In this respect AI researchers mostly use the notion of rationality; this describes the ability to choose the best course of action to achieve a certain goal, given certain criteria to be optimised and the available resources.

AI achieves rationality by perceiving the environment in which the system is immersed by means of ‘sensors’, which collect and interpret data; applying reason to what is perceived or processing the information derived from that data; deciding what the best action is; and then acting accordingly by means of ‘actuators’, thus possibly modifying the environment. AI systems can either use symbolic rules or learn a numeric model, and they can also adapt their behaviour by analysing how the environment is affected by their previous actions.

A **general AI system** is one which is intended to be able to perform most activities that humans can, while **narrow AI systems** can perform one or a few specific tasks. The AI systems currently deployed are examples of narrow AI. In the early days of AI, researchers used different terminology (weak and strong AI). There are still many ethical, scientific and technological hurdles remaining on the path to building the capabilities that would be necessary to implement general AI, such as common-sense reasoning, self-awareness, and the ability of the machine to define its own purpose.

B AI AS A SCIENTIFIC DISCIPLINE

A very simple abstract description of an AI system consists of three main capabilities: perception, reasoning/decision-making, and actuation. Robotics is another very relevant discipline.

A learning rational system is a rational system which, after taking an action, evaluates the new state of the environment (using *perception*) to determine how successful its action was, and then adapts its reasoning rules and decision-making methods.

The group of techniques related to *reasoning and decision-making* includes knowledge representation and reasoning, planning, scheduling, search, and optimisation. These techniques facilitate the reasoning process carried out on the data from the sensors.
To make this possible, it is necessary to transform data into knowledge, which is why one area of AI concerns how best to model this knowledge (knowledge representation).

Once the knowledge has been modelled the next step is to apply reasoning to it (knowledge reasoning), which includes making inferences through symbolic rules, planning and scheduling activities, searching through a large solution set, and optimising from among all possible solutions to a problem. The final step is to decide what action to take, potentially utilising the learning concept described below.

Learning techniques include machine learning, neural networks, deep learning, decision trees and other well-established approaches. These techniques enable an AI system to learn how to solve problems that cannot be precisely specified, or problems that have a solution method which cannot be described with symbolic reasoning rules. Machine learning techniques can be used for many other tasks beyond just perception. Machine learning techniques produce a numeric model (that is, a mathematical formula) which is used to compute the decision from the data.

Machine learning comes in several varieties. The most widespread approaches are supervised learning, unsupervised learning, and reinforcement learning.

- In *supervised machine learning*, rather than being given behavioural rules the system is provided with examples of input-output behaviour, with the hope that it will be able to generalise from the examples (which typically describe past events) and from there also behave appropriately in situations not given in the examples (and which could be encountered in future). Supervised learning is a machine learning approach which is characterised by its use of labelled datasets. These datasets are designed to train or 'supervise' algorithms into accurately classifying data or predicting outcomes. Using labelled inputs and outputs, the model can measure its accuracy and learn over time.

- *Unsupervised learning* uses machine learning algorithms to analyse and cluster unlabelled data sets. These algorithms identify hidden patterns in data without the need for human intervention (hence they are 'unsupervised').

- When applying a *reinforcement learning* approach, the AI system is free to make its own decisions over time, and then with each decision we provide it with a reward signal that indicates whether it was a good or a bad decision. The system has a long-term aim of maximising the positive reward received. This approach is used in recommender systems (such as those powering lists of suggested customer purchases in online retail) as well as in marketing.

Current AI systems are *goal-directed*, meaning that a human gives them a specified goal to achieve and the system uses techniques to achieve that goal; these systems do not define their own goals. That said, some AI systems may have more freedom than others to decide which path to take in order to achieve the specified goal.

Robotics could be defined as 'AI in action in the physical world', and is sometimes also called embodied AI. A robot is a physical machine that has to cope with the dynamics, uncertainties and complexity of the physical world. Perception, reasoning, action, learning, as well as interaction capabilities with other systems are usually integrated in the control architecture of the robotic system. Alongside AI, other disciplines are involved in robot design and operation, such as mechanical engineering and control theory. Examples of robots include robotic manipulators, autonomous vehicles (e.g. cars, drones, flying taxis), humanoid robots and robotic vacuum cleaners.

Because many AI systems – such as those which include supervised machine learning components – rely on huge volumes of data to perform well, it is important to understand how the data is influencing the behaviour of the AI system (*ethics and possible bias*). For example, if training data is biased, i.e. not balanced or inclusive enough, an AI system trained on that data will not be able to generalise effectively and will potentially make unfair decisions that favour some groups over others. The AI community has recently been working on methods to detect and mitigate bias in training datasets as well as other parts of AI systems.

