

The Impact of Big Data and Artificial Intelligence (AI) in the Insurance Sector



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Foreword

Big data and artificial intelligence (AI) are two words that are widely used when discussing the future of business. Their potential application in diverse aspects of business has caught the imagination of many, including with respect to how AI could replace humans in the workplace. Using big data and AI to customise business processes and decisions could result in outcomes better suited to individual needs and expectations while also improving efficiency.

As big data and AI (also referred to as machine learning) are increasingly deployed in the insurance sector, the great benefits expected are also accompanied by risks. The ability to exploit the granularity of data brings can potentially enable insights into a variety of predictable behaviours and incidents. Given that insurance is based on predicting how risk is realised, access to big data has the potential to transform the entire insurance production process.

This report examines both the benefits and risks big data and AI can bring to the insurance industry. In particular, it describes how the OECD Recommendation on Artificial Intelligence and the European Commission's Independent High-Level Expert Group on Artificial Intelligence's (HLAG AI) Ethics Guidelines for Trustworthy AI should be considered in the context of the insurance sector. The report then presents areas related to big data and AI in the insurance sector where policy makers may consider taking action going forward.

Acknowledgements

The importance of insurance as a foundation for economic activity was acknowledged at the inception of the OECD with the creation of the Insurance Committee in 1961. The scope of activities of the Insurance Committee has gradually widened, and now covers the topic of private pensions, reflecting the growing importance of private pension systems in OECD countries (the Committee was accordingly renamed the Insurance and Private Pensions Committee in 2005).

As digitalisation transforms the world economy, technology and innovation in the insurance sector is has become a significant part of the work of the Committee. This report on big data and AI builds on a 2017 report on the technology and innovation in the insurance sector (OECD, 2017), focusing on two of the most important developments in terms of innovation likely to impact the insurance sector in a wide ranging manner.

This report benefited from the input of OECD country contributions, including from ministries of finance, insurance supervisors, and private sector associations. It results from discussions within the Committee throughout 2019.

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Executive Summary

Big data and artificial intelligence (AI) are two words that are widely used when discussing the future of business. The potential to applying them in diverse aspects of business has caught the imagination of many, in particular, how AI could replace humans in the workplace. Big data and AI could customise business processes and decisions better suited to individual needs and expectations, improving the efficiency of processes and decisions.

While much benefits can be expected from big data and AI, there are also a number of risks that require some policy considerations. General guidance or regulation related to the use of big data and application of AI could eventually be developed by governments, and the insurance sector should be prepared to incorporate them in their specific context.

Big data constitutes diverse datasets, which can be anything from expanded datasets to social media data. The granularity of data has the potential to give insights into a variety of predicted behaviours and incidents. Given that insurance is based on predicting how risk is realised, having access to big data has the potential to transform the entire insurance production process.

However, the granularity of data can also lead to the furthering of risk classification, where insurance premium is set based on a group of people who have similar risk profiles. The more detailed sets of data permits the fine-tuning of risk classification, which could lead to decrease of premiums for some consumers on the one hand and exclusion from insurance offerings for other consumers on the other.

Due to machine learning, AI has the potential to learn and adapt in a way that conventional machines were not able to, and are able to enhance their performance with more data. It could be adopted for a wide range of processes and decision making in insurance production.

The OECD adopted the Recommendation on Artificial Intelligence in May 2019, and the European Commission's Independent High-Level Expert Group on Artificial Intelligence (HLEG AI) published the Ethics Guidelines for Trustworthy AI in April 2019. Both international guidance provide valuable recommendations in terms of what areas of AI should be monitored and regulated, and provide some practical insights into what areas regulators and supervisors should be discussing on.

There are number of policy areas in which policymakers may consider action in the insurance sector in relation to big data and AI:

- The insurance sector should be encouraged to engage actively with big data and AI, and regulatory sandboxes or innovation hubs could be one way to support this. In addition, addressing the skill shortage will be important for both the regulator and the insurance industry as it becomes an increasingly mainstream process.
- Insurance regulators and supervisors should strive to keep abreast of developments in big data and AI--including general regulation in these areas as well as cooperate with the relevant competent authorities for privacy and data protection, where needed, and explainable AI-- to ensure that the appropriate action can be taken when necessary, in a timely manner.

- Technology can accelerate externalities and lead to oligopolistic market structures. Competition in the market should be monitored closely, depending on the authorities' mandates and in cooperation with the respective relevant competent authorities, so that big data and AI do not only benefit certain market segments.
- Big data could theoretically lead to risk classification that excludes certain groups. While such a risk-adequate calculation is beneficial from an insurer's risk management perspective, insurance regulators could decide, based on societal/political considerations, to monitor policy offering to ensure that the vulnerable population is not excluded from affordable insurance.
- The insurance sector could learn from the international guidelines on AI, and regulators and supervisory may wish to consider the benefits of having a governance requirement related to AI.
- International cooperation among insurance supervisors and regulators in the area of big data and AI would support the sharing of experiences, as well as lead to the facilitation of their cross-border activities.

The OECD's Insurance and Private Pensions Committee (IPPC) undertakes surveillance of market developments, including on technological developments, and will continue to monitor related developments so timely policy recommendations can be made for policymakers.

1. Introduction

The advance of technology and innovation in processes has enabled the global economy to benefit in terms of improved productivity and other economic benefits. In 2016, the information industries contributed to around 6% of total value added and 3.7% of employment across OECD countries (OECD, 2019^[1]). In addition, the level of labour productivity in information industries of OECD countries is about 65% higher than that of other industries in the business sector (OECD, 2019^[1]).

In addition, digitalisation has the potential to transform the way we work, enabling more diverse groups of people to gain employment, as well as engaging technology where automation can be introduced in processes (Manyika, 2017^[2]). It is estimated that 60% of all occupations have at least 30% of activities that are technically automatable (Manyika, 2017^[2]).

These predictions are in line with developments in the insurance sector, although funding deals in insurance start ups (venture capital funding, VCs) (8% of all fintech funding) is far surpassed by investment in lending (19%), wealth and asset management (30%) and payment (23%) VCs (Accenture, 2019^[3]). Nevertheless, the number of activities related to InsurTech is high and has the potential of improving insurance business processes and business models (OECD, 2017^[4]).

The OECD's Insurance and Private Pensions Committee has been actively engaged in discussing the impact of technological development and innovation in the insurance sector. The OECD has also been a leader in policy discussions related to cyber risk insurance (OECD, 2017^[5]), and a report on InsurTech was published in 2017 (OECD, 2017^[4]).

While there are a number of technologies that are being developed and employed to improve the experience and business of insurance in general, the potential that artificial intelligence (AI) and big data may play in insurance production is strong. There is much interest expressed from both the industry and regulators in how technology can benefit the insurance sector, especially given the potential of improving the customer experience.

Insurance is based on the idea of pooling risks, and underwriting is most often based on past loss experiences and/or risk modelling. The prospect of having more data leads to the possibility of greater data analytics and in particular improving predictive analytics, enabling pricing that is better suited to expected risk, and is more granular or adjusted to policyholder behaviour.

