Institute
and Faculty
of Actuaries

Insurtech – Applications in General Insurance

A Primer for Actuaries

by IFoA GI Insurtech Working Party

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Introduction to Insurtech

The first two decades of the 21st Century have seen the full realisation of the 3rd Industrial Revolution – which ushered in the information and digital era, driven by the PC, the internet, and more recently the smartphone. The world is now seeing the first flowering of the 4th Industrial Revolution. This is encapsulated in the phrase cyber-physical systems, connecting the 'real' physical and biological worlds to the 'virtual' digital world.

Insurtech began as an offshoot of Fintech. This synthesis of finance and technology had been introduced as a concept since the 1980s, but really gained traction in the mid-2000s, and since then has driven a huge transformation in banking and investment services. Insurtech is a much more recent concept – the first stirrings started around 2010, and it is only since 2015 that it has started to attract significant investment.

As insurtech has gained traction, the meaning of the term has become rather abused. Technology firms offering software or services to the insurance industry have hitched themselves to the bandwagon, whether or not they are offering anything particularly new.

The definition of insurtech that the working party adopted for its research was the confluence specifically of new technologies (coming from the 3rd to 4th Industrial Revolution transition) with the insurance industry. This works in two directions. The forward direction is the application of these transition technologies to the transformation of insurance itself. The reverse direction is the innovation and adaptation of insurance to the economic and societal changes that arise from the technology transition, and the shifts in the risk landscape that follow on from that.

The application of new technology in insurance

For the first direction, how these technologies apply to insurance, there are three key elements:

1. The Data Funnel
2. The Processing Layer – AI (Artificial Intelligence) and IA (Intelligent Automation)
3. Digital Delivery

The data funnel refers to the huge increase in the breadth of data capture that is being enabled by technology. This is driven by several sources, including the Internet of Things, capture of video, image, and audio data, data from all the digital traffic on the internet, and the unlocking of unstructured data through AI.

In the processing layer, the two factors driving change are firstly the huge increase in processing power and storage capability – and its accessibility via cloud computing, and secondly the emergence of new data science algorithms and processes. Together, these are enabling the use of the much larger data sources in the data funnel. Artificial intelligence and machine learning can make sense of data like video or images or free text that previously required human interpretation and, as such, was difficult to scale.

AI and IA are also enablers of the third element, digital delivery. A lot of the initial focus in insurtech was on customer experience, both in buying insurance and making claims, and ideas on how technology could improve that. That remains a significant theme of insurtech, but digital delivery also extends beyond these front office functions into the middle and back office. The full benefits of efficiency, agility, and scalability from digitalisation come from addressing the whole process, not just the front end.

These elements are interconnected, and in combination they are allowing new business models for insurance and related services to emerge.

There are many other technology developments in quantum computing, nanotechnology, biotechnology, neural links, that are not mentioned here. Some of these are more embryonic and insurance impacts may be a bit further in the future.

Blockchain or distributed ledger technology has received a lot of attention as well. This may have applications in insurance, perhaps the clearest of these being 'smart contracts', which could, for example, allow complete automation of claims payments for parametric index-based insurance products. But opinions remain divided on the benefits of blockchain for insurance, and so far no definitive use case has emerged.

The effect of new technology on the risk landscape

The reverse direction of insurtech is how insurance is adapting to the impact of technology in transforming the economy and society, and the changes to the risk landscape that flow from that transformation. Risk is becoming more virtual and intangible, and at the same time becoming more interconnected and systemic.

Already it is the case that intangible assets far exceed the value of tangible assets – for the S&P 500, intangibles overtook tangibles in the early 1990s, and by 2018 the ratio was over 5:1. In 1995 the top 5 companies were GE, Exxon Mobil, Coca Cola, WalMart and Altria (tobacco), whereas now they are Microsoft, Apple, Amazon, Alphabet (Google) and Facebook.

At a more personal level, we have witnessed the rise of the gig economy, the sharing economy, online retail, remote working, streaming services, and so on. The Coronavirus pandemic in 2020-21 has further accelerated some of these shifts.

The impact of AI may perhaps be the biggest disruption factor in the risk landscape. The future of work, as the capability of AI develops to take on more complex tasks, is one area likely to experience profound change – with significant knock-on effects to the global economic model. And fully autonomous vehicles may change the whole premise of motor insurance; this makes up around 45% of the total global P&C premium income that could become largely obsolete.

New business models

Traditional insurance products do not always match well to these new exposures, and insurers and start-ups alike are responding with innovations to meet these new needs. In many cases, these responses to technology-driven change are also enabled by new technology. To mention a few themes:

- **Parametric insurance** may be a solution for intangible risk and other protection gaps.
- **On-demand** or **PAYG products** may fit better with the gig and sharing economy than annually renewable products.
- Digital delivery makes **microinsurance** a viable proposition.
- **Risk service models**, where technology is used to help prevent or mitigate losses – for example through predictive maintenance, or cybersecurity services – alongside an insurance backstop.

- **Embedded insurance**, where the insurance is seamlessly integrated as a component of broader online platforms and services, rather than a product sold in itself.

The value chain

The application of insurtech runs right across the value chain, enabling new types of product and services, new forms of distribution, new information for underwriting, and better ways to onboard and service business, particularly around claims. Insurtech solutions are driving analysable data into parts of the value chain that have not historically had that data. This opens up opportunities for actuaries to get involved in these new areas outside the traditional fields of pricing, reserving and capital.

Investment in insurtech

There are huge sums of money being poured into insurtech - $6bn was invested into insurtech startups in 2019, over $18bn since 2012, and rapid year-on-year growth. There are no reliable figures for how much existing insurers are investing in internal innovation, but $20bn is likely to be a conservative estimate.

Those are large numbers, but as a proportion of global insurance premium income (~$5tn) it is less than 0.5%. And if you compare to FinTech, covering the investment and banking sectors, the figures would be around 10x higher than that, so there is still room for insurtech to ramp up.

The impact of Covid on investment is a little unclear. Some companies have reduced investment as a result, although there have also been large capital raises by some insurtechs, such as the Lemonade IPO. And while there are still concerns around the economic shape that the world will be in at the end of the pandemic, Covid has been an accelerant for some of the macro trends driving technology adoption – so this may translate into faster growth for insurtech.

To date the insurtech sector has created a few unicorn companies – these are companies valued over $1bn. Probably the most familiar name among these is Lemonade – they executed an IPO in July 2020 and the stock price more than doubled on the opening day. While it has been very volatile since then, it is still over 3x the original IPO price of $29 per share at the time of writing, with a market cap approaching $6bn. This is an impressive valuation considering that they write just over $200m of premium, and that at a considerable loss. There are things to like about Lemonade – the CX is good, their PR operation is fantastic, and it is built on a digital foundation that should scale very well – but for now at least, customer acquisition costs are too high, and their core business model does not seem compellingly different.

Along similar lines, other full stack US insurtech unicorns include Root, Metromile, Hippo and Next. Root is a telematics motor offering that also executed an IPO in October 2020. Their current market cap is $3bn, although it has lost considerable ground since the IPO – and there are pending class action lawsuits around the accuracy of information in the offering documents. Their business model does not appear to be very radical compared with, say, some of the telematics offerings we have had in the UK for some years. Metromile is another usage-based motor insurance company that recently went public via a reverse merger with a SPAC (special purpose acquisition company). Hippo, which is focused on smart home insurance, is in a similar process. And Next Insurance is focused on SME insurance, which does have some potential for disruption as a segment, and perhaps more so after the business interruption issues with Covid. They have recently signed a distribution partnership deal with Amazon.

Historically, insurtech investment has been highly concentrated in the US (and Silicon Valley in particular), and primarily in retail and consumer lines. However, investment has diversified by both geography and target lines in more recent years, and the UK has emerged in a clear, if distant, second place as a market for insurtech investment. London is a strong focal point for insurtech activity in commercial lines, but the UK is clearly a much smaller market for retail insurance propositions such as those of the US unicorns.

Nonetheless, we do now have three UK-based insurtech unicorns after recent funding rounds – Zego, Bought By Many, and Tractable:

- Zego provides motor insurance to self-employed drivers (e.g. working for food delivery services), integrating with the work platforms of these services, as well as telematics-based motor fleet insurance.
- The original concept of Bought By Many, the second UK unicorn, was to bring together communities of people with similar insurance requirements in specific niches, and to negotiate better insurance deals as a collective group. They launched a pet insurance offering in 2017 and now cover almost half a million pets globally with GWP of around $220m.
- Tractable, meanwhile, uses AI to streamline claims assessment. They are discussed in more detail later in this report, as a case study in the Image, Video and Audio section.

WeFox, based in Germany, is the only other European insurtech unicorn to our knowledge. There are also two noteworthy unicorns in Asia – policybazaar is an aggregator in India, and Zhong An is an insurance company in China. Zhong An is perhaps the most interesting example of all. It was established as a JV between Ping An, a large Chinese insurance company, and two major technology firms – TenCent and AliBaba – which you could characterise as a Chinese Facebook and Amazon respectively. They are a genuine success story with over 460m customers and a staggering 5.8bn policies across several lines of business.

From disruption to partnership

There has been a shift in focus over the last couple of years in the insurtech scene.

Around 2015/16 when insurtech really started in earnest, it was largely regarded as a disruption strategy – the pitch was that incumbent insurers had legacy technology and were incapable of innovating, and so it was only a matter of time before technology companies came in with shiny new CX platforms and took over the market.