Some machine learning techniques may be very successful in terms of accuracy, but very opaque in terms of understanding how they make decisions. The concept of black box AI refers to such scenarios, where it is not possible to trace back to the reason for certain decisions. *Explainability*[6] is a property inherent to AI systems which are able to provide some kind of explanation for their actions.

6 Different ethical topics and transparency and explainability as a prerequisite of ethical use of AI is discussed in the EIOPA paper https://www.eiopa.europa.eu/media/news/eiopa-publishes-report-artificial-intelligence-governance-principles_en. Actuaries were heavily involved in the group.

4 THE CHALLENGES AI PRESENTS TO THE CONCEPT OF INSURABILITY

We will now continue our journey with a discussion about what different features of AI (noted in chapter 3) mean in relation to the prerequisites for insurability. We will at the same time provide the reader with some additional discussion around the concept of insurability.

Insurance operates through the pooling of risks, and this needs **a large number of similar exposure units**. The majority of insurance policies are associated with individual members of large classes, which enables insurers to make use of the law of large numbers in various ways. While there are probably only limited ways novel technologies could challenge the idea of having a large enough number of exposure units, they may well give rise to the question of whether there are enough similar units to be covered.

In the simplest case when applying the law of large numbers, an assumption is made that the risks are similar and independent from one another. In actuality this cannot be the case because exactly identical risks are hard to find. Risks within an **insured** pool are only somewhat similar and they may be charged at different premiums. These premiums should correctly correspond to each individual risk to be covered.

AI can be valuable when thinking about the independence of risks from one another – not only in relation to insurers using AI, but in considering what using AI systems in society means for insurability. Our communities are becoming more and more networked. This can mean that a risk materialising in one part of the network triggers broadly distributed collateral damage in other parts of the network. This phenomenon is not solely connected to cyber risks, though these are certainly a central topic in risks propagating in networks. In the years ahead, insurers will have to tackle increasing dependencies between different risks. AI will be a tool that helps insurers understand such risk dependencies.

It has been claimed that with better and better tools for analysing risk, the probabilities will diminish to nothing so that the concept of pooling collapses. However, it should be emphasised that pooling deals with the actual outcomes and not the probabilities. To put it another way, even when the probabilities are more accurately predicted the outcomes are still stochastic.

AI and related techniques will aid in more accurately analysing risk. This will be helpful for more individually setting a risk-based premium to each risk. Accurate pricing and premium affordability will be discussed at a later stage.

An insurable loss needs to be a **definite loss** taking place at a known time, in a known place, and from a known cause.

The key elements in insurance claim forecasting are the probability of occurrence and the cost of the claim. Insurers' appetite is generally higher for cases that have less prediction error, as this results in better portfolio management, more accurate pricing and easier handling of claims. The occurrence of an event depends on how the event is defined and how it is covered. Probability of loss is generally an empirical exercise and engages with the problem of predicting the occurrence of a loss accurately enough.

The cost of the claim represents the description of the insured loss, i.e. the ability of a reasonable person in possession of a copy of the insurance policy and a proof of loss associated with a claim presented under that policy, to make a reasonably definite and objective evaluation of the amount of the loss recoverable as a result of the claim.

Novel technologies can decrease the prediction error and so increase the scope of insurability. Innovative solutions such as the collection of large volumes of data, Internet of Things applications and AI methods help improve claims forecasting and add value to the actuarial pricing methods.

The event that constitutes the trigger of a claim should be an **accidental loss**, or at least an event outside the control of the beneficiary of the insurance. The loss should be 'pure' in the sense that it results from an event which only has the potential to incur costs: speculative risks offering both an upside and a downside are not considered to be insurable risks. This is of course a somewhat idealised view that is only absolutely accurate in a few areas. As such, novel technologies probably do not fundamentally change the scenario here.

Another thing to note is that, traditionally, the insured party tends to have an advantage over the insurer. This balance could change with better technology, as AI and big data will give insurers better tools for assessing the probability of losses.

The result of an insured risk event occurring should be a large loss, i.e. the loss must be meaningful from the perspective of the insured party. Structural inefficiencies make it unprofitable to insure small risks, due to expenses beyond the cost of the claim. Insurance premiums need to cover the expected costs of losses plus the cost of issuing and administering the policy, adjusting losses, and supplying the capital needed to reasonably assure that the insurer will be able to pay claims.

Insurers generally deal with two types of risk, which are characterised by the frequency and severity of the events.