However, this is too simplistic a way of understanding how data contributes to insurance, as there are a variety of questions and implications that arise when considering potential scenarios that could occur with the arrival of big data. One of the first and principal questions is what big data means in the insurance context. There is also the question of whether pricing would, in fact, be more accurate in terms of risk and whether this would lead to an overall better production of insurance products.

Further, big data has implications for AI. AI is developed by using machine learning which inputs data for the algorithm to learn responses. Big data is a valuable source of data for machine learning, but the extent of their potential contribution is uncertain, given that big data often involves unstructured free text.

The benefit of AI has been demonstrated in its application of many business processes, in particular in forms such as chatbots, optical character recognition, sentiment analysis (Eiopa, 2019^[6]) and social media algorithms, and these could easily be applied for insurance purposes.

The potential for greater AI application in the insurance sector is high; however, while this could have a positive impact in terms of profitability and hence solvency, there remain aspects of AI that raise questions in areas such as data collection and pre-processing, privacy and ethical issues, and how insurance regulators should approach this.

There are also regulatory issues as well as wider considerations such as data protection and privacy. In this context, UK's Financial Conduct Authority (FCA) published a Feedback Statement in 2016, which lists many of the issues involved in big data for general insurance. The US's NAIC has established a working group on big data, and NAIC and EIOPA have jointly been discussing issues of big data (EIOPA and NAIC, 2018^[7]) and published a paper on the European insurance market. It is also important to recognise the potential social and ethical questions on using big data, and to that extent EIOPA established a Consultative Expert Group on Digital Ethics in Insurance in late 2019.¹

This reports has been developed to bring better understanding to what big data and AI are, as well as what impacts it might have on the insurance sector. It will conclude with potential policy actions countries may consider to ensure that are prepared and proactive in light of these developments. As the OECD's Insurance and Private Pensions Committee (IPPC) undertakes surveillance of market developments, including on technological developments, IPPC will continue to monitor related developments so timely policy recommendations can be made for policymakers

¹ EIOPA Consultative Expert Group on Digital Ethics in Insurance <<https://eiopa.europa.eu/Pages/News/EIOPA-establishes-Consultative-Expert-Group-on-Digital-Ethics-in-Insurance.aspx>>.

2. Big data

2.1. What constitutes big data

Big data is increasingly ubiquitous, with big data often being cited as a source for better understanding politics, economy, society etc. However, it is not always clear what is meant by big data, so understanding what big data is, especially given that insurance could potentially use big data as a source of its data analytics, is important.

One of the common definitions of big data is to view it in the 3Vs (Laney, 2001^[8]) or the three challenges in data management: volume, variety and velocity (Chen, Chiang and Storey, 2012^[9]), which are all “high” in the case of big data.

High volume is the size of the data, which for big data could be reported in multiple terabytes (which is 1,000 gigabytes and would fit as much as 1,500 CDs or 220 DVDs) or petabytes (1 million gigabytes).

High variety is when there is structural heterogeneity in the dataset. Structured data, which constitutes only 10-15% of all existing data, refers to the tabular data found in spreadsheets or relational databases. Text, images, audio, and video are examples of unstructured data, which sometimes lack the structural organisation required by machines to be used for analysis and makes up about 80% or more of all enterprise data. Spanning a continuum between fully structured and unstructured data, the format of semi-structured data does not conform to strict standards. Extensible Markup Language (XML), a textual language for exchanging data on the Web, is a typical example of semi-structured data. XML documents contain user-defined data tags which make them machine-readable. Semi-structured data constitutes around 5-10% of data (Gandomi and Haider, 2015^[10]) and (Taylor, 2018^[11]).

Velocity refers to the rate at which data is generated and the speed at which it should be analysed and acted upon. The proliferation of digital devices such as smartphones and sensors has led to an unprecedented rate of data being produced (Gandomi and Haider, 2015^[10]). This in turns requires greater speed at which data needs to be filtered.

FCA carried out a feedback statement in 2016 outlining what big data means. Big data is referred as being (FCA, 2016^[12]):

- using new or expanded datasets and data, including from unconventional sources such as social media;
- adopting the technologies required to generate, collect and store these new forms of data;
- using advanced data processing techniques;
- sophisticated analytical techniques such as predictive analytics; and
- applying this data knowledge in business decisions and activities.

Thus, it is not limited to the type of data, but also includes the data processing and analytic aspect of big data. On the other hand, the FCA report identifies the main sources of big data that insurers may be using as (FCA, 2016^[12]):

- Proprietary data (e.g., data from connected companies such as personal data of products purchased or loyalty cards)
- Data acquired from third parties (e.g., aggregated search engine data such as credit checks, license details, claims discount databases, price comparison website quote)
- Social media data (e.g., consumer-specific data taken from Facebook or Twitter) and
- Connected devices data (e.g., telematics devices such as could be used in motor, home or health telematics).

Proprietary data and data acquired, as well as connected device data, would likely be structured data, including data from Internet of Things (IoT). Social media data would likely be unstructured, which could make it costly to make it useable for big data analytics purposes. Both structured data could include audio and visual data, which could assist in instances of disasters.

AI is closely related to big data, but distinct. Big data refers primarily to the information data that is collected, while AI is the process of machine learning that uses data or big data to achieve the learning process of the algorithms. AI is a specific process which may or may not use big data, while big data is the data that could be inputted for a variety of processes in the insurance value chain.

2.2. How and where insurance may be affected by big data

Big data is anticipated to affect insurance in a number of ways. The most widely anticipated is data analytics, although what this specifically means is not always clear from the coverage of this topic. The second is underwriting and pricing, with different views on how big data could affect them. Distributions and sales are more obvious avenues given the way big data might enable better targeting and understanding of consumer behaviour. Claims handling and complaints could be streamlined using big data, and marketing could be more targeted with big data.

Data analytics is the science of drawing insights from raw information sources. Data analytics is a broad term that encompasses many diverse types of data analysis. Essentially any type of information can be subjected to data analytic techniques to get insight that can be used to improve understanding and processes. Many of the techniques and processes of data analytics have been automated into mechanical processes and algorithms.

There are four types of data analytics (Investopia, 2018^[13]):

- Descriptive analytics: what happened over a given period of time (analysis of past data).
- Diagnostic analytics: why something happened, which involves more diverse data inputs and some hypothesising.
- Predictive analytics: what is likely going to happen in the near future.
- Prescriptive analytics: suggesting a course of action going forward.

Based on data analytic tools, insurers can take advantage of big data to apply diagnostic and predictive analytics to predict the behaviour of potential policyholders and take action based on the outcomes.

It should be mentioned that without expert input, big data analytics could be subject to spurious correlation and caution needs to be taken in interpreting data. Spurious correlations occur when two random variables track each other closely on a graph, leading one to suspect correlations. This may lead to assumptions that one of the variables is linked to the movement of the other variable.² However, this does not always

² You can see a number of clearly spurious correlations at <http://www.tylervigen.com/spurious-correlations> for example.

confirm causation between the variables, and only through expert analysis can causation be well established.

In the insurance industry, firms have primarily relied on traditional generalised linear models (GLMs) to assess and price risks.³ This is a statistical technique used to estimate the relationships between the probability of making a claim and different risk factors.