That really has not happened – there is clearly nothing in that list of unicorns that has revolutionised insurance in the way that Amazon did to retail or Uber to taxis, for example. A big part of that is that customers do not really care all that much about insurance. It is a very low-touch product for consumers, generally a grudge purchase once a year. The exception is when you have a claim, and – while the track record of the industry is not perfect – still the vast majority of claims are paid in reasonably good time and without dispute. There are also high barriers to entry as an actual risk carrier, so for start-ups with ambitions to become an insurance company, the agency model is often the only practical entry route. That clearly involves working with incumbents, and perhaps limits the digital advantages you could otherwise deliver.

Still, the threat of disruption has not gone away, just the focus is less on start-ups and more on big tech firms and whether they decide to make a play in the market. In many cases it is more a question of when rather than if – Tesla has declared its ambitions, and Amazon has recently dipped a toe into the Indian motor market. The example of Zhong An seems to indicate that this could be a successful model.

So the industry has recognised that doing nothing is not really an option, and at the same time the start-up community has pivoted more towards providing solutions that enhance specific parts of the value chain, rather than trying to compete as disruptors. That has led to some much more interesting value propositions, where the start-up is bringing some specialist knowledge to the table. And, while the disruption play was much more consumer-focused, this shift has meant that insurtech has become much more relevant to commercial lines and London Market business.

These are positive developments. Maybe we are not going to see the Uber or Netflix of insurance emerge with a wholly new business paradigm and fully digital delivery, but this more modular approach of plugging in innovations along parts of the value chain still creates a lot of potential for insurance to evolve its way into the challenges of the 4th Industrial Revolution, and lots of opportunities for actuaries as well.

This report

This report documents the work to date of the IFoA GI Insurtech working party. The working party has focused on the current developments in insurtech and those expected over the likely near-term (the next 5-10 years, broadly). We have concentrated on the actuarial perspective, context, and implications. The stated purpose of the working party has been to:

- Connect the GI actuarial community with developments in the insurtech scene, and
- To prepare the profession for the changes, opportunities and threats technology will bring to the industry and actuarial work

We have looked at four broad areas that we believe cover the majority of insurtech development activity relevant to actuaries:

- The Internet of Things, or IoT – a key source of new data for the data funnel.
- Image, Video, and Audio data – another key source, including consideration of satellite imagery and drones.
- A more general look at the use of Artificial Intelligence (AI) and Intelligent Automation (IA) in the industry, including the unlocking of unstructured data.
- An overview of parametric insurance, focused on new use cases that are enabled by technology, and its application to the emerging risk landscape from new technologies.

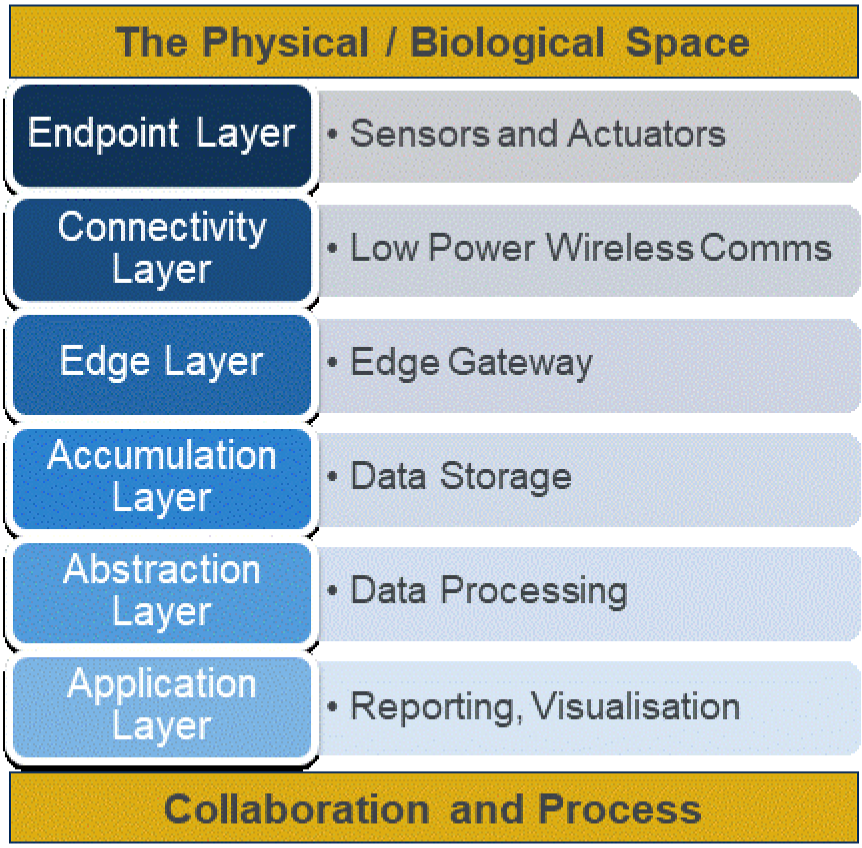
These are all huge topics in themselves, and this report is only really intended as a basic primer in each. We have included actual case studies within each section, and some additional references for readers who are interested in further detail.

In the final section of the report, we look at the actuarial context – the opportunities and threats, our strengths and weaknesses, the main impacts by technology area and to each of the main actuarial fields. We hope this will help to show where we need to focus our efforts, both individually and as a profession, to succeed in the face of the changes wrought by technology.

The Internet of Things

The Internet of Things (IoT) lies at the heart of the 4th Industrial Revolution concept, the connection between the physical or biological world and the digital world. In practical terms, that means sensors embedded in ‘things’ communicating state information – whether it be temperature, pressure, light, acceleration – to a data platform. There is often also a reverse mechanism with actuators again embedded in ‘things’, receiving instructions back from the platform and taking actions as a result – based on specified rules, or increasingly AI elements.

IoT architecture



There is typically a layered architecture to an IoT implementation. The endpoint layer is the sensors and actuators embedded in the physical devices (or biological entities).

The next layer is connectivity – usually a low-power wireless protocol of some description – that connects these endpoints to the internet. This entry point to the internet is an ‘edge gateway’, and this may include some simple processing or rules (‘edge computing’). This edge layer then feeds into an accumulation layer – a platform, usually cloud-based – that accumulates the data.

These elements of the architecture perhaps sit more within the IT domain, but they are important, and it can be useful for actuaries to have an idea on how these layers work and what you can do with them.

The actuarial interest will mostly lie in the final two layers – the abstraction and application layers. The abstraction layer is where the data processing and analytics is done, and the application layer provides the reporting that feeds back into business processes and human collaboration.

IoT use cases

IoT is a very general concept that has applications across a whole range of activities; these are some of the key uses – and note how these align closely with many of the major lines of non-life insurance.

Vehicle telematics

This is clearly the application that has had most impact to date on insurance, and devices are increasingly becoming embedded into new vehicles and producing much richer data than the earlier black boxes. We are moving towards connected vehicles, connected road infrastructure, and ultimately fully autonomous vehicles. These will change the whole nature of the motor insurance risk.

Smart home devices

These are another familiar manifestation of IoT. This goes beyond Alexa turning the lights on and off; IoT devices can be used for security, fire prevention, energy consumption, water leaks, and many other applications.

Commercial property and urban infrastructure

The smart home device concept can be extended to commercial buildings and the engineering within (air conditioning, water systems, heating and power, lifts, etc.). Monitoring of these sensor networks is useful for loss prevention and predictive maintenance but can also assist with reducing energy and water usage, and with other cost-saving and sustainability measures.

The idea further extends into the 'smart city' concept of embedding IoT into urban infrastructure – traffic management, street lighting, waste management, environmental monitoring, etc.

Manufacturing and others

The manufacturing segment is an important area too, particularly with automated production lines; IoT in this context is referred to as the 'Industrial Internet of Things' or IIoT. With the current push for global supply chains to become more localised or regionalised, less reliant on Chinese manufacturing capability, and more automated, this is a rapidly growing area.

There are many other major applications – supply chain and logistics, agriculture, energy, for example – that are already finding their way into insurance offerings.