- High frequency x low severity
- Low frequency x high severity

The frequency of events has a significant impact on the predictability of losses, and subsequently on the level of the expected loss ratio and the capital/risk charge. Again, in this area novel technologies can improve insurability by making estimates better.

While AI could be useful for looking at low frequency and high severity events, the high economic value of resources involved means that very exact risk analysis and underwriting is already possible in this area. So it can be expected to have a far bigger impact in respect of high frequency and low severity risks. In this area the overheads arising from various policy administration tasks can effectively make risks uninsurable. AI and related novel technologies have the potential to increase the efficiency of an insurer's processes. In a competitive market this should lead to lower premiums that may also make the underwriting of high frequency and low severity risks insurable in practice.

A risk is only insurable if the insurer can charge an **affordable premium** from the point of view of the client. If the likelihood of an insured event is so high, or the cost of the event so substantial that the premium is disproportionately large relative to the amount of protection offered, it is not likely that anyone will buy the insurance (unless they are legally required to do so).

Insurance company portfolio management is based on the principle that a portfolio of assorted risk types with varying correlations to one another will have negligible unsystematic or idiosyncratic risk, which leads to reduced volatility of the total claims and makes risk-sharing more efficient. The insurer considers several factors when underwriting a particular risk, including:

- **Risk appetite:** The shape of the risks underwritten by the insurer should be representative of the deployed capacity within the market. The solvency of an insurer in terms of capital and resources should reflect the risks it covers. The insurer should be able to assess the risks within the portfolio and deploy its capital efficiently.

- **Scale and diversification:** Size of the market and competition affects the ability to diversify – what is impossible in a smaller pool might be possible with more players involved.

- **Claims management/characteristics:** Being able to benchmark novel technologies on past experience and trends results in better predictability of claims, especially when considering insuring emerging risks.

It should be noted that the criteria above are interconnected and can also be highly interdependent. For example, low market capacity coupled with high demand will likely drive up the rate – this can encourage additional capital to be deployed, driving capacity up and eventually lowering the price. Here too, it can be concluded that novel tools will more likely improve insurability than undermine it.

There might however be some ambiguity in this area. Generally insurers use a fairly scientific approach to assess the risk, while for most insured parties the assessment is to a large extent subjective. This can mean that these approaches do not align, i.e. in some cases consumers think that the price is too high even if it is in fact very affordable when considering the risk in mathematical terms. The client's assessment can also change rapidly when something extraordinary happens. For example, after a major terrorist attack insured parties are ready to pay substantially higher premiums for risks, where prices before the event had been considered unreasonable. This discrepancy between the assessments of insurers and insured parties is one element that can make 'premium optimisation' possible (though the main opportunity for premium optimisation comes from different clients being more or less price-sensitive and therefore more or less likely to switch insurance provider). While it is clear that modern tools bring more opportunities for premium optimisation, it is not certain that the industry is willing to make such practices more commonplace.

Losses arising from catastrophic events are by definition large, and threaten the solvency of an insurer. They are typically more than a normal primary insurer can or would like to cover. Insurers need to protect themselves against **large catastrophic losses**. Catastrophic losses can essentially occur in two ways, either as a single major event (such as a large industrial plant being destroyed in a fire), or as a cascade of associated events (for instance lots of modest claims due to a flooding river).

Insurable losses are ideally independent and non-catastrophic, meaning that losses do not happen all at once and individual losses are not severe enough to bankrupt the insurer. Insurers will prefer to limit their exposure to a single-event loss to some small portion of their capital base. Larger risks are usually only manageable by the global insurance system. As reinsurers already have very advanced risk management in place, novel technologies have little to offer them that is fundamentally different from earlier practice.

Though these general characteristics make a risk insurable in principle, there are additional requirements that influence the situation. Insurability can be threatened by issues like adverse selection, moral hazard and insurance fraud.

Adverse selection describes a pool populated with a higher average level of risk than was intended when designing the pool. This may happen because less-risky insured parties abandon the pool when they think the premiums are unreasonably high in relation to their risks. Adverse selection may arise in a situation where the pricing is correct but market conditions are not favourable (i.e. another insurer offers different pricing due to different segmentation of risks) or when potential clients decide not to take insurance at all.

Novel technologies can help the insurer avoid adverse selection by means of improved tools which lead to better differentiation of risks, and then premiums correspond as closely as possible to the actual risk. Precision in pricing ensures less danger that the pool will be biased towards worse risks.