However, some firms have started to use other analytical techniques as well to create inputs to GLM. For example, decision tree analytics or non-linear techniques, such as machine learning techniques, are being used (FCA, 2016_[12]).

The IAIS is looking across the produce lifecycle of insurance, and thinking on a number of cases when big data is being deployed⁴.

Big data is being employed in **product development**, for example, through the use of telematics (see Box 1). While the most widely known and actually applied use case is auto telematics, there are a number of potential ways in which telematics may become more integrated into insurance products going forward.

Box 1. Telematics insurance

While the most widely known form of telematics insurance is for automobile insurance, there are a variety of telematics insurance which are being deployed or have a strong potential of being applied.

Motor insurance related data has been abundantly accumulated in insurance companies as it is one of the largest lines in most countries. Telematics motor insurance is when a device (blackbox) is fitted into motor vehicles or by using an app on a smartphone, and used to track driving. For example, the Italian Insurance Association estimates that blackboxes have been installed in over 2 million cars in Italy to support the provision of blackbox insurance, “telematics car insurance” or Usage Based Insurance (UBI), and is one of the large markets for telematics car insurance. Blackbox devices track speed, braking, acceleration, cornering and the time of the day a journey is made via satellite technology. The data is transmitted to the insurer by GPS which enables the insurer to estimate the likelihood of a claim being made. Such programmes benefit young drivers that do not have a track record to influence their premiums, for example.

There are a number of *home devices*, such as Hive which is a home security product, Nest which is a thermostat, which have the potential to link to insurance. These products are controlled through an application on your smartphone to manage how your security or energy use is regulated in your home. While premium discounts are offered to more traditional security measures for property insurance, such as deadbolts, burglar alarm, fire alarm, there are few examples of home telematics being applied for insurance. Allianz and Deutsche Telekom have formed a partnership in which digitally connected homes automatically alert Allianz’s

³ The Generalised Linear Model (GLM) is a generalisation of the general linear model. In its simplest form, a linear model specifies the (linear) relationship between a dependent (or response) variable Y , and a set of predictor variables, the X ’s, so that $Y = b_0 + b_1X_1 + b_2X_2 + \dots + b_kX_k$. In this equation b_0 is the regression coefficient for the intercept and the b_i values are the regression coefficients (for variables 1 through k) computed from the data.

⁴ From a confidential draft of July 2019, IAIS is developing an Issues Paper on the Use of BDA in Insurance which has been subject to public consultation in late 2019.

emergency hotline if there is a problem, such as a burst pipe (Allianz SE, 2014_[14]). However, the objective does not appear to automatically lead to premium discounts, for example.

Personal devices such as Fitbit and Apple watch permit device operators to collect individual activity data as well as health related data. These devices collect a wide range of lifestyle data, such as heart rates, exercise information, and GPS, which are data that could lead to better predictive and diagnostic analytics. Fitbit recently released a new tracker, Inspire, which is available only to corporate employees and health insurance members. In addition, Fitbit is a named covered fitness benefit in 42 Medicare Advantage plans across 27 US states, while it is working with insurance firms like United Health (Russell, 2019_[15]) and the logical step for those affiliated insurers would be to better link the data with insurance.

Vitality offers life and health insurance in the UK, and offers premium discounts based on the activity points that can be earned via use of Apple watches and demonstrated activity levels. Vitality activity points can also contribute to ISAs (individual savings accounts, which allows individuals to hold cash, shares, and unit trusts free of tax on dividends) (Vitality, 2019_[16]).

In addition, some companies are starting to offer premium discounts on pet insurance for pets that use a Fitbit like device, PitPat. Regularly exercising dogs can receive a cash reward of up to GBP100 a year (Howlett, 2019_[17]).

Marketing, both direct and indirect, is the other area in which big data could be effectively used to target consumers. Search engine optimisation is increasingly being employed, by improving the visibility of a website or a webpage in a search result, and which itself is a result of processing and analysing large datasets.

Aggregated search engine data is being used to analyse potential groups of consumers who may have a specific insurance need. By understanding what a consumer is searching for, more tailored marketing can be carried out. For marketing in particular, access to social media data is a potential source of data.

In terms of **distribution and sales**, the increasing popularity of price comparison sites have changed how consumers search for insurance products. Firms can use a variety of data sources to verify consumer information during the sales process. Most insurers predict that big data should make it easier for consumers to obtain quotes.

Connected devices and social media are likely to assist with **claims verification** process, which is being improved through digitalisation. Social media can also be used to detect **fraudulent claimants**. For example, social connections can be analysed to identify suspected fraud rings.

2.3. Pricing and risk classification

In insurance, it is sometimes useful to distinguish between "costing" (the calculation of the technical premium) and "pricing" (the actual commercial decision to offer a policy at a certain premium level). Insurance rates must be based on predictions rather than actual costs. Most rates (costs) are determined by statistical analysis of past losses based on specific variables of the insured. Variables that yield the best forecasts are the criteria by which premiums are set. However, in some cases, historical analysis does not provide sufficient statistical justification for selling a rate, such as for earthquake insurance. In these cases, catastrophe modelling is sometimes used (thisMatter, n.d._[18]).

The advent of big data has given rise to the possibility that risk-based pricing is increasingly applied given that more data could improve the predictability of policyholder behaviour or incidents. However, given the competitive landscape of insurance, insurers may not wish to distinguish between similar risk level policyholders but based on risk sensitivity or propensity to switch (FCA, 2016_[12]).

Insurance sets prices by groups of people who have similar risk profiles, whether, for example, by gender⁵ or age for auto insurance, which is called risk classification. Big data provides new sources of information for understanding policyholders, fine-tuning the risk classification.

There are benefits and drawbacks that may arise from risk classification being further broken down. The benefits to greater risk classification is pricing based on risk, allowing insurers to combat adverse selection by marketing to low risks. Potential policyholders that are low risk may not want to pay for a price that reflects the wider population of the risk pool. Pricing based on risk may be far more fair to low risk policyholders as low risk policyholders would usually subsidise a high risk policyholder in a risk pool. Pricing based on risk provides a signal to the policyholder about their riskiness. On the other hand, a signal of a higher price may encourage a change of behaviour (Swedloff, 2014^[19]).

Nevertheless, there are risks to greater risk classification. It may be socially beneficial to the extent that insurers succeed in bringing new, low risk entities or individuals into the overall risk pool. If it results in exclusion or difficulty of obtaining a quote for a high risk policyholder, this could result in sub-optimal market outcomes.

While insurance can be viewed as spreading risks through a population, risk classification could undermine these risk spreading, since some policyholders may be burdened or locked out of insurance as a result. It is particularly troubling when a risk classification is based on a suspect category. There may be constitutional, legal or regulatory concerns of discriminating groups based on ethnicity, race, gender, etc. too⁶ (Swedloff, 2014^[19]).

If the policyholder has no control over the characteristic which risk classification is based on, such as genetics, it could be viewed as unfair. Even if the characteristic does accurately reflect a risk, it may not be socially acceptable for this classification to take place (Swedloff, 2014^[19]), although it could become a relevant consideration for policyholders in taking preventative care, for example.