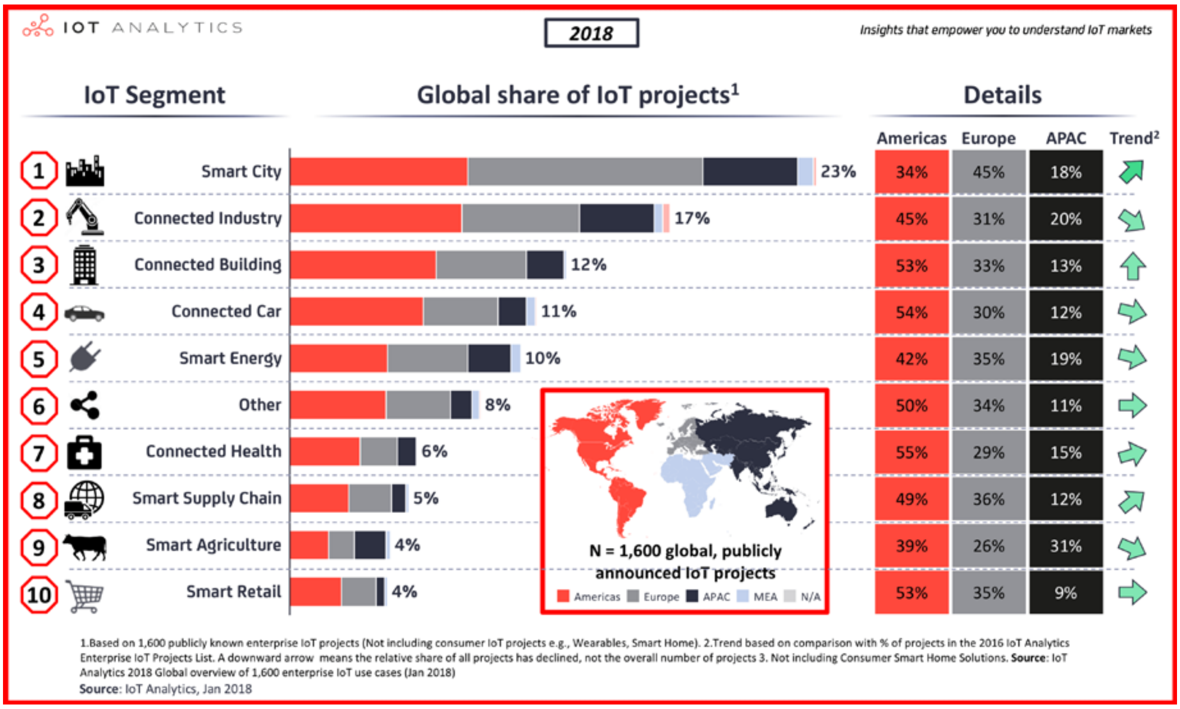
Health and safety

The 'things' in IoT include biological entities, and in that space, wearables and health devices are clearly of relevance to life and health insurance. In a workplace context, IoT devices can help to manage health and safety risk, with clear applications in EL and Workers Comp lines, and public liability.

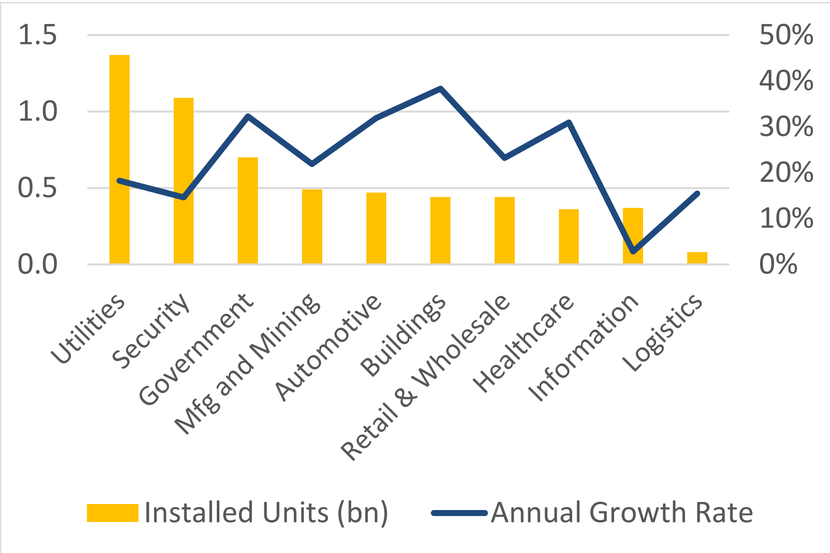
Growth of IoT takeup

There were an estimated 10bn live IoT devices by the end of 2019 generating 14 Zettabytes of data per year (a zettabyte is 1bn terabytes). And the number of devices is forecast to quadruple to 40bn by the end of 2025, with around 2000 new devices being connected every second.

The figure below, based on 2018 data from IoT Analytics, shows both the sectors and regions where there is most activity.



And the figure below shows the number of installed IoT units, based on data from Gartner in 2019, by sector – as well as the annual growth rates.



Analyzing IoT data

It is clear that IoT is generating huge amounts of data, but a key question is how to make sense of it.

IoT is a broad concept; however, as a generalisation, the data it produces comes in the form of time series data. This may be very simple – one sensor that has a binary output, for example. (Floodflash, which is covered as a use case in the Parametric Insurance section, has exactly this – a sensor in the wall of a building that triggers when it is wet.) But it can also be highly complex with real-time data streaming of many concurrent time series, covering both different measures and different individual sensors across a network of devices or 'things'.

In its raw form this may be difficult to even store never mind interpret, so it generally needs some processing. This is typically done at the 'edge' – using distributed processing power (rather than the centralised cloud server) to filter and cache data. For example, a constant stream of data just showing entirely normal readings may not be overly informative, so this might be filtered at the edge to only report readings outside a specified range.

Edge application services can also be used to run automated decision or AI models. These might trigger automatic actuator responses based on sensor readings, or something more complex such as a facial recognition AI model run on video data. The training of such models is not done at the edge – that happens in the abstraction layer using the full processing power of cloud computing – but the implementation of those pre-trained models can be done more locally at the edge.

This filtered data then gets passed into the accumulation layer – the cloud database – and the abstraction layer – where it is processed and analysed.

To become meaningful, it may also need to be combined with additional data that is not coming directly from the sensors. For example, the sensor data might include GPS co-ordinates of a cargo shipment. External data can tell you where that is located and, say, what the weather was like in the area.

So one component of the analytics skills needed to deal with IoT is time series analysis and transformations, including detection of anomalies. An important data quality issue is that sensors may give false readings, and you need to be able to detect which anomalies are genuine and which are false readings.

The interaction between different readings and time series is also important. Perhaps it is not an issue in itself if the pressure is high at sensor 1, but if the valve at sensor 2 is not fully open then there's an explosion risk, for example.

An important part of the analysis stage falls within the data science concept of 'feature engineering' – in essence, filtering out what is interesting and predictive from the huge range of possible variables you could look at.

From a traditional actuarial pricing perspective, if you are trying to predict claims frequency and severity from past data, you may only have a fairly small number of claims – as the response – compared with the number of dimensions – the explanatory variables – available.

While it might seem like a good thing to have lots of variables to work with, with IoT data often there will be too many possibilities. This is known as the 'curse of dimensionality'; the data you are training your model with is too sparse to support the number of available explanatory factors. The ability to deal with high-dimensional data is the other main component of analytics skills needed for IoT applications.

Useful techniques in this field include dimension reduction or feature extraction techniques such as PCA or autoencoders, and penalised regression techniques such as LASSO and Elastic Net. For this report, we are not going into technical details on modelling techniques. However, this is an active area of research for the working party and our intention is to develop some worked examples as a practical illustration.

Domain knowledge is important too; knowing the engineering relationship between the pressure at sensor 1 and the valve at sensor 2, in our earlier example.

Insurance use cases

Perhaps the most obvious use of IoT is to leverage all that additional data into improving underwriting, pricing, risk selection and portfolio exposure management decisions.

Historically, for most lines of business, we have relied on proxy rating factors that are only tangentially related to the actual risk, or that only differentiate at quite high level, between industry groups for example. Through use of IoT, potentially we have lots of data about the actual risk itself that we can use. If anything, the issue may be too much information, not too little, and as mentioned in the previous section, the question is how to boil down all this real-time information from multiple sensors into the actual risk factors – can this person drive a car safely? Or is this factory likely to break down?

Similarly on the claims front, IoT readings may allow us to collect a lot of information about the circumstances of a claim or an incident automatically. The insured may not even need to notify a loss because the insurer will know about it already. The insurer may even know enough about it to be able to settle the claim – in the case of a parametric-based insurance product, perhaps almost instantly. At least it should help to make a more accurate estimate, and to know better where to focus loss adjustment and investigation efforts.

IoT can also enable new business models, particularly on-demand or usage-based models. An on-demand insurance product that requires customers to consciously turn coverage on and off may seem like too much effort for the end user, but if this can be made automatic and seamless based on the sensor output, then this becomes viable.

The main benefits of IoT, though, may be more in risk prevention and mitigation.

One facet of this is behaviour change. It is often true that just the fact of knowing that you are being monitored doing something will change behaviour. Empirical evidence certainly seems to show that is true with telematics in motor insurance. Furthermore, introducing a feedback loop back to the insured about things they are doing that are making the risk worse – and more expensive – can make that an even more powerful effect.

More generally, IoT can be used to stop losses before they happen, or at least to mitigate a loss when it does happen. If sensor readings on a particular machine, for example, start to drift outside normal operating parameters, that can trigger a maintenance intervention to fix the issue. Or this could be automatic – a smart home turning on the heating if the pipes are about to freeze, for example. Or turning off the water supply if a leak happens.

In a sense, this may be anti-insurance – the more risk you can prevent or reduce, the less insurance you need. The need for insurance may not completely disappear – there is always the unexpected – but it may shrink the premium pool. And it may remove the more attritional loss elements that are the more stable and predictable part of current insurance offerings, leaving behind the more volatile and challenging large and catastrophic loss elements.

But these things are likely to happen whether the insurance industry likes it or not, and the industry has an opportunity here to embrace IoT, and sell the analytics, risk management, and prevention elements as a service, alongside a discounted insurance element.

This can be a positive future for insurance, where the insurer is not just there to pay out when things go wrong, but instead is pro-actively stopping the bad things happening in the first place. The insurance industry can, in this way, be an enabler and a force for progress in the 4th Industrial Revolution, rather than a victim of it.

Case study: Concirrus

Concirrus is an insurtech firm, established in 2011 and based in London. Initially focused on the marine insurance market, they have developed software ("Quest") that leverages IoT data to give highly detailed "behaviour" information that is far more effective at differentiating risk than traditional static risk factors alone.