However, it should be added that AI can end up facilitating platforms which *increase* the possibility of adverse selection, as such systems can monitor the offerings of different insurers in real time and select the best offer for each client. This can lead to a situation where an insurer's portfolio is clustered with higher risks than was anticipated. Initiatives like Open Finance[7] and Open Insurance[8] need to be looked at also in this context.

Moral hazard describes the scenario of insured parties' behaviour becoming less risk-averse because cover is in place. Novel technologies will most likely improve the tools the insurer has at hand to control moral hazard.

Insurance fraud differs from moral hazard in that it refers to intentional actions by the insured party, which are committed in a fraudulent manner to gain benefit at the expense of the pool. From the insurer's point of view, novel tools can help combat insurance fraud.

At the same time, it needs to be highlighted that novel technologies can also vastly benefit those who want to commit insurance fraud. Criminals can develop efficient automated AI-based systems to commit insurance fraud against insurers.

Finally, it should be understood that insurance is not a static concept which remains the same over time. Insurers have developed a range of solutions to adapt insurance techniques in the face of various challenges. AI can be used in loss prevention to limit risks to a tolerable level. Insurers can use their AI systems to inform their clients about how to protect themselves from risks materialising. This will be especially true in the world of the Internet of Things, where continuous loss prevention will be a possibility. Adjustments to terms and conditions can play a role too, for instance deductibles and co-payments can combat moral hazard, while coverage limits can transform unquantifiable underlying risks into known maximum exposures. Private-public partnerships have been developed when the private sector market has failed to provide coverage for a critical risk.

7 https://ec.europa.eu/info/law/better-regulation/have-your-say/initiatives/13241-Open-finance-framework-enabling-data-sharing-and-third-party-access-in-the-financial-sector_en

8 https://www.eiopa.europa.eu/browse/digitalisation-and-financial-innovation/open-insurance_en

5 CAN AI HELP WHEN IT COMES TO INSURING RISKS PREVIOUSLY CONSIDERED UNINSURABLE?

In previous chapters we discussed the limits of insurability and what AI can mean for this. In this chapter we will discuss how novel tools may render insurable those risks previously left uninsured. It will further highlight how new technologies can add value to the insurance market. Threats are discussed later on.

New technologies come with opportunities and threats. Both should be evaluated by asking whether they improve or undermine the wellbeing of our societies. In making this calculation, there is often a tendency towards assuming that everything which disturbs the status quo is inherently bad; in fact, some things about the way we live benefit from being shaken up and replaced with something new. As such the relevant measure should be to consider whether a factor generally improves welfare.

The current AI trend has emerged mainly from advances in digitalisation and automation in the insurance industry. Most insurance companies implementing digital transformation are improving their business. The new wave of ‘InsurTech’ companies and start-ups illustrates that the traditional insurance sector needs to change and provide more dynamic product propositions in the market. These new companies are implementing innovative business models and using AI disruptively in many areas, including claims management, product pricing and data collection. Some companies, such as Lemonade, Wefox and Trov, use AI within the property and casualty insurance space, providing improved claims analysis and more dynamic and customer-centred product propositions. Others, such as Clover (health insurance) and ManyPets (pet insurance) use huge volumes of data to create customer profiles, identifying gaps which more traditional insurers tend to miss or are unable to provide adequate cover for.

Generally speaking, when AI is adopted by insurance companies – whether traditional ones or more disruptive players – it is often in the form of machine learning, and implemented to help by improving business efficiency. Insurers use methodologies and algorithms for image recognition patterns, automated claims management, fraud detection and insurance product pricing. This approach makes use of past events and predicts the future, but also has the capability to adapt dynamically and adjust in real time. These AI systems process raw data from various sources, while still involving the human factor and interaction or selection of parameters and risk variables when needed. Traditional actuarial models rely on calibration of parameters and data assumptions by means of the human intelligence factor – from an efficiency point of view this can be considered a shortcoming, as human error cannot be excluded.

More advanced applications of AI include systems that follow a more cognitive approach, mimicking human intelligence and incorporating it into automated processes. This approach is less reliant on the past and more on the present and future. It is expected that such cognitive technologies will be heavily reliant on large volumes of complex data and real-time processing capability. Novel active insurance products could be directly connected to an individual's behaviour and activities at any given time. This could be facilitated by Internet of Things (IoT) sensors capturing extensive data volumes and sending them directly to insurance companies. Once IoT becomes part of daily life for everyone (in autonomous cars, self-scanning vehicles, smart homes, etc.), it is likely that a shift towards a more cognitive AI approach for insurance products will be imminent.

Among the benefits of AI to insurability we have identified the following aspects.