Returning to the spurious correlation mentioned above, while risk classification is based on correlation and not causation, there must be a strong causal backbone for the correlation to be considered. This does not include the fact that risk classification is imperfect and expensive, creating incentives to take advantage of correlations found as much as possible.

Finally, risk classification may require insurers inquiring about otherwise irrelevant information, such as credit score, genetic information and sexual orientation raising privacy concerns. If policyholders refusal to respond to such queries were to affect pricing or offering of a policy, or even higher premiums, this could raise concerns over the merit of risk classification (Swedloff, 2014^[19]).

2.4. Regulatory considerations of the use of big data in insurance

While there are significant benefits from using big data in the production and business of insurance, there may be certain social costs in doing so. While not directly from big data, the example of New Zealand's earthquake insurance is a case in which more granular data has led to the exclusion of some from being insured as discussed below (see Box 2).

⁵ Discrimination by gender is forbidden in the EU since December 2012 (According to the European Court of Justice's ruling on the Test-Achat case (Case C-236/09) of 1 March 2011).

⁶ For example, in the U.S., all states have unfair trade practices laws/regulations, modeled after the NAIC Unfair Trade Practices Act (#880). These laws prohibit unfair discrimination, which, among other things, includes refusing to insure or limiting coverage to an individual due to ethnicity, race, gender, religion, national origin, and other protected classes.

Box 2. Risk-based pricing in the New Zealand property insurance

New Zealand experienced a magnitude 7.1 earthquake (EQ) in Canterbury in September 2010, and then the Christchurch earthquake in February 2011 which had a magnitude of 6.2. Christchurch's central city and infrastructure was badly affected with liquefaction affecting some areas as a result of the 2010 EQ, making the damage wide spread and deadly.

New Zealand's Earthquake Commission (EQC) provides government-backed natural disaster insurance for residential properties, covering perils that are a result of EQs. It is an automatic extension to property insurance, and cover building, content and land. It is estimated to have paid around NZ\$11 billion (USD7.3 billion) by the time it settles its claims (RMS, 2018^[20]).

The losses have exposed significant shortfalls in the country's insurance market, in terms of deficiencies in data and gaps in portfolio management. Since then, policy terms have been tightened, and restrictions introduced on coverage and efforts made to improve databases. A cap will be introduced on government-backed residential cover from NZ\$100,000 to NZ\$150,000. While an increase, it is well below the average house price in New Zealand, which was NZ\$669,565 with a rebuild cost of NZ\$350,000 in December 2017 (RMS, 2018^[20]).

However, in March 2018, Tower Insurance announced a move to risk-based pricing for home insurance, which has resulted in 300% price hikes for some Wellington properties. (Stepanova, 2018^[21]) This was possible as a result of the increasing quality and granularity of underwriting and claims data, and in particular the advance in liquefaction module, leading to the development of a high-definition EQ model. The model is built upon a variable resolution grid which is set at a far more localised level (RMS, 2018^[20]).

Following this, a number of other insurers, including IAG, the largest property insurer, followed on with their transition to risk-based pricing, with IAG's chief risk officer predicting that there will soon be an end to low risk parts of the country subsidising the higher risk places. (Tibshraeny, 2018^[22])

This has resulted in IAG refusing to take on any new property contents business in the Wellington area although IAG did not to take on risk-based pricing in the end. ((n.a.), 2019^[23])

The EQC removed contents coverage at the end of 2018, given submissions from the private insurance market that this could be privately provided.

Besides FCA's work on big data, the NAIC has established a Big Data (EX) Working Group which discusses how to improve the understanding of predictive models (NAIC, Big Data Working Group, 2018^[24]).

In addition, the EU-U.S. Insurance Project hosted a dialogue on big data in October 2018 (EIOPA and NAIC, 2018^[7]). The working group on big data is currently focussed on better understanding the types of big data, and how this is being used for underwriting, and how supervisors are addressing their data needs to appropriately monitor insurance markets.

Even within these groups, one of the main concerns that have been raised appears to be **privacy and data protection** concerns. This stems primarily from the fact that much of big data is often linked with personal information. The NAIC model law of 2000, the Privacy of Consumer Financial and Health Information Model Regulation, requires insurers to (1) notify consumers about their privacy policies; (2)

give consumers the opportunity to prohibit the sharing of their protected financial information with non-affiliated third parties; and (3) obtain affirmative consent from consumers before sharing the protected health information with any other parties, affiliates and non-affiliates.

In the EU context, the European Supervisory Authorities (EIOPA, EBA and ESMA) conducted a joint cross-sectoral review on the use of big data and published a report with key findings in February 2018 (European Supervisory Authorities, 2018^[25]). EIOPA also set up a multi-disciplinary InsurTech Task Force and a thematic review was published in April 2019 (Eiopa, 2019^[6]) on the use of big data specifically by insurance undertakings and intermediaries. One of the objectives of the thematic review was to gather empirical evidence on the impact of big data across the insurance value chain. (EIOPA, 2018^[26]) As a follow up of the thematic review, the InsurTech Task Force is currently developing a common understanding on machine learning algorithms and their implications from a supervisory standpoint to promote supervisory convergence in this area. Furthermore, through the Consultative Expert Group on Digital Ethics in Insurance, EIOPA is developing a set of principles on digital responsibilities. The principles will address the use of new business models, technologies and data sources in insurance from the perspective of fairness and considering ethical considerations.

In the EU, the General Data Protection Regulation (GDPR) requires EU firms (*i.e.* not only insurance undertakings) increased transparency and creates new rights for consumers, additional records, application of enhanced security measures, compliance checks and impact assessments. The GDPR recognises the overarching principle of fair treatment of consumers when it comes to processing personal data, and enables consumers to demand the removal of their data from insurers' databases (commonly known as "right to be forgotten").

Box 3. EU General Data Protection Regulation (GDPR)

The EU Parliament and the European Council agreed on the General Data Protection Regulation (GDPR) in December 2015. It is applicable to firms that process personal data from those residing in the EU, irrespective of whether their services are free or fee-based, whether the firm is based in the EU or not. It is an update to the Data Protection Directive which came into force in 1995.

Under the GDPR, fines can be up to €20 million or 4% of global annual turnover, whichever is the higher, if the action of the firm leads to a loss of information or a data breach. It took effect in member states from May 2018.

GDPR requires private information to be erased without undue delay when the data is no longer required in relation to the purpose for which it was collected. The data used must also restrict use of data when the data quality has been contested by the data subject. The firm must maintain an accurate record of the data subject's agreement for their data to be used for primary and any secondary purposes, without which the firm may not have the right or ability to use the data.

Depending on how and where insurers process their data, this could have implications on how new technologies could be introduced.

In Germany, the supervisor published its circular concerning supervisory requirements for IT in the insurance sector (*Versicherungsaufsichtliche Anforderungen an die IT – VAIT*). VAIT primarily targets senior management, and clarifies what BaFin expects from insurance undertakings with regard to the management and control of IT operations, including the required access rights management. In addition, VAIT lays down requirements for IT project management and application development, which also encompasses end-user computing in business units.