The working party would like to thank Concirrus for their contribution below:

Today's view of risk is based primarily on account status at a specific point in time. This snapshot view is often based on static factors that do not account for behavioural variance or ongoing risk management activities. With the volume of information collated from vessels, supplemented with data related to external risk factors, it is now possible to profile behaviour over time using big data analytics and insight platforms. Behaviour is a far better indicator of risk, allowing you to assess accounts based on unique traits. Incorporating behavioural traits into pricing models allows for a more accurate assessment of expected loss on an account-by-account basis.

An improved calculation of expected loss enables underwriters to make far more informed decisions around writing risk. Better decision making will be reflected in overall portfolio performance and loss ratios.

The analysis of vast datasets is made possible through machine learning, segmenting data into highly detailed subsets to derive trends. Actuaries benefit by gaining a faster method of assessing large data volumes vs traditional methods. Models can vary and multiple methods of analysis are explored to find the right machine learning model for each client. If clients prefer, they can opt to deploy Concirrus' market model instead of building a bespoke pricing model. The market model leverages the insight of multiple contributors to deliver a market-wide perspective on valuing an account.

Concirrus uses two models to derive expected loss. They assess the frequency and severity of a claim over the coming year. They are then multiplied to derive an expected loss valuation. The approach is completely transparent, providing a list of influential factors contributing to the valuation with an associated score. Individual vessels can also be segmented to provide an individual expected loss complete with bespoke influential factors. When integrated, Concirrus' predictive pricing module provides a quick, holistic and accurate assessment of risk. It is a strong benchmark for Underwriters to use when writing business vs traditional pricing techniques. Automation allows machine learning models to be updated more regularly than traditional models for a more competitive pricing structure that is reflective of current market conditions. It also improves productivity, so more time can be spent building client relationships and attracting new business. (Re)Insurance Brokers, MGA's and Underwriters can utilise vessel score to advise their clients on account investment through data-led consultation.

The Importance of Digital Tools

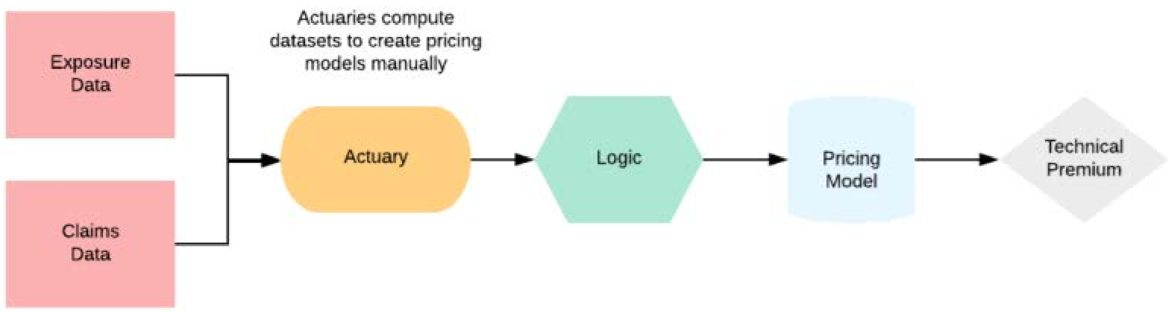
Actuaries within insurance firms already use Decision Trees and Generalised Linear Models to create pricing frameworks for Underwriters to value business. They would typically take portfolio information and run models manually. Whilst previously viable, the sheer number of data sources, as well as type *of data available now means that such methods are less efficient. The scale of information needed to gain an accurate understanding of risk would be very taxing for a typical team of Actuaries to process in time to meet the needs of Underwriters. Therefore, today's pricing models must leverage automation to remain effective.*

In short, there is now too much information to process in the time scale required.

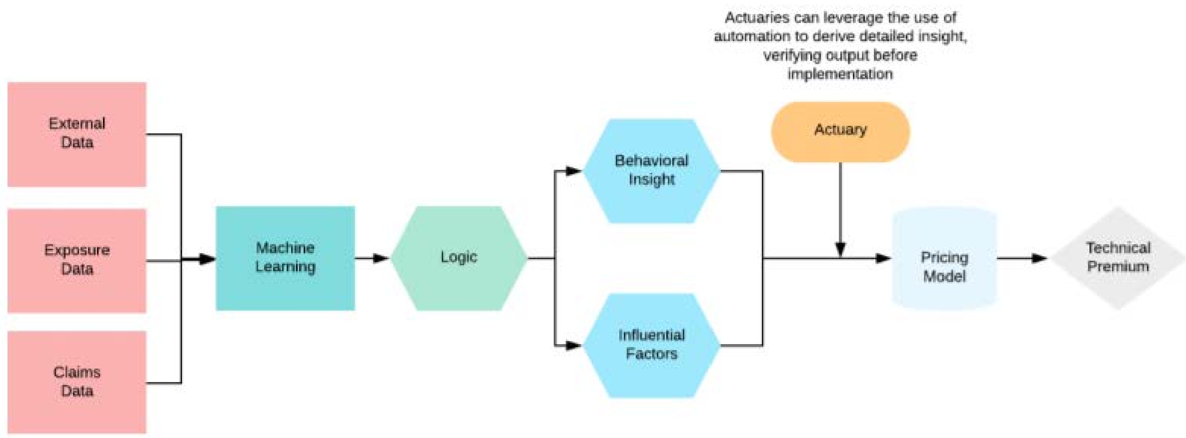
Even when a Broker or insurance firm collects information, the format of the data can be completely different per source. If you were a Broker evaluating an account based on one format of data, the Insurer may not be able to interpret it in the same format. This creates a barrier to entry for businesses within the insurance value chain and limits the value new technology delivers. This problem has the potential to multiply every time a new data source appears.

Digital tools solve both issues. Data aggregation platforms can consolidate large, varied data sets, whilst Machine Learning algorithms can segment and analyse the vast quantity of data collated. The efficiency of Machine Learning algorithms is particularly impressive, running thousands of models in a short timeframe. Using Machine Learning algorithms at scale, you can segment vast data sets to a granular level of detail and find specific trends for more accurate predictions. Moreover, the process can be automated which gives a huge capability benefit to the industry.

While such methods have been touted as de-valuing Actuaries, the reality is quite the opposite. Actuaries benefit from the ability to process vast amounts of data quickly. Combined with their expertise, Actuaries can make the best possible assessment with which to advise Underwriters. It is this insight that will ensure they remain an important part of the regulation framework. Concirrus' transparent approach supports this view, allowing anyone to clearly see the factors contributing to the expected loss valuation and understand what the relative weight of each variable is in calculating each valuation.



In a traditional model, Actuaries would apply the logic used to generate pricing models.



With machine learning applying logic, Actuaries can leverage far greater datasets, uncover behavioural insight, and validate the output.

Case Study: A Tale of Two Ships

The following results have been deduced from a live model and anonymized for public use. Here we have two vessels that are identical based on static rating factors. They are owned and operated by the same company, have the same gross tonnage, deadweight, age, and flag.

Ship A	Influential Factor	Ship B
Bulk Carriers	Vessel Type	Bulk Carriers
34,748	Gross Tonnage	34,748
61,288	Deadweight	61,288
2	Age	2
Liberia	Flag	Liberia

Based on these factors alone, the market would likely price both vessels the same. However, individual vessel behaviour has not been accounted for. Behaviour is a far more accurate indicator of risk and can therefore influence the price of insurance for each vessel. We can understand the impact of individual vessel behaviour by analysing the Expected Loss value for each ship using the Quest Marine Pricing Module.

Ship A	Influential Factor	Ship B
$36,163	Expected Loss Valuation	**$19,892**
1 in 13 year loss	Frequency	1 in 17 year loss
$464,962	Severity	$343,507

Now, with behaviour considered, we can see that the Expected Loss valuation of Ship A is 1.8 times that of the Ship B.

Ship A	Influential Factor	Ship B
5,021	Average distance travelled per month	4,174
32	Fleet size technical manager	32
6	Main engine number of cylinders	6
37	Total number of unique journeys	16
0.011	Casualty score	0.009
0.066	Engine model score	0.066

The influential factors highlight which specific behaviours are causing the disparity between the two vessels. From the selection of factors In the table above, we can see that Ship A travels further on average per month than Ship B. Average distance travelled per month is a critical factor in a Behavioural Pricing Model, hence the relative influence on the Expected Loss valuation. Ship A is also a greater risk because it does more unique journeys than Ship B. A journey is defined as a vessel travelling between two ports, which means that Ship A is more exposed to port risk than Ship B. The Casualty Score, which is based on vessel incidents reported, is also higher for Ship A.

Highlighting the unique behavioural differences between these two assets reinforces how a behavioural view on risk improves decision making. The impact on pricing can be dramatic, leading to *a better understanding of what appropriate cover looks like for new prospects, as well as the positioning existing accounts within a portfolio.*

Image, Video, and Audio

Cameras and microphones are everywhere – from the smartphone in your pocket to satellites up in space. There is a huge volume of data being captured in the form of images, video, and audio. And even a single image can be a bountiful source of data – a picture paints a thousand words.

Tapping into this rich seam of data, then, can bring significant benefits to insurers. The challenge is analysing the data at scale. Interpreting audio-visual data is straightforward for humans – eyes and hearing first evolved around 500 million years ago – but technology is now providing the capability to automate this analysis.

Image

Image data includes photos from all types of cameras, satellite images and medical images.

Digital photographs

The first true digital consumer cameras emerged in the late 1980s and early 1990s. Initial products were expensive and offered poor image quality relative to traditional film cameras. By the end of the 1990s, though, the technology had advanced significantly and by 2003, sales of digital cameras had overtaken film cameras.