- AI offers potential for **better assessment of risks**. Geographically sectored financial, social and health-related data, as well as meteorological data and geological data, allow for more nuanced models and better assessment of the underlying risk.

- **Natural Language Processing (NLP)** and **Natural Language Understanding (NLU)** allow insurers to utilise unstructured data such as web-based page reviews, press releases and social media. Web crawling initiatives such as the Common Crawl[9] non-profit endeavour, which seeks to collect data to create a copy of the entire internet, are game-changing interventions that enable institutions, start-ups and individuals to analyse data which was previously unavailable. The challenge is to move towards a more foresighted assessment as opposed to the traditional hindsight approach.

- There is an opportunity for **increased detection of fraud**. AI helps insurers identify suspicious claims and therefore reduces fraudulent losses and overall costs for the insurance company.

- AI can lead to **improved processes** for insurers. Simple claims handling can be automated, to reduce costs and accelerate the process. Chat bots can handle many simple requests from customers in full. They can be available 24/7 and free up operator time for more complex interactions. Help bots can listen to calls and provide the human operator with relevant information, facilitating faster and higher-quality customer support and claims handling. More AI also means less human error, resulting in improved quality of service and reduced costs.

- New technologies can offer numerous **preventive initiatives**. AI can also support customers and insurance companies in preventing losses. Connected devices with sensors (IoT) such as cars, home assistants, smartphones etc., and generally available information provide opportunities to identify potential future losses, for example by

9 Common Crawl, https://commoncrawl.org, offers high-quality crawl data by collecting huge amounts of web data centrally and making it freely available to the public.

identifying a need for roof repairs from aerial photos, spotting sites for potential burst water pipes based on leak sensors or diagnosing the future risk of stroke based on health data.

Extrapolating from experience in other industries, AI has only just begun to unfold its full range of applications in the insurance industry. There is no doubt that AI can help to improve insurability and provide cover for risks that would previously be considered uninsurable. Ultimately, it comes down to regulators, policymakers, and governments to set the right incentives and create the right environment for public and private insurers to apply AI in a favourable way via existing regulation (such as the social component of ESG) or new measures.

One central element of insurability is affordability of the premium. It is essential not only that the pricing of risks done by insurers is correct, but also that clients feel premiums are reasonable. We can look at this issue by considering how AI can impact insurability by increasing 'supply' (increasing the pool through more or better offerings) or 'demand' (bringing existing offerings to the right place). Below, we list some ideas for how AI implementations could benefit insurability.

One task AI could help with is creating a **large enough number of similar exposure units**. Pooling at European-country-level is sometimes impossible or too expensive due to the small size of the pool. There is no easy solution to this, as it's not possible to expand the pool with multiple regulatory frameworks. But AI can help by automatically configuring or simplifying products so they can fit different jurisdictions, e.g. via NLP (natural language processing). In a similar fashion, AI can help to foster cross-border insurance offerings by creating large enough pools for new risks or for risks that are scattered among different countries. While this opens the possibility for insurers to pool similar risks across countries, it can also provide access to new insurance offerings for smaller countries.

On the other hand, once real-time data with high granularity becomes available, the actuarial approach towards pricing and modelling of risks is sure to change. For example, analysing images, text, or data from connected devices will make more accurate predictions possible. Also, premiums, losses and costs can be attributed at an individual level, meaning insurance companies can much more quickly distinguish between bad and good risks in a portfolio. The advantage of using AI algorithms in this approach is that insurance companies will be able to form new homogenous risk groups with an accurate and affordable premium, and derive risk-relevant information based on large volumes of data. The disadvantage, of course, is that bad risks could be penalised into a less affordable premium category, contrary to the insurability criterion of affordable premiums.

When dynamically generated data becomes accessible and part of an insurer's business, new insurance risk profiles will be created, and as mentioned earlier these will enable immediate pricing by proactively generating premium quotes. Usage-based insurance will increase in importance and demand in the future. There will be shared insured assets (shared mobility is an example here) and such products require a more detailed administration of data. Once implemented, new opportunities arise at the micro level of insurance. Sub-elements of bigger insurance products will give more flexibility to policyholders to choose what they want and when they want to be insured.

AI can reinforce **affordability of the premium** through the refinement of underwriting by considering more risk factors or bigger data sets, potentially making previously uninsurable risks insurable. One concrete example is to replace strict exclusion from health insurance due to pre-existing conditions with a more nuanced underwriting that also accounts for dietary and sport habits. Such methods mean uninsurable risks can become insurable, with an incentive for a healthier lifestyle that benefits the individual and society as a whole. While various insurers have already adopted similar concepts (e.g. Vitality or telematics), the relevance of AI in this area of insurability has much further to go.