The other main concern is with regards to the **competition**. On the consumer-side, while big data creates the potential for greater information being available and more customised insurance products, a source of big data could unfairly advantage any one insurer that has been able to take advantage of big data (FCA, 2016^[12]). Given that some of the biggest firms are technology firms like GAF A (Google, Amazon, Facebook and Apple), there is a tendency for digital technology to result in oligopolistic outcomes due to the network externalities. (Keller et al., 2018^[27]) (European Union et al., 2019^[28]), and the insurance entity with the best access to the appropriate data could benefit mostly.

3. Artificial intelligence (AI)

Improvement in artificial intelligence (AI) is impacting many facets of life, even if the way in which AI is applied often times is not obvious. While the advent of AI has many positive aspects, media coverage of incidents like Facebook data harvesting and questions on the extent to which robots may take over jobs have led to some scaremongering of AI. In this context, it is important to contemplate and understand how AI is changing business operations, and what regulatory and ethical questions need to be discussed given the developments in AI technology.

3.1. What is AI and how is it being applied

The field of AI research was developed in the 1950s (Anyoha, 2017^[29]), although there have been a number of cycles and it has experienced what is generally called “AI winter” with disappointments in the technology to deliver on its promise and funding cuts to its research after this period. The technology has been experiencing a renaissance in the last 20 years, as a result of growth in computing power and memory capacity, developments in cloud computing and distributed and parallel processing, availability of large databases, and improvements in theoretical understanding (Kessler, 2018^[30]). The potential impact of AI is estimated to drive global GDP up to USD15.7 trillion by 2030 (PwC, 2018^[31]), and 85% of customer interactions could be managed without a human by 2020 (Deloitte Digital, 2017^[32]).

AI encompasses all intelligent agents (computer systems) that have the capacity to learn, adapt and operate in dynamic and uncertain environments (Mialhe, 2018^[33]). To achieve this, smart systems use advanced algorithms that learn with every additional data record and continually adjust and enhance their predictions (Hehner et al., 2017^[34]). Machines mimic cognitive functions associated with human minds, such as learning, perceiving, problem solving and reasoning to achieve this (Balasubramanian, Libarikian and Mcelhaney, 2018^[35]).

Machine learning is one of the main ways in which AI is being applied, with algorithms that can learn from examples and can improve their performance with more data over time (PwC, 2018^[31]). Deep machine learning is a branch of machine learning which relies on complex statistical models and algorithms with multiple layers of parallel processing that loosely model the way the biological brain works. Neural networks “learn” to perform tasks by considering examples, generally without being programmed with any task-specific rules. Deep machine learning requires powerful computers and huge amounts of data to enable the self-learning to take place and hence why it has been able to develop more in the last 20 years. Defence and security have been an important part of these developments, which has accelerated with the need for general cyber and terrorism defences needing to be deployed (Mialhe, 2018^[33]).

The difference between machine learning and deep machine learning can become significant when considering what goes into AI for any given output. Machine learning involves decision trees and Bayesian networks (a type of probabilistic graphical models) thus making the process of decision making more transparent and any biases easier to detect. On the other hand, deep machine learning is based on neural networks or genetic algorithms (a search heuristic inspired by the theory of natural evolution reflecting the process of natural selection) produced by directed evolution (a method used in protein engineering that mimics the process of natural selection to evolve proteins or nucleic acids towards a user-defined goal).

This makes it nearly impossible to understand why or how the algorithm is reaching certain decisions (Bostrom and Yudkowsky, 2018_[36]).

When AI or machine learning is being applied for business purposes, such as online retail and recommender systems, the outcome would be to show products, social media posts and search results, which would require accuracy of data, but may not necessarily lead to considerations of an ethical nature or on its criticality. When an AI decision has a large stake, such as a financial decision, a diagnostic medical decision, or a critical safety decision of an autonomous vehicle, the decision making process of the algorithm becomes important and the fact that it is a black box causes concerns on the potential assumptions that are made by the algorithm (PwC, 2018_[31]). Even with recommender systems, there is potential for algorithms to push inappropriate images and products, and push dangerous social circumstances.⁷ (Fisher and Taub, 2019_[37]). There is also the risk of so called “filter bubbles”, where previous search results will already filter the outcome of a search.

The best known example of machine learning is google search, which can be posed questions instead of simple search terms, as well as Amazon and Facebook sites, which make recommendations and ads based on browsing history and past purchases in the case of Amazon. Siri and Window’s Cortana are examples of deep machine learning applications, which will learn to understand the nuances and semantics of language to closely resemble real-life conversations. Another example is AI being used to root out exam cheats and reduce costs by including plagiarism detectors, and randomly changing numerical variables for mathematic questions (Jack, 2018_[38]).

Box 4. Work on AI in the OECD

The OECD has been developing three main avenues of work related to AI:

1. Analytical work in a report called ‘AI in society’ (DSTI/CDEP(2018)9/REV1). The draft report describes economic and social applications and impacts of AI technologies and their policy implications with an overview of i) the technical landscape; ii) the economic landscape; iii) applications (including financial services); iii) public policy considerations; and; iv) the policy landscape.
2. Scoping principles to foster trust in and adoption of AI with an AI Group of experts at the OECD (AIGO). AIGO brings together experts nominated by national delegations, by business, civil society, trade union and technical community advisory committees, and a experts invited by the Secretariat.
3. An OECD AI policy observatory: an AI Policy Observatory launch is being planned for the 2019-20 period, working with committees across the OECD and a wide spectrum of external actors.

Work by the OECD in relation to AI can be found [here](#).

⁷ A recent New York Times article exposed how YouTube’s recommendation algorithm was exploited by paedophiles, by recommending videos with images of children in the background of home videos.

3.2. International guidelines on AI and ethical considerations

A number of international organisations and fora have been discussing and producing guidelines related to the ethical application of AI, and it is important to understand their framework to be able to consider how it could be approached in the context of insurance.

The OECD Council adopted the [Recommendation on Artificial Intelligence](#) in May 2019. It was the first inter-governmental standard on AI, and will be followed up by the development of practical guidance for its implementation. The OECD Recommendation was also the basis for the G20 adopted human-centred AI Principles.⁸ The OECD AI Principles aims to promote AI that is innovative and trustworthy and that respects human rights and democratic values (see Box 4). The OECD Recommendation contextualises the world that surrounds AI, and tries to ensure that AI is developed in a conscious and inclusive manner.

Box 5. OECD Recommendation on AI

The OECD Recommendation identifies five complementary values-based principles for the responsible stewardship of trustworthy AI:

- AI should benefit people and the planet by driving inclusive growth, sustainable development and well-being.
- AI systems should be designed in a way that respects the rule of law, human rights, democratic values and diversity, and they should include appropriate safeguards – for example, enabling human intervention where necessary – to ensure a fair and just society.
- There should be transparency and responsible disclosure around AI systems to ensure that people understand AI-based outcomes and can challenge them.
- AI systems must function in a robust, secure and safe way throughout their life cycles and potential risks should be continually assessed and managed.
- Organisations and individuals developing, deploying or operating AI systems should be held accountable for their proper functioning in line with the above principles.

Consistent with these value-based principles, the OECD provides five recommendations to governments:

- Facilitate public and private investment in research & development to spur innovation in trustworthy AI.
- Foster accessible AI ecosystems with digital infrastructure and technologies and mechanisms to share data and knowledge.
- Ensure a policy environment that will open the way to deployment of trustworthy AI systems.
- Empower people with the skills for AI and support workers for a fair transition.
- Co-operate across borders and sectors to progress on responsible stewardship of trustworthy AI.