The advent of the smart phone, with Apple launching the first iPhone in 2007, meant that the market dominance of digital cameras was short-lived – sales peaked in 2010 and there was a precipitous decline thereafter. On the other hand, close to half the world's population now owns a smart phone with digital camera capability, and this has made digital photography ubiquitous. We now capture an estimated 1.4 trillion images globally each year on our smartphones and digital cameras.

Aerial photographs

Aerial photography can be highly informative as a data source, and the use of drones to capture images has made this dramatically less expensive in recent years.

Satellite images

While the first satellite, Sputnik 1, was launched by the Soviet Union in 1957, it was not until the 1990s when satellite imagery became commercially available. Costs have fallen significantly over time, and image quality has improved.

Satellite images have been used in a wide range of applications: meteorology and weather forecasting, oceanography, fishing, agriculture, environmental monitoring, geology, cartography, archaeological surveys, construction, town planning, education, intelligence, and warfare, to name a few.

Satellite images of Earth can be obtained for free; all satellite images produced by NASA, for example, are publicly available through the NASA Earth Observatory. Commercially available images, though, can offer much higher resolution and more regular updates.

Satellite images give similar information to aerial photos. However, they can cover larger areas, can be monitored over time more consistently, and are less affected by weather conditions.

Medical images

The most common types of medical images are generated from computerised tomography (CT) scans, magnetic resonance imaging (MRI), ultrasound scans, X-Rays and Positron Emission Tomography (PET) scans.

The concept of medical imaging began in 1895 with the discovery of X-rays by the German physicist Wilhelm Röntgen. Other types of scan are of much more recent vintage – CT, MRI, and ultrasound all saw their first medical use in the 1970s, for example.

All these medical scans are used to take images inside of the human body with the level of sophistication varying by type. For example, PET scans may be used to detect the progression of cancer or get high resolution images of the brain. X-rays are more commonly used to detect broken bones. Medical scans in general are highly complex images that contain a lot of information.

Specific applications of medical scan analysis include:

- Detection of cancer
- Object or lesion classification[1]
- Disease diagnosis or classification
- Surgery planning
- Virtual surgery simulation
- Intra-surgery navigation

Image analysis applications

Applications for image analysis cover a huge range – from aardvark digging systems to zygote viability analysis. Commercial uses include security and surveillance (facial or fingerprint recognition, motion detection, security scans), manufacturing (quality inspection, robotic assembly), automotive (driver assistance, number plate recognition), to name just a few.

Image analysis is not limited to the visible spectrum – multispectral imagery can focus on specific wavelength ranges such as infra-red light. This can be useful in a variety of applications; examples include geological feature analysis, fire risk management, soil moisture mapping, and vegetation analysis and classification.

As mentioned previously, satellite images can capture a lot more information than aerial photos (including multispectral data). These images can be processed to extract information such as:

- Geospatial data – the location of features, such as structures and facilities, land use and vegetation classification.
- Relationships between features, numbers of features within an area.
- Activities happening in certain areas or its surroundings.
- Progression or change in a specific area over time. This can be used for real time monitoring of large-scale construction or engineering projects, for example.

[1] Source: https://arxiv.org/pdf/1702.05747.pdf

Example of satellite image application in Investment Banks – Using satellite imagery to predict investment price movements.

Before using satellite imagery, the founder of Walmart, Sam Walton, used to count the number of cars in the parking lot to monitor how the stores are doing. One analyst in USB Investment Research, Neil Currie, took a leaf out of Sam Walton's playbook and applied it to a whole different level.

Currie used a company which had scoured satellite images of more than 100 Wal-Mart stores chosen as a representative sample. By counting the flow of cars in Wal-Mart's parking lots over the year of 2010, they were able to estimate the company's customer flow and based on the information to predict the company's quarterly revenue each month.

Using this traffic information in the parking lots, Currie suggested that Walmart stock was undervalued. He concluded that there was enough correlation between what he was seeing in the satellite pictures of Wal-Mart's parking lots to the quarterly earnings. In contrast, the other UBS's team using traditional methods predicted that the sales would be down. Currie's prediction proved correct and the results surprised the UBS team.

Sources: https://www.cnbc.com/id/38722872

https://www.theatlantic.com/magazine/archive/2019/05/stock-value-satellite-images-investing/586009/

Video

Closed-circuit television (CCTV) was first developed in 1927 and became commercially available from the late 1940s. The invention of VCR in the 1970s was an important development that allowed the capture of the images, at least in analogue form. Digital video, though, only really started in the 1990s. Even then, storage limitations meant that it was typically capturing limited information using recording techniques such as motion only and time lapse recording. In recent years, particularly with the use of cloud servers, those storage limitations have largely gone away, and the amount of digital video footage captured has greatly increased.

There are an estimated 770 million surveillance cameras installed around the world in 2020. Just over half of these are in China. In terms of cameras per head of population, though, the US slightly edges out China, with the UK in third place. London has the 2nd highest number of cameras per square mile among the cities of the world, behind only Delhi in India.

There has also been a rise in the use of IP cameras, video door bells and similar devices that can record videos for personal surveillance purposes.

As with aerial photography, drones are increasingly being used to capture video footage; drones can access areas that may be difficult for humans to reach, and at relatively low cost. For example, some insurance companies are using drones to help them assess property damage after a catastrophe event.

Vehicle dashboard cameras have also risen in popularity in the last few years. They can be used to combat fraudulent car accident claims or used as part of the claims assessment process to establish liability.

Video analysis & applications

Some examples of video usage are by firms and government organisations are:

- Video surveillance, such as monitoring of properties, commonly paired with motion detection and systems that alert users when suspicious or unusual activities are detected
- Traffic control systems like measuring speed, reading number plates, issuing parking tickets, monitoring road usage, monitoring cars in and out of certain areas, and incidents alerts. Some traffic cameras are even able to detect if the driver was holding a mobile phone while driving.
- Machine vision – counting number of people entering or exiting a venue, facial recognition, body language detection

Example of combined use of image and video data – Onfido, identity check software

Onfido was established in 2012 by three Oxford graduates who were frustrated at the length of time it took to do background checks as part of job applications within the finance industry. It provides identity verification, using a combination of images and video, through its online platform.

Using your phone camera, the platform is able to cross-reference the user's facial biometrics with their identity document, such as driver's license. The person's identification can then be checked against various databases.

It uses both manual and automated machine learning technologies, including optical character recognition, face detection and motion detection, to verify the identification documents of an applicant to prevent fraud.

Their use cases include Know Your Client (KYC) checks, driver registration, user and identify verification.

Banks, gambling firms, and healthcare companies are just a few of the industries that are using their platform.

Source: https://onfido.com/

Audio

The main source of useful audio data is speech data, whether recorded or live.

Speech recognition development goes as far back as the 1950s. However, like video and image technologies, practical application of speech recognition and analysis technology has only really been possible since the 2000s, and the involvement of big tech firms such as Google, Amazon, and Apple in developing voice-based assistant services has helped to accelerate development and improve quality.

Using audio mining techniques to identify key words and phrases, useful data can be captured from unstructured voice interactions (e.g. call centres), both to gather information about the customer and about the performance of staff. As well as identifying topics and keywords, speech analytics can identify the tone and sentiment from the words used, and characteristics of the audio – other than the identified words – can provide emotion indicators. This information can be used for more effective direction of calls.

Some insurers have used voice stress analysis for fraud detection purposes, although its efficacy has been questioned[2], with some studies suggesting it is no better than chance at identifying deceit.

While increasingly customer contact in insurance is online, call centres remain an important mechanism of interaction, particularly for more complex questions, and in the claims process.

Speech analytics is often part of a broader analytics suite that includes extracting the 'voice of the customer' from multiple channels such as phone, email, chat, and social media. Many of the speech analytics concepts carry over to online text-based interactions, although clearly there is not the need to convert audio into text first. Indeed, they can form the basis of 'chatbot' interactions that can automate many straightforward enquiries.

Market research indicates that speech analytics is already a billion-dollar industry globally, with North America having the largest market share.

With the increased use of video-calls brought on by the COVID-19 pandemic, combined video and audio analytics may be a growth area in future. Particularly for emotion analysis, video can provide information on facial expression, gestures, and physiological signals, that should be more effective than audio on its own.

Audio analysis & Applications

There are two main approaches to speech analytics:

Phonetic indexing and search: This is the fastest approach for processing, because there are only few tens of unique phonemes in most languages. A phoneme (sequence of sound) is a basic recognition unit. The output of this recognition is a stream (text) of phonemes, which can then be searched. An advantage of this system is that words that are not in a dictionary can still be found, provided the phonemes are recognizable.

However, phonemes for some words can be quite similar and can generate high false positive matches. The storage requirement for this method is larger than the other approaches as it generates a large volume of files.

Automatic speech recognition (ASR) / Large-vocabulary continuous speech recognition (LVCSR) (or speech-to-text) relies on the system recognising the known words from a large database. This approach can be slower than the phonetic approach and words that cannot be found in the database will not be identified. The accuracy of this approach is higher than the above method.

Another advantage of this approach is when the speech is converted to text; this can be combined with data mining and natural language processing to understand the meaning of the text.

Two commonly used techniques are:

- **HMM** (Hidden Markov Models) based engines has been used successfully for a long time.