On one hand, the estimation of losses will change as the process is accelerated by AI, and this will impact the way claims management is handled as well as the corresponding payments. The reserving policies will have to be adapted, i.e. paid and reported losses will be accounted for differently given the speed of information and payment. If temporary products can be activated by the policyholder in the form of a low-severity high-frequency class, and then losses occur at micro level, the speed of assessing these losses is crucial. The loss assessment should carefully reflect the length of time for which the insurance protection is being used, and the nature of it. The estimation of such losses has to be accurate and must meet the criterion of an affordable premium. The loss severity and frequency estimation have to be accurate, together with the accounted costs, and this reduces the risks from having a more general premium, which would not be individually applicable to customers' needs.

Another aspect of AI relevant to affordability is that it can help to reduce costs along the full value chain, to support insurability with affordable premiums, e.g. via automation of customer service or economies of scale in cross-border offerings. AI and digitalisation in general will reduce administration costs and in a competitive market this will lead to better pricing benefiting the customer. It can be expected that in a competitive market, premiums will fall and move close to the actuarially fair premium, with an additional risk margin that only corresponds to the variability of the risk. This is in stark contrast to today's situation where administration costs can constitute tens of percent, especially in B2C non-life insurance. Specifically, AI could help to improve the adoption of concepts like PEPP (Pan-European Personal Pension Product[10]) by decreasing costs and increasing the pool across borders.

10 See e.g. https://www.eiopa.europa.eu/browse/regulation-and-policy/pan-european-personal-pension-product-pepp_en

One element of insurability is the concept of a **calculable loss**. AI can help to address the protection gap and assist in better understanding risks and markets via increasing pools or leveraging more data. The latter is particularly interesting in the context of Open Insurance, with respect to connecting services for more insights for the benefit of the customer.

On the 'demand' side, AI can help to increase visibility of insurance offerings for different stakeholders. AI can help customers by creating transparency of the available products by means of portals or search engines which make people aware that there are insurance solutions available for their specific needs. Insurance is still broadly a 'push' product with volume incentives for sales, which can counteract the problem of insurability and finding the right coverage for a certain risk.

AI can underpin sales processes with building tools that offer enough transparency to find the right product and understand the true needs of a customer, paired with setting the right incentives. In respect of the latter, a first step has been taken with recent regulation (IDD) but this is not yet going far enough in the context of insurability.

Data and AI can help regulators, policymakers, and governments to understand which risks or groups are lacking coverage and should be enabled to get access. This equips them to set the right incentives via appropriate communication, education, or regulation.

6 WILL AI EXCLUDE CERTAIN RISKS FROM INSURANCE?

Insurance, in the form of sharing risks, generally offers societies one form of safety net that helps to counter the threat of individuals being socially excluded. However, this only helps people who have been able to get insurance in the first place. Those denied coverage and those who do not take insurance, whether from lack of awareness or for other reasons, are not helped by this characteristic of insurance.

Predictability of losses and the law of large numbers are important for (re)insurers and financial institutions. When adopting AI applications, they need to ensure that there is enough independency between products, reflecting a controllable loss exposure and loss size. When it comes to low- and high-severity risks, AI will move boundaries by making existing insurance risks more insurable.

AI will make the differentiation of risks more exact. It also offers the possibility of a more scientific basis for underwriting. There will always be some risks that cannot be included in pools of private insurers – as the saying goes, a house that is already burning can no longer be insured. The introduction of AI into the processes can mean that some risks currently covered will no longer be insurable, at least not without a higher premium. At the same time, it could mean that some risks currently left without cover are better understood and become affordably insurable. If AI is going to live up to expectations, the result should be that in future, more risks than previously will be eligible for coverage on reasonable terms. However, it is not possible to rule out that some currently covered risks will no longer get insurance.

In the area of social exclusion there are some products which are understood to be essential while other products are rather ‘luxury’ and less essential to benefit social inclusion. Insurers should pay special attention to insurance products that are understood to be essential for social inclusion. There can be no single definition of such essential products; their actual scope depends on the legal framework and especially on the social security system in each country.

It is crucial to understand that not everything is possible in the private marketplace. Private insurance must work as a public-private partnership with society. Care must be taken in this area so that society’s actions do not crowd out private risk-sharing in areas where the private market would do the job better. In all cases insurers should guarantee that the use of AI generally expands insurability and creates a more scientific foundation for their underwriting.