⁸ From the G20 Ministerial Statement on Trade and Digital Economy (8-9 June 2019), <https://www.mofa.go.jp/files/000486596.pdf>.

The other guideline comes from the European Commission's Independent High-Level Expert Group on Artificial Intelligence (HLAG AI), Ethics Guidelines for Trustworthy AI (High-Level Expert Group on Artificial Intelligence, 2019^[39]). The assessment list included in the Guidelines is undergoing a pilot phase. The HLEG AI's Guidelines are more focussed on ethics related issues, and due to this is more specific on the nature of AI and how it should be developed. It is in fact derived from four ethical principles, which are rooted in fundamental rights: respect for human autonomy, prevention of harm, fairness and explicability (High-Level Expert Group on Artificial Intelligence, 2019^[39]).

Box 6. Ethics Guidelines for Trustworthy AI: High-Level Expert Group on Artificial Intelligence (AI HLEG)

The Guidelines put forward a set of 7 key requirements that AI systems should meet in order to be deemed trustworthy:

- **Human agency and oversight:** AI systems should empower human beings, allowing them to make informed decisions and fostering their fundamental rights. At the same time, proper oversight mechanisms need to be ensured, which can be achieved through human-in-the-loop, human-on-the-loop, and human-in-command approaches
- **Technical Robustness and safety:** AI systems need to be resilient and secure. They need to be safe, ensuring a fall back plan in case something goes wrong, as well as being accurate, reliable and reproducible. That is the only way to ensure that also unintentional harm can be minimized and prevented.
- **Privacy and data governance:** besides ensuring full respect for privacy and data protection, adequate data governance mechanisms must also be ensured, taking into account the quality and integrity of the data, and ensuring legitimised access to data.
- **Transparency:** the data, system and AI business models should be transparent. Traceability mechanisms can help achieving this. Moreover, AI systems and their decisions should be explained in a manner adapted to the stakeholder concerned. Humans need to be aware that they are interacting with an AI system, and must be informed of the system's capabilities and limitations.
- **Diversity, non-discrimination and fairness:** Unfair bias must be avoided, as it could have multiple negative implications, from the marginalization of vulnerable groups, to the exacerbation of prejudice and discrimination. Fostering diversity, AI systems should be accessible to all, regardless of any disability, and involve relevant stakeholders throughout their entire life circle.
- **Societal and environmental well-being:** AI systems should benefit all human beings, including future generations. It must hence be ensured that they are sustainable and environmentally friendly. Moreover, they should take into account the environment, including other living beings, and their social and societal impact should be carefully considered.
- **Accountability:** Mechanisms should be put in place to ensure responsibility and accountability for AI systems and their outcomes. Auditability, which enables the assessment of algorithms, data and design processes plays a key role therein, especially in critical applications. Moreover, adequate an accessible redress should be ensured.

There are some common themes between the guidelines, which is worth highlighting. Both guidelines are human-centric, emphasising the need that AI be beneficial to people. In addition, the need for security and transparency of AI are echoed in both guidelines.

An important element that is included in both guidelines is that human intervention or agency and oversight should be made possible to ensure that AI contributes to a fair and just society (OECD) and empowers people (HLAG AI). This is a critical component of ensuring that AI is applied in a way that can remedy unfair bias or can be made accountable in certain circumstances.

As the HLAG AI is a more comprehensive set of principles, there are additional elements which go beyond that of the OECD Recommendation. In particular, they raise the need for traceability, as well as to have adequate data governance which includes privacy and data protection. HLAG AI also raise the potential of marginalisation of vulnerable groups, with the need to foster diversity, so that AI is accessible to all.

When considering these in the context of insurance, it is clear that all themes should be adapted in a manner that encourages inclusive growth, while maintaining safeguards that will ensure AI is operated for the benefit of people and any externalities are swiftly addressed. The OECD Recommendation is supported by recommendations towards governments, which would be an important factor for insurance regulators and supervisors to take into account (High-Level Expert Group on Artificial Intelligence, 2019^[39]) while being subjected to the wider policy framework that is developing related to AI.

A number of supervisors have established regulatory sandboxes and innovation hubs to spur innovation in the financial sector by establishing platforms to enable experiments with their technology and relaxing some of the regulatory requirements within the platform.⁹ The UK Financial Conduct Authority (FCA)'s Innovation Hub is one of the first applying the “regulatory sandbox” approach. Singapore’s Monetary Authority of Singapore (MAS) has also adopted the regulatory sandbox approach. Australia’s Securities and Investment Commission (ASIC) has established an Innovation Hub to mitigate risks by engaging early with innovators and helping new entrants understand the regulatory requirements. The Hong Kong Monetary Authority and Canada’s Ontario Securities Commission have also launched similar platforms. These platforms are all designed to assist new market entries that would encourage greater competition and innovation in the market, ultimately benefiting consumers.

The regulatory sandbox approach intentionally creates a space for insurance technology to be experimented in a different regulatory regime from the regular regulatory requirements. This supports better understanding of when technologies are deemed successful and scalable, and how they will be graduated into the regular regulatory framework if this is the case. Another possible approach in that regard are Innovation Hubs, which do not create different/parallel regulatory regimes. Going forward, this will be important in ensuring that a level playing field is applied at the appropriate stage.

A relevant development that is taking place between MAS, FCA and the Australian Securities and Investment Commission are bilateral cooperation agreements between the authorities that allow them to make referrals on innovative businesses seeking to enter each other’s market. This would assist in enabling innovators transfer their business models on a cross-border basis, assisting with the businesses to scale when the opportunity arises. This responds to the OECD AI Recommendation in having better international cooperation to progress on responsible stewardship of trustworthy AI. This is also relevant with regards to data transfer, as data is a key component of the insurance sector and cross-border cooperation to enable this, where appropriate, should be discussed.

The more important aspect is how could insurance regulators and supervisors appropriately monitor and take necessary action when inappropriate decision making by AI has been detected. This is in fact an economy wide issue which governments are struggling to respond to. There are principally two ways in which the two

⁹ Some OECD countries have expressed a preference to innovation hubs given the need to maintain equal treatment of market participants.

international guidelines foresee government intervention: explainability/traceability/auditability, and human intervention.

As the OECD Recommendation is subject to development of implementation guidelines, the HLAG AI Guidelines provide some context on human intervention. Human oversight is intended to ensure that AI does not undermine human autonomy or causes other adverse effects. It refers to oversight in the form of governance mechanisms such human-in-the loop (HITL), human-on-the-loop (HOTL), or human-in-command (HIC) approach¹⁰ (High-Level Expert Group on Artificial Intelligence, 2019_[39]). Practically speaking and given the need for traceability, it seems that a combination of HOTL and HIC would be important in any circumstances in which AI is being developed.

The need to have a HIC approach in particular is implied in the HLEG AI report, in terms of fallback plans and general safety, including AI systems switching from a statistical to rule-based procedure, or that they ask for a human operator before continuing their action in certain circumstances.