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[2] http://su.diva-portal.org/smash/get/diva2:687257/FULLTEXT01.pdf

- **Deep Learning** – neural network speech engines tend to significantly outperform HMM engines, but this comes at the expense of increased computing time. Neural network techniques tend to be more robust and resilient to accents and background noise, and most of the big players in this space have shifted to this approach recently.

Example of audio application – Apple's intelligent assistant, Siri

Siri is a built-in "intelligent assistant" that enables Apple users to speak natural language voice commands to operate the mobile device and its apps. It was first rolled out in 2011 but has developed over time and expanded to accommodate new languages.

When bringing Siri into a new language the team first finds pre-existing databases of local speech.

They supplement that by hiring local voice talent, and having them read books, newspapers, web articles, and more.

Apple's team transcribes those recordings, matching words to sounds—and more importantly, identifying phonemes, the individual sounds that make up all speech.

Source: https://www.wired.com/story/how-apple-finally-made-siri-sound-more-human/

Insurance use cases

Why are insurers using it?

Most of the focus in the insurance industry to date has been on the use of image data. Image data can provide a lot of useful information about risk and exposure at underwriting stage, and at claim stage, that is difficult or expensive to obtain and verify by traditional means.

Some of the main benefits include:

- Improved data to support underwriting, pricing and claims decisions;
- Faster loss notification and claim settlement;
- Improved accuracy of data and reduced need for manual surveys or assessment;
- Lower cost of acquiring high quality, verified, data;
- Improved risk management and fraud detection.

Use of video and audio data appears to be much less common; we did not find any insurtech firms in our research that are concentrating on these areas. Some mentioned video as an area of future interest; autonomous vehicles, for example, rely heavily on video data (in conjunction with other sensors) so that may be a spur for future development.

How is it being used?

Image processing can be applied across the insurance value chain. The biggest areas of impact currently are:

- enrichment of data sources to support better pricing and underwriting decisions, and
- use of image data to improve efficiency and speed in claims processing and estimation.

Challenges

While image analysis and processing technology in general is reasonably well developed, its application to the insurance industry is relatively immature. As such, there are some challenges in developing specific solutions:

- Generic models will need to be adapted and trained to meet the specific requirements of the use case; this may require a large volume of data, and potentially a lot of human effort to label that data. One of the insurtech firms we spoke to used more than a million images to train their models.
- The outcome of the AI models will need to be reviewed to ensure the results are appropriate and accurate. Insurance is a highly regulated industry, and insurers have an obligation to treat customers fairly, so there is a need to demonstrate that the model and/or its deployment does not lead to biased or unfair decisions.

Case study 1: Tractable

Company brief background

Founded in 2014, Tractable has a world-class research and development team with over 30 years of combined research experience, and its solution is built on five years of dedicated research and development work undertaken by a team of Oxford/Cambridge-trained researchers. Tractable has raised $55m from Georgian Partners, Insight Partners and other top-tier investors, with their latest Series D round in June 2021 valuing the company at over $1 billion. The company is based in London, with offices in New York City and Tokyo.

They are working with 20 top insurers in 13 different countries. Clients include Tokio Marine in Japan, Ageas in the UK, Covéa in France, and Warta in Poland.

Proposition - what they do and how they do it

They use AI to assess damage to cars involved in insurance claims. They also provide an estimate of the costs of repairs by linking up with car parts and labour costs from car manufacturers databases. In this way, the cars can be assessed immediately, and repairs approved much quickier than sending out claim assessors to evaluate the claims. In many cases the body repair shops can get instant approval for repair.

They worked with insurers to gather millions of images from insurance claims and reports from repair shops. At the beginning, they worked with motor experts, machine learning experts and researchers to mark these images manually, using it as source data to train their model via deep learning techniques. They then compared the results from their model with the reports from repair shops to refine the model where results were different. The company started in 2014 and deployed their first model in 2016 with an insurer.

Their system is not designed to replace the claims assessor but to help them prioritise claims that need their attention the most. For simple claims, they can spend less time to investigate if the AI assessment is acceptable.

The technology is being used to improve first notification of loss processes at insurers. Policyholders take photos of damage which are uploaded through an app on their smart phone. The insurer then uses this information to triage the claims for further assessment or make a cash settlement. Typically, *this manual process may take a week to run but Tractable's image assessment technology means it can be done in 3 minutes.*

Their models cover 98% of passenger cars. It can be applied to all manufacturers and production models. At the moment motorbikes are not covered. Note that the models cannot make a condition assessment, they report back either: to be replaced, to be repaired or undamaged.

The technology is also being used at the point of underwriting to provide a car condition assessment. A physical inspection is currently required in certain countries including Spain and Australia.

Benefits/ Other comments

- *Claims team can process more claims with the same resources and can spend more time on the complex claims with the triage system.*
- *Customers received a better experience with the insurers.*
- *Quicker turnaround time for the customers and repair shops. Tractable estimated that they save 1 week of time when their AI estimator product is used.*
- *Tractable estimated that they could save the insurer 1% off the combined ratio by using the AI review product, mainly through efficiency benefits.*
- *Interest in their products has increased due to COVID-19. The successful deployment of image assessment technology is seen as an opportunity to gain a "cutting edge" over competition; providing a better and faster service is a big differentiator.*
- *Tractable's models should also drive increased consistency in claims assessment for insurers.*

Case study 2: Mckenzie Intelligence Services (MIS)

Company brief background

MIS is a geospatial imagery, data and intelligence consulting business that was founded in 2011 by Forbes McKenzie, a former military intelligence officer with deep experience in spatial, aerial, and remote sensing technologies.

MIS services clients in various industries; insurance, conservation, defence, and emergency response. On the insurance front, MIS has been working with Lloyd's of London since 2016 and currently has over 700 active users in 120 enterprises across the Lloyd's ecosystem, ranging from managing agents and brokers to TPAs and loss adjusters. MIS has partnered with Lloyd's of London and the Future at Lloyd's programme[3] to deliver fast claims service through geospatial technology[4].

Proposition – Catastrophe Losses

***Proposition** - MIS collects pre-and-post event data from multiple sources and aggregates and analyses this data using machine learning techniques with the aim of providing fact-driven outputs (e.g. exposure and claims reports) which MIS believes is capable of delivering quicker and less expensive loss adjustment, faster settlement and more accurate reserving compared to traditional models.*

***Data sources and collection -** The sources of data used by MIS include satellite imagery, aerial imagery (through drones or private flights), radar imagery, IoT data feeds (such as images from smart doorbells*

[3] https://www.mckenzieintelligence.co.uk/news&insights/post/press-release-mis-build-claims-demo-future-lloyds

[4] A video of the claims prototype can be found here: https://www.youtube.com/watch?v=uaLf801NwI8

depending on access permissions), CCTV data, and vessel / offshore rig tracking. MIS also utilises data obtained from scraping news and social media feeds, emergency services and other official publicly available government data. In some instances, MIS brings together as many as 150 elements of data to create a holistic view of the loss.

***Data aggregation and delivery** - Once this data has been collected, MIS overlays it with machine learning algorithms to estimate the extent of the loss and delivers these insights to clients through a proprietary portal wherein they can view a damage grid or heat map to assess the extent of loss for different exposures (often at an individual property level). In addition to the portal, the raw data can also be accessed via APIs which can potentially have downstream applications in the actuarial world.*

***Track record** - So far, MIS has analysed nearly 100 catastrophe events (pre-event, during the event, and post-event) including Texas Freeze in February 2021, forest fires worldwide and Hurricane Ida. In additional to natural disasters, MIS has also covered man-made disasters and industrial accidents such as the Beirut explosion in August 2020. It has also been exploring techniques to quantify the impact of COVID-19 on business interruption by analysing supply chain disruptions, local lockdowns (traffic and footfall) and differences in legislation.*

Benefits/ Other comments

***Faster claims settlement and better customer experience** – MIS utilises remote sensing technologies that can assess the loss even if on-ground experts are unable to access the area, which may often be the case in a catastrophe event and its aftermath. By reducing the reliance on on-ground loss adjustment, the company believes its technology has driven a 40% improvement in the claims lifecycle, thereby improving the customer experience through expedited payment.*

***Reduction in 3rd party spend** – MIS reduces the reliance on expensive on-ground loss adjusters and despite having to pay suppliers to access satellite imagery or conduct private aerial imagery flights, MIS believes it is less expensive than traditional methods – so much so that it can potentially drive a 2% improvement in profitability.*

***More accurate reserving and capital allocation** – a key benefit of estimating losses using post-event data (as opposed to modelling assumptions) is greater reserving accuracy. In our discussions, MIS referenced the following benefits:*

- *Improvements in loss reserve accuracy in approximately 93% of cases compared to traditional modelling tools.*
- *A case where a client was able to reduce its initial reserves for hurricane Laura by $100 million by using MIS data.*

***Reduced resourcing strain on in-house teams** – MIS claims it can produce high-quality reports within 24 hours of the event, thereby providing actionable insights that can help triage claims, manage workflows and potentially smooth resourcing strain experienced by claims handlers and other in-house teams post large CAT events. However, it must be noted that the quality of outputs depends heavily on the quality of the insurer has exposure data provided to MIS.*

***Better fraud identification and dispute resolution –** MIS is able to access pre-and-post event satellite imagery, thereby enabling comparisons which can help identify potentially fraudulent claims and reduce the number of disputes due to the existence of firm evidence.*

__More confident underwriting__ – MIS is currently exploring the applications of utilising its data sources to develop insights into the riskiness of a potential client which can help inform underwriting decisions.