One issue in the adoption of AI revolves around whether it makes insurance more or less understandable. There are both opportunities and threats here:

- Insurers are not traditionally thought to be the most transparent sector in the society, and AI can certainly help in this area, but

- AI applications can be seen as 'black boxes' that are not completely understood by anybody, even insurers.

The biggest positive that AI and digitalisation could provide here is that they always leave a trail behind a decision process – unlike when human decisions play an important role. This creates an opportunity to eliminate hidden biases in human decision-making. When a decision process is documented, it becomes possible to analyse and correct the processes involved. This creates opportunities to improve the transparency of insurers. Moreover, documenting the applied technologies will provide enough evidence to regulatory bodies to prove that an insurer is operating within the pre-defined boundaries.

A difficulty arising from the use of AI is that different kinds of machine learning can lead to applications that might become difficult to explain. Insurers should use all possible tools to make their practices more transparent and explainable. One way would be to use tools that provide a validation process of the techniques applied, documenting them, or benchmarking against traditional much better-known methods. In fact, several applications of machine learning techniques already use recognised underlying actuarial techniques through the algorithms to estimate risks.

There is extensive literature on how to make such applications understandable. Studies such as that by Henckaerts et. al. (2019)[11] present examples of how machine learning applications outperform classical generalised linear models (GLM) that are traditionally applied by insurance companies and their actuaries. The paper demonstrates how regression-tree-based machine learning methods can be interpreted and analysed using visual/plotting techniques. Visual or numerical comparison of different variables or risk factors can provide useful insights on how traditional pricing methods perform versus machine learning, and how AI, in this case in the form of machine learning, can be made transparent. In this way, insurance pricing using AI can become explainable and transparent.

One example of strong documentation for how to interpret machine learning models is provided by Christoph Molnar's book[12]. The book provides methods for interpreting black box models, such as feature importance, partial dependence or accumulated local effect plots. Moreover, from an insurance product pricing perspective, another important

11 Roel Henckaerts, Marie-Pier Cote, Katrien Antonio, Roel Verbelen, 2020, Boosting insights in insurance tariff plans with tree-based machine learning methods.

12 Christoph Molnar, Interpretable Machine Learning, https://christophm.github.io/interpretable-ml-book/

issue to mention is the incorporation of well-known and traditionally used generalised linear pricing models (GLM) with neural networks (NN). While GLM is unable to capture all the interactions between the features / risk factors, NN methods help in doing so. This integration of methods goes by the name the Combined Actuarial Neural Network (CANN)[13] approach.

Individuals can be left behind not only because they are too risky but also because they are less technically able. Insurers should make sure their practices do not create excessively high barriers for those who are not technically skilled. Insurers should of course also make sure that their services are technically safe and robust in order to avoid protracted interruptions to their service.

When using AI, actuaries and insurers need to make sure that technologies are used responsibly. This means that

- the design of the systems is done in a responsible manner
- models are thoroughly tested, using advanced and documented standards, in order to avoid all kinds of biases and technical errors
- exceptional care is taken to make sure the models do not cause harm to vulnerable groups, with extra care in relation to cover that is essential for social inclusion
- when inclusiveness cannot be achieved with private market solutions, the problem should be flagged to appropriate stakeholders with a view to creating solutions utilising, for example, public-private partnership
- the models need to be made transparent and understandable.

13 Jürg Schelldorfer, Mario V. Wuthrich, 2019, Nesting Classical Actuarial Models into Neural Networks.

7 HOW TO COMBAT OPERATIONAL RISKS WHEN AI IS USED

Insurability is also connected to the operational efficiency and safety of an insurer. If and at the point that AI makes insurers more efficient, risks currently left without cover can become insurable.

Operational risks currently present within an organisation expose certain vulnerabilities for insurers. While they are accounted for, it is well-known that they are present in daily operations. Thinking of failures of internal systems, personnel, procedures or external events, these risks will most probably be redefined once AI is implemented in the main value chain components of an insurance company. One could argue that if AI automates and digitalises most of the human input and human-related work, events such as failures of personnel, manual procedures and decision-taking processes will be fully mitigated. Central concerns in the area of operational risks include;

- consistent predictive performance of AI in production

- impact of shortfall in performance, for the insurer/shareholders and for the policy holder

- issue of fairness:
  - Selecting the fairness metric
  - The threshold of the metric
  - The performance of the fairness metric

Here it is useful to recall the ‘Impossibility Theorem of Fairness’ by Kleinberg[14] et al., which states that some fairness metrics cannot be simultaneously fulfilled for an AI application.