Another relevant issue, however, as raised in the OECD Recommendation, is the need for policies that build human capacity in AI. The skill shortage related to AI development is a wide ranging problem, with some research suggesting that while 95% of US and UK organisations consider AI to be a business priority, 51% acknowledge they do not have the right mix of skills within their organisation to execute this (snapLogic, 2019_[40]). The French financials sector supervisor, Autorité de contrôle prudentiel et de résolution (ARPC), published a report in 2018 which includes a glossary of AI jobs¹¹ (Fliche and Yang, 2018_[41]). This list is long and presents the challenges of any supervisor, or company for that matter, trying to monitor their AI activities.

It is imperative that at this stage of adoption of big data and AI in the insurance sector, which is still relatively early, a basic governance structure that can tract and manage AI does seem important and is suggested in the ARPC report too (Fliche and Yang, 2018_[41]). This could ensure a level of responsibility within an insurance entity that is using the technology, as well as providing the supervisor with a way to address any supervisory concerns. It should be expected that as soon as any potential bias or unintended consequences from AI are detected, which could also be indirect and affecting individuals and groups, a human intervention be made to examine and rectify the situation to ensure fairness of the process.

However, the way in which AI works could make it almost impossible to make this determination unless there is a consultation process with supervisors at the HOLT or design stage, or data analysis of AI outcomes is made. Article 22 of the European Union's General Data Protection Regulation (GDPR)

¹⁰ From the AI HLEG report:

- HITL refers to the capability for human intervention in every decision cycle of the system, which in many cases is neither possible nor desirable.
- HOTL refers to the capability for human intervention during the design cycle of the system and monitoring the system's operation.
- HIC refers to the capability to oversee the overall activity of the AI system (including its broader economic, societal, legal and ethical impact) and the ability to decide when and how to use the system in any particular situation. This can include the decision not to use an AI system in a particular situation, to establish levels of human discretion during the use of the system, or to ensure the ability to override a decision made by a system.

¹¹ The ARPC's list of AI job include:

- Data governance, chief data officer, data privacy officer, chief data quality officer
- AI jobs more generally: data scientist, data analyst, data engineer, ontologist, expert in automated processing of natural language, expert in computer vision, and expert in human-machine interaction.

requires when automated decision-making for profiling an individual is involved, the data subject can object to an automated decision-making process being used (Proust, 2015^[42]). The data controller must then implement “suitable measures” to safeguard the rights of individuals, and permit human intervention and importantly to obtain information on the basis by which the automated decision was made. This has been widely referred as the GDPR’s “right to explanation” and the European Commission has prioritised support in developing explainable AI (European Commission, 2018^[43]).

However, practically speaking, it is unclear what explainable AI would require and how regulators might be able to get the necessary expertise or information to make this requirement viable. Discussions with experts in the Committee did not provide any clarity on the issue, whether in a specific insurance context or a more general context, although this requires further consideration among regulators.

Thus, insurance regulators and supervisors should keep abreast of developments related to AI in the insurance sector either in terms of planned or being undertaken, and learn from developments in other sectors. In addition, and depending on the level of market development and size of entities, insurance regulators and supervisors may wish to develop basic governance requirements as a first step to ensuring that a minimal level of understanding and responsibility of AI is *in situ* in the insurance entity, as well as providing supervisors a way to monitor developments.

3.3. Ways in which AI can/is being applied in the insurance sector

When there is an article on how AI can be taking over workforces, insurance, and in particular claims handling, is the prime example that is always provided. (Wright, 2019^[44]). While there have been a number of insurance entities attempting to harness AI to their processes, the level of adoption has not been as straight forward as has been suggested.

In the insurance sector, there are a number of ways in which AI could be adopted to improve the efficiency of transactions and business processes. Some examples that have been previously examined by the OECD, include robo-advice (OECD, 2017^[4]). Robo-advice is being developed for investment management and in particular to provide quotes with automated advice and offerings calculated through algorithms. Automated advice could assist pockets of population that do not have access to financial advice to gain input in a more cost efficient way than a human advisor.

While price comparison and distribution sites are becoming wide spread, much effort is being made to develop sites that provide financial guidance, which is tailored to the policyholder’s income and needs with greater automation through algorithms for products with investment and/or long-term saving components. This could assist in narrowing the protection gap of the lower income population as the cost of such services is lowered. For example, robo-advice has the ability of developing a financial plan addressing multiple goals, including retirement, protection needs, estate planning and health/long-term care coverage. Robo-advice has the privacy which some may feel more comfortable with given the sensitivity in discussing money matters.

Insurance start ups such as Lemonade and PolicyGenius use AI to support their policy offerings. AI can simplify and tailor policy offerings to match the needs and financial situation of the policyholder. A number of start ups are integrating AI to their processes, and their success will affect how the wider insurance sector introduces AI into its businesses as well.

An area that is considered to be well suited for AI adoption is claims management, as AI processes can speed up claims payment significantly (Hehner et al., 2017^[34]). However, there are also concerns that the rapidity can compromise the optional payment, as well as potentially being open to fraudulent claims (Ralph, 2019^[45]), although EIOPA’s thematic review, in fact, identified fraud detection to currently be the most common case use of big data analytics (Eiopa, 2019^[6]). While companies like Claim Technology have been providing machine learning systems for claims handling, it appears that the experience has not

been uniform. Zurich, for example, has benefited from machine learning automation for human resource management, it is not clear whether current machine learning would be able to handle complex analytical and sorting work, such as assessment of insurance claims for car crashes or burglaries (Wright, 2019^[44]). Humans had to override the computer's decision too often in the past.

However, the scope in which AI can be deployed in insurance is significant, and how conventional insurers, as opposed to start ups, are applying AI in their processes will provide important input into this development.

Box 7. Impact of AI on insurance business models

AI application in the insurance sector has the potential to improve the efficiency of processing data and making decisions in terms of both contracting and claims processing, as the more obvious areas. Where there is interaction with consumers, and where transaction costs are particularly high, are particular areas in which efficiency gains could be had.

However, AI could also be introduced into the internal systems of insurers to harness data that is being collected to support the data analytic process.

Life insurance which includes an investment component could leverage AI to support the investment decision of policyholders.

Non-life insurance, such as parametric insurance, takes advantage of pre-determined criteria to trigger claim payments, which AI could process in an automated fashion, and is particularly suitable to AI processing and could reduce premium level. This could benefit less developed insurance markets which parametric insurance is being widely deployed.

3.4. Considerations for policy and regulation in AI

The underlying algorithm of AI is not transparent in most cases, and especially in deep machine learning, and biases could be built in, both unintentionally and intentionally, potentially leading to inappropriate advice/output. The understanding of how this impacts policyholder behaviour but also insurers solvency and reputation and how regulation should address this is unclear, but is an area that requires greater discussion.

Given the potential for AI to become ubiquitous in the insurance sector, it is imperative that while encouraging innovation, regulators and supervisors are investing in better understanding the underlying technology. Innovation Hubs or regulatory sandboxes are part of this process for then determining the appropriate regulatory approach, especially when there are cross-border cooperation arrangements. But as conventional insurance companies introduce new technology into their internal processes, it will become increasingly important to hold dialogues with insurers to be able to understand the data that is being used, and potential impacts that could be built into the AI.