What does the data look like and how to analyse it?

The most commonly used data items are:

- photo images, collected by claimants and submitted to insurers, most often in motor claims.
- satellite images, usually from third party providers, that are used in property underwriting and claims assessment.

In this section, we discuss at high level how these images can be processed. We will not go into the full technical details of how image recognition works but we have included some references to technical papers for interested readers.

Images can be decomposed into their constituent pixels, which can then be represented as numerical values. For monochrome or greyscale images, each pixel corresponds to a single value (brightness), and for colour images we have three values or 'channels' per pixel (red, green, and blue intensity – although other representations are possible). These can then be represented as matrices.

For example, starting with this image of a house:

we can convert into greyscale pixel values as shown below. The result is at lower resolution than the original – partly this is for illustration purposes, but actual image recognition algorithms do often work at relatively low resolution to reduce the size of the model.

Focusing in on the bottom left window (the red box is to highlight some specific numbers used later in the description):

79	74	84	95	84	77	69	75	87	82	81
62	233	226	233	237	220	233	235	233	232	235
70	110	238	234	230	235	227	236	231	237	222
56	57	151	130	104	104	163	100	124	145	94
63	47	136	101	104	113	108	112	99	155	78
72	68	186	69	23	12	37	24	12	196	72
77	59	197	78	21	12	35	20	10	213	65
71	64	203	88	18	11	36	15	10	209	75
62	65	203	92	8	3	42	4	34	221	73
72	69	207	104	11	4	40	14	34	223	80
70	77	203	143	59	61	84	67	140	227	70
80	76	201	67	57	40	46	47	67	192	62
62	60	210	104	94	79	89	96	118	218	81
65	52	211	129	118	104	109	118	139	226	72
64	66	221	135	122	110	115	123	143	228	55
77	79	216	140	127	117	121	127	151	222	55
74	82	210	131	129	124	123	133	152	229	72
82	64	221	242	244	252	243	242	246	243	83
72	88	234	231	228	233	222	217	210	209	178
82	89	61	66	44	44	47	58	70	61	61
76	69	63	65	64	64	60	65	69	60	69

Here 0 represents black and 255 white; in practice these values would be normalised before being used as inputs.

In processing an image, there are two main considerations. The first is that, even in a relatively low-resolution image, there are many individual pixels, and to reduce the classification problem to something more manageable, this needs to be collapsed into a smaller number of inputs. The other consideration is that individual pixels in themselves may not carry much useful information; it is the relationship of pixels to their neighbours, and the shapes and forms that these relationships reveal, that really describe the image.

This leads to the idea of convolutions, which look at these relationships by effectively 'sliding' a small matrix filter across the larger matrix of the image pixels, to create a new matrix of values. These convolutions can indicate certain features of the image. To take a (very simple) example, a matrix filter (or 'kernel') such as this:

-1	1	0
-1	1	0
-1	1	0

can detect vertical edges on the left, as the result of the convolution will be high if there is a big increase in pixel intensity between the left column and the middle column of the section of picture it is 'sliding' over.

For example, taking the numbers in the red box, from the window pixel matrix above, we get:

$$\begin{bmatrix} -1 & 1 & 0 \\ -1 & 1 & 0 \\ -1 & 1 & 0 \end{bmatrix} * \begin{bmatrix} 59 & 197 & 78 & 21 & 12 \\ 64 & 203 & 88 & 18 & 11 \\ 65 & 203 & 92 & 8 & 3 \\ 69 & 207 & 104 & 11 & 4 \\ 77 & 203 & 143 & 59 & 61 \end{bmatrix} = \begin{bmatrix} 415 & -345 & -211 \\ 415 & -329 & -247 \\ 402 & -274 & -261 \end{bmatrix}$$

Note this is convolution, not matrix multiplication, the top left value of the result matrix is given by multiplying each value of the 3x3 filter matrix with the corresponding values in the 3x3 submatrix in the top left corner of the 5x5 matrix, and then summing:

(-1x59)+(-1x64)+(-1x65)+(1x197)+(1x203)+(1x203)+(0x78)+(0x88)+(0x92) = 415

This calculation is mathematically referred to as the Frobenius Inner Product of the filter matrix and the image submatrix. And then the top middle value of the result matrix, -345, is given by the same calculation, but sliding the submatrix one column right:

(-1x197)+(-1x203)+(-1x203)+(1x78)+(1x88)+(1x92)+(0x21)+(0x18)+(0x8) = -345

and so on.

You can see that the white edge of the window frame clearly shows up in the high values of the first column of the result matrix. Applying the convolution to the whole image, we get the following picture (high values are dark in this representation, and the red box shows the 3x3 result matrix from the calculation above):

And similarly with a filter matrix like:

0	0	0
1	1	1
-1	-1	-1

we can detect the horizontal edges.

Or – perhaps a bit less intuitively – with

0	1	0
1	-4	1
0	1	0

we can pick up both horizontal and vertical edges:

With deeper and more complex convolution layers, more complex elements of the image can be identified. This is termed feature extraction.

Having extracted these features from the images, the next step is to classify each image according to its features.

This is the basis of the most commonly used deep learning approach for computer vision – the Convolutional Neural Network (CNN). CNN is an architecture designed to efficiently process, correlate and understand the large amount of data in high-resolution images. The inputs flow into a network with a number of convolution layers (broadly as described above), with the learning algorithm effectively fitting the weights of the filter matrices, interspersed with pooling layers that further reduce the dimension of the problem. The reduced and transformed inputs then feed into the classification step of the algorithm, a series of fully connected layers – the more familiar type of neural network – that links to the output classifications.

Although first developed in the 1980s, practical use of CNNs for image recognition – outside of a few narrow applications – was limited. They are resource-hungry, and it is only in the last ten years or so that the computational capacity has been available to use these at scale. Now that obstacle has been overcome, they are generally regarded as the best available approach for image recognition.

There are other image recognition techniques that were used before CNNs were practical. Broadly, the 'feature extraction' stage was more handcrafted in these older approaches, using a variety of algorithms, such as edge detection and colour thresholding, to identify the salient features of the image. These are then fed into a classification algorithm, such as a neural net. The classification step is basically the same approach as the CNN; the difference with CNN is mainly in the automated detection of the feature set.

These traditional techniques can still be useful for certain applications. They can also be used alongside the deep learning approach in hybrid models.[5]

For insurance-specific applications, the problems we need to solve are often unique to our industry – for example, recognising a type of roof or material of a roof, or assessing the damage to a car – so we cannot rely on open-source models alone.[6] We need to build on those models to meet a specific purpose. This can require significant volumes of labelled training data for classification.

Once the model is trained, tested and refined, the model can be used to predict the features in a new image.

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[5] This paper 'Deep Learning vs. Traditional Computer Vision' (O'Mahony, Campbell, Carvalho et al.) provides a more in-depth discussion on the comparison between CNN and traditional computer vision approaches: https://arxiv.org/ftp/arxiv/papers/1910/1910.13796.pdf

[6] 'Applying Image Recognition in Insurance' (Kailan Shang) published by the Society of Actuaries is a highly recommended paper for anyone interested in more detail on this topic: https://www.soa.org/globalassets/assets/files/resources/research-report/2018/applying-image-recognition.pdf

Artificial Intelligence and Automation

Artificial Intelligence ("AI") is a difficult term to define precisely.

A machine that has been pre-programmed via a set of rules to react to input data can appear to be acting 'intelligently'. This type of 'rules driven' AI is perhaps not what we would consider true AI today. It has nonetheless played a key role in the evolution of all industries, not least insurance, for over half a century.

The modern manifestation of this is RPA (robotic process automation). These applications seek to replace tasks, previously completed by people but that can be captured in algorithmic form, to enhance productivity, efficiency, and/or quality in the value chain of an industry.

Increasingly these approaches to task automation are evolving so that the algorithms are not completely static but also include a 'learning' component. This can be trained how to cope with new input data, for example by incorporating information on how humans deal with exceptions. This can be classified as 'intelligent automation' or IA.

The other main form of AI is 'data driven' AI. This focuses on learning algorithms that take data as inputs and infer results – in various forms, depending on the algorithm – from them. Arguably something like regression could be regarded within this category, and that long predates computers. Again, though, that is probably not what we would consider true AI.

The modern manifestation of data driven AI is in deep learning applications, natural language processing, and machine perception, motion, and manipulation. It is a broad and fast-evolving field.

The practical development of data driven AI of this sort had been limited by computational resource constraints until the 21st century. The ability to deal with higher volumes of data, unstructured data, and to simulate and synthesise new data, is now allowing machines to self-learn beyond the limitations of human intellect.

Artificial General Intelligence

For now, at least, though, these are limited to 'narrow AI' applications – expert systems in highly specific domains. Artificial General Intelligence (AGI) or High-Level Machine Intelligence (HLMI), on the other hand, refers to AI that can learn a wide range of tasks unaided. This is a much more difficult problem.

AlphaGo, an AI that defeated the number one ranked Go player, Ke Jie, in 2017 is a well-known example of a 'narrow AI' application. AlphaGo was only taught the rules of the game but was initially trained on a large database of human games. A more recent version of the algorithm, AlphaZero, was entirely self-taught and did not need the human games as a start point. It did still need to know the rules to generate the simulations for learning. A further iteration, MuZero, does not even need the rules – it can play not just board games such as Go, Chess, and Shogi, but has also learned to play several early Atari video games.