In practice we know that automated and digital systems also include vulnerabilities. While operational risks can be mitigated, the algorithmic liability of AI products could be a cause for concern. Algorithmic liability is a topic that is regularly discussed, especially by regulatory supervisors, and it covers the possibility of a technical shutdown, or hacking which impacts the appropriate operation of the AI algorithms. While the liability of algorithms may pose a threat in the first instance, it may also give rise to the possibility of developing new types of insurance products.

How AI and AI-driven insurance products impact the insurability of risks will be strongly driven by which type of AI a company chooses to implement, and for which business processes. As mentioned earlier, current AI is still generally heavily powered by human

14 https://jeremy9959.net/Blog/KleinbergsClusteringTheorem/

intelligence, while strong AI of the future will mimic human intelligence. Insurability and insurance of risks are highly impacted by how much human intelligence will be involved when applying AI.

Today's insurance companies tend to have a complex organisational structure, and paying attention to how data is handled is of major importance. This organisational complexity sometimes results from the fact that many departments are involved, with specific sets of skills, such as data science, IT, actuarial science or underwriting. They generate and transfer huge amounts of data on a constant basis. The specific expertise and skills, as well as responsibilities for data and models, is distributed and allocated to different departments within an organisation. We believe AI applications will handle data, methods and reports more collectively. These applications will need several disciplines to work together in order to comply with governance policies relating to data or model implementation. With effective design and implementation of these applications, human error and potential miscommunications between departments can be eliminated. Moreover, a more collective approach means AI can exclude operational risks and enable more transparency on data usage. The value chain of an insurance company is implicitly improved.

AI algorithms will undoubtedly bring a lot of benefits for insurers. However, their implementation will have to follow a specific strict governance structure within an organisation. Without guidance, insurance companies – including their actuaries and data scientists – may end up with a faulty implementation of AI that does not benefit the society they serve.

The implementation of AI within each business part of an (re)insurance company or financial institution is very important. This implementation of the AI algorithms needs to be supervised and it needs to follow a strict and well-understood governance policy. When deploying algorithms, work and business ethics are important. Experts and specialised departments need to work closely to ensure a match between the company's strategy and the application of AI algorithms.

Within this landscape risks will arise for insurers. The dependency on real-time data is very high, and in the event of a potential technical outage (e.g. from cyber-attacks, hardware issues etc.) the insurer cannot properly monitor risks and price them, or even accept them. On one side there are implementations of AI which apply to a larger group of insured parties, representing more common insurance product types such as property insurance, motor insurance etc. On the other side, more specific insurance products will be offered to individuals based on their needs, some on a dynamic, real-time basis. As an example, we can imagine the value of insured goods within a property at different times, when an insured party is either at home or away for a longer vacation. The insured party might consider the risks to be different in each case, and wish to have more dynamic and relevant coverage for a specific situation. In motor insurance other situations apply, for example times when an insured party is driving the car, as opposed to when an insured party shares the vehicle to someone else as part of a shared mobility plan.

The interoperability and dependency of different AI implementations is crucial and has to work perfectly. This interoperability of algorithms can shed light on how risks which were traditionally considered unrelated, can now accumulate and have a different impact.

A more cognitive approach by the AI may solve some of the issues. However, where human intelligence is involved, financial institutions must carefully choose how to apply different algorithms interchangeably, between a higher-scale insurance product and a more individual one. As a consequence, insurance portfolios' performance can be impacted by the choice of AI algorithms and how they perform. An outage or error among one of many AI applications can have an outsized impact.

THE ACTUARIAL ASSOCIATION OF EUROPE

The Actuarial Association of Europe (AAE), founded in 1978 under the name of Groupe Consultatif Actuariel Européen, is the Brussels-based umbrella organisation, which brings together the 37 professional associations of actuaries in 36 countries of the EU, together with the countries of the European Economic Area and Switzerland and some EU candidate countries.

The AAE has established and keeps up-to-date a core syllabus of education requirements, a code of conduct and discipline scheme requirements, for all its full member associations. It is also developing model actuarial standards of practice for its members to use and it oversees a mutual recognition agreement, which facilitates actuaries being able to exercise their profession in any of the countries concerned.

The AAE also serves the public interest by providing advice and opinions, independent of industry interests, to the various institutions of the European Union - the Commission, The Council of Ministers, the European Parliament, ECB, EIOPA and their various committees - on actuarial issues in European legislation and regulation.

aae actuarial association of europe

ACTUARIAL ASSOCIATION OF EUROPE

MAISON DES ACTUAIRES
1 PLACE DU SAMEDI
B-1000 BRUSSELS
BELGIUM
+31 2 201 60 21
INFO@ACTUARY.EU
WWW.ACTUARY.EU