Regulators will also need to monitor whether AI outcomes are leading to inappropriate pricing and/or marketing, in particular related to retail policyholder protection. Generally speaking, the transaction cost of a retail policy offering is higher than a commercial policy offering. This provides an incentive for insurers to seek ways to reduce the transaction cost with retail policyholders, and applying AI to such processes would seem an ideal way to do so.

Digital security and data protection would also become a consideration, as AI could request data via an open internet connection or a database which could allow for the system to be hacked, requiring

approaches to prevent such security incidents and developing contingency measures for when such an incident occurs.

AI also raises ethical questions, as election hacking has well demonstrated. While ethical questions are applicable for any AI, there are some questions that may be more relevant for the insurance sector. As we have witnessed from video games and click-bate headlines, humans are already starting to behave in certain ways in response to machine generated contents as the reward centre of the brain reacts positively to such contents (Bossmann, 2016^[46]). The long-term implications of having mainly machines interacting to conclude a transaction could lead to customers reacting in unexpected ways, assuming that they are interacting with a human customer service agent.

Ethical questions are complex as machines take on cognitive work with social dimension for duties that were previously performed by humans. International guidelines by OECD and HLAG AI are key starting points for thinking how to approach ethical issues of AI. There are a number of elements that AI may need to strive to achieve, to ensure that it is ethical. This includes being predictable to those that govern the system, robust against manipulation, and finding the person responsible for getting things done (Bostrom and Yudkowsky, 2018^[36]). These may also be some of the elements that policymakers should consider whether necessary in a regulatory context, for AI to be integrated into system in the insurance sector.

In relation to this, some have explored the idea of “explainable AI” which encourages the notion that AI also needs to be able to respond to questions on “why” it has reached certain decisions. AI is often not trusted to reach the appropriate decision given that its tendency to enhance any biases that may be learned (PwC, 2018^[31]). Such approaches could support the development of AI that is more widely acceptable in society.

In Germany, the Federal Financial Supervisory Authority (BaFin) established a new division in 2016 to identify and assess innovations in financial technology and their impact on the financial market. In 2018, BaFin published the report “Big data meets artificial intelligence – Challenges and implications for the supervision and regulation of financial services” (BaFin, 2018^[47]). Based on potential market scenarios, the report outlined various implications of big data and artificial intelligence for the supervision of financial services.

In France, the Autorité de contrôle prudentiel et de résolution (ACPR) launched a Task Force on Artificial Intelligence in April 2018 to investigate challenges that AI poses to the financial sector. They are gathering information from insurers, banks and fintech companies to better understand how AI is being applied, risks and opportunities from AI and regulatory impediments for adopting AI in the financial sector.

In the US, NAIC has launched a State Ahead Initiative to develop a new data platform and business intelligence framework to allow more self-service analytics and facilitate more sophisticated predictive analytics and AI projects to support market, solvency and macro prudential surveillance needs of state supervisors. As State Ahead matures through 2020, the NAIC will experiment with an AI solvency tool to complement these tools. In 2019, NAIC will be discussing the use of AI-models by insurer, including governance, data quality and how to reduce the opacity of complex (‘blackbox’) models.

As a first step, regulators should discuss the possibility of having a governance requirement related to the management of AI in an insurance entity, which may be useful for a corporate to consider as the focus of AI increases and to have a handle on ethical aspects. Regulators and supervisors should look to gain a better understanding of AI developments so that any skill gap within the supervisor can be identified and filled as the need arises.

In the future, there may come a point when supervisory analysis may become necessary to ensure that AI are not resulting in bias or discriminatory outcomes. Transparency of AI would support this to a certain extent, but there could come a point when greater accountability of outcomes will become necessary. Supervisors could actively monitor complaints data, for example, in the meantime, which could indicate if there is a continuous trend.

4. Concluding policy and regulatory considerations

Big data and AI will continue to be an area in which much attention will be given for many businesses, especially as they become increasingly integrated into business processes. While the insurance sector may be in relatively early stages of adopting big data and AI, the potential for it to impact every step of insurance production as well as business models of insurance is high, and it should serve to improve individuals and society well-being and welfare.

The benefits that can be gained from use of big data and AI could potentially be wide ranging and high. Thus, it is important that opportunities are available to develop potential innovations that can be brought to insurance production, and **regulatory sandboxes and innovation hubs** could facilitate such developments. At the same time, there are risks to the technology as well as potential unintended consequences. A balanced but vigilant approach is necessary to ensure that the maximum benefits can be reaped for all stakeholders.

Being conscious of the potential social costs of using big data and AI, including privacy and ethical concerns, and being proactive when issues are arising is a key role that policymakers should play in ensuring that consumer protection and fairness in the market can be achieved. While in most cases regulation may be technology neutral and not necessitate the development of specific regulation, there are particular areas in which good cooperation with other governmental agencies will be key to having a better understanding of how to ensure that broader regulation is being appropriately applied, as well as how it should be interpreted and applied in the insurance sector.

Privacy and data protection requirements are, generally, an issue for the general data protection agency to prescribe, but given the nature of insurance, if the insurance sector is taking advantage of big data it could become necessary to ascertain the means in which databases are acquired, and the appropriateness of the data being used for its analytics. There are already some instances of the insurance supervisors imposing additional requirements, and the advent of big data and AI could become such an occasion too.

Technology has the tendency of exacerbating existing **market structures**, and companies using big data and AI could accelerate this process. Whether technology, and in particular the access some firms have to particular big data or AI technology, should be monitored to ensure that it does not result in an oligopolistic market structure. Digitalisation has encouraged some regulators to look into different norms and principles to establish consumer welfare (European Union et al., 2019^[28]). This could be an important consideration for insurance regulators too and should be carefully monitored.

Risk classification can lead to potential exclusion from an insurance policy or could have affordability hampered, and big data can accelerate this process. Understanding and drawing lines on what types of big data can be used will become an important part of how insurance regulation ensures reasonable and appropriate use of big data.

There is much that can be learned from the recommendations on AI of OECD and HLAG AI for the insurance sector. While broader guidance and requirements could be implemented at the national level for

AI applications in general, insurance regulators could take steps to better monitor AI developments by requiring a **governance structure** that manages this in insurance entities. This will be particularly important for insurance regulators, so they might be able to request human intervention when unintended consequences or bias is detected from AI decision making. Regulators may need to analyse whether AI is resulting in unwarranted biases or discriminatory practices.

Given the GDPR's wide reach, a better understanding of how to make **AI explainable** is needed. It will be imperative to keep abreast of developments in relation to this aspect of AI for insurance regulators too, as the criteria on what constitutes an explainable AI could emerge, in addition to what actions can be taken when any inappropriate decision making is detected from AI.

There is a lack of skills related to AI both in the regulatory/supervisory side, as well as in the industry. This is not limited to the insurance sector, as the **skill shortage** is a challenge to all industries.

Greater **international cooperation on technological developments** and **facilitation and cooperation on cross-border activities** would also be an important consideration, regardless of whether there is a regulatory sandbox/innovation hub or not. This could be particularly important for **data transfers** that may be happening and being able to ensure that data is being collected and used in an appropriate manner.

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