Another recent high-profile AI application is GPT-3. This is a generative language model which can produce convincingly human-like articles or other forms of text, even poetry, given some subject prompts. This gives the illusion of more general intelligence, but it is an illusion: GPT-3 does not actually understand what it is talking about. (Although perhaps the same could be said of many human intelligences!)

So we are edging towards AGI / HLMI but there is a long way to go. Two recent surveys of expert opinion suggest we may be a few decades away from this goal.

- Defining HLMI as a "machine intelligence that can carry out most human professions at least as well as a typical human", a 2012 survey by Vincent Müller and Nick Bostrom of Oxford University[7] suggested that there was a 50% chance that HLMI would be achieved by 2040, based on the median response from ~550 AI experts. And a 90% chance by 2065.
- A similar 2016 survey, this time defining HLMI as "when unaided machines can accomplish every task better and more cheaply than human workers" suggested that there was a 50% chance of achieving HLMI by 2061, again based on the median result of 352 AI researchers.[8] This survey asked about specific occupations and did also suggest that it would be 2100 before machines were smart enough to replace AI researchers! (Unfortunately, actuary was not one of the occupations included in the survey.)

There is a wide range of opinion on this even among the experts, though, and they have been wildly wrong on this before. In 1965, for example, Herbert A. Simon – one of the pioneers of AI research – claimed that "machines will be capable, within twenty years, of doing any work a man can do."

This is not really the subject of this report, which is focused on near-term trends. The actuarial profession may still have a few decades left before the machines fully take over. Still, even if HLMI proves more elusive than these surveys suggest, there is little doubt that AI will advance in the coming years and that will have some profound effects on how we work.

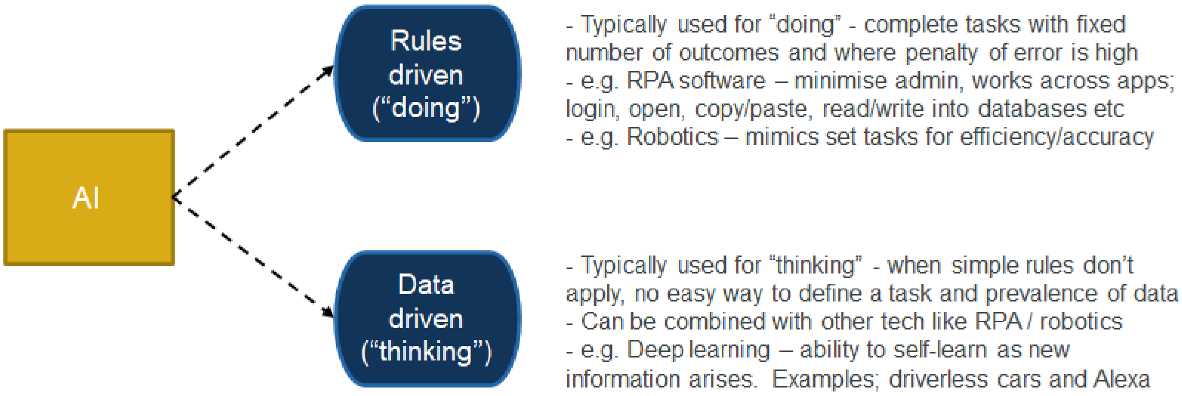
The Current State of AI

Current practical forms of AI, as mentioned already, can be broadly classified into 'rules driven' and 'data driven', albeit there is often some crossover between the two.

Both types of AI can further be categorised as 'attended' or 'unattended' once set up, depending on the amount of human involvement still required. The illustration below provides simplified definitions for both types of AI that we have adopted for the purpose of this report.

[7] 'Future Progress in Artificial Intelligence: A Survey of Expert Opinion' (Vincent C. Müller, Nick Bostrom 2012) https://nickbostrom.com/papers/survey.pdf

[8] 'When Will AI Exceed Human Performance? Evidence from AI Experts' (Grace, Salvatier, Dafoe et al.) https://arxiv.org/pdf/1705.08807.pdf



AI is one of the key technologies that underpins both new insurtech propositions and the digital evolution of traditional insurance carriers. In the rest of this section, we will look at the impact of AI on both business models.

Technology

Technological developments are enabling a seismic change in how Artificial Intelligence evolves and disrupts all industries, including insurance. Key enablers of this change are:

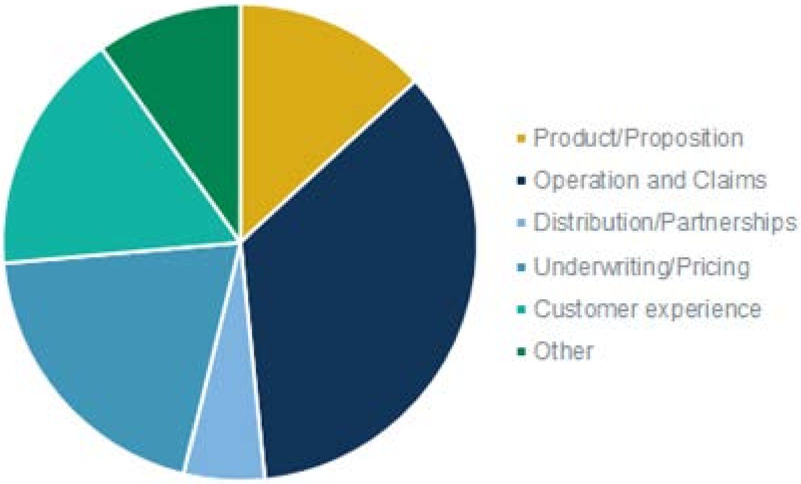
1. Greater availability of **(big) data:**
    a. as discussed in the IoT and Image, Video and Audio sections, developments such as connected devices are making available significant volumes of data unseen in the past (e.g. location attributes from satellites and drones).
    b. more data is being captured by organisations about their interactions with customers and other external parties. Increased use of digital channels naturally generates and captures more data, but traditional channels, too, are becoming more connected.
    c. more data is also being captured by organisations on their internal operations. As more of the value chain is digitised, the availability of detailed operational data is expanding.
    d. as well as an increased volume of internally generated data, this is also driving increased availability of external data as other organisations, public and private, make their data available to third parties, as a monetised service or – in many cases – for free.
    e. the amount of data published via online media sources, including social media, has been rapidly growing.
    f. AI is also opening up the use of unstructured data (e.g. scanned documents, free text, images, video, audio, media sources) that previously was too expensive to analyse.

2. Increased availability of supporting technology, tools, and skilled resources has enabled widespread use of AI throughout industry; capability is no longer limited to large technology firms:
    a. the availability of the technology stack to run AI at scale – large scale databases, cloud server capacity, cloud processing power and specialised AI chips – has greatly increased, while costs have decreased.
    b. AI SaaS solutions have also drastically reduced upfront investment costs.
    c. human resource trained in AI development and implementation has also greatly expanded although this does remain a limitation.
    d. analytical tools that are easy to use, including low code and no code solutions, have become available.
    e. API technology allows for straightforward integration of data feeds and AI models into operational processes.

Technology continues to evolve, and one avenue of research that has interesting potential for AI applications is quantum computing. Although many technical hurdles remain, quantum computers can – in theory – solve certain classes of problem very much faster than normal binary computers, and this does include some types of problem that are used in AI algorithms. This is perhaps beyond the near-term time horizon of this paper, but Quantum AI is an emerging field that we should watch closely.

Investment in (re)insurance

The investment of AI technology into Insurance has been quite wide ranging and covers most parts of the value chain. The pie chart below provides a market view of the proportion of AI investments by function.



Source: Ninety Consulting

The pie chart highlights that the most significant investment has been into the Operations and Claims functions of an (re)insurer. This suggests a focus on those functions which carry out many administration tasks, using automation to realise efficiency savings. (Although there are analytical AI use cases in the Claims function as well, such as fraud detection, and damage assessment.)

However, the chart also suggests a reasonable spread across different functions with Underwriting/Pricing, Customer Experience and Product/Proposition also being areas of focus. The growth in use of internal and external data is likely to see an increased impact on these functions in future.

Interestingly, Distribution/Partnerships do not feature prominently in this market view. This could be a sign that disruption is more likely to occur from non-traditional business models, falling outside the insurance market as captured in this chart.

We sought to further understand the investment made into AI through a 'Chatham House Rules' market consultation process to facilitate a more open discussion and consideration of use cases in the public domain.

Market consultation

The working party sought to further understand the investments made in the market to date through discussions with c. 10 market participants that were known early adopters or that have overseen sizeable AI technological developments for either traditional carriers or insurtech companies. The participants included insurers, reinsurers, consultancies and regulators.

The meetings focused on the participants' perspectives on the following questions:

1. Where is AI investment taking place?
   - the functions that have been impacted to date and how, and
   - any planned AI developments for the future

2. How are organisations leading this change?
   - approach to defining scope (e.g. narrow vs north star, success criteria)
   - organisational structure supporting disruption and involvement of BAU
   - approach to bridging skills gaps (internal only, academic collaborations, consultancies, etc.)
   - approach to governance
   - key lessons learnt

Where is AI investment taking place?

Consistent with the insurance market view of AI investment in the earlier pie chart, our discussions with the market highlighted AI investment across a wide range of (re)insurance functions. Our discussions had a focus on early adopters who we met directly or discussed through our meetings with consultancies and regulators. The discussion included investments made to date and planned future developments.

The table below summarises key themes from these meetings by function, and seeks to highlight:

1. The different types of AI deployed
2. The extent to which this AI compliments or replaces tasks completed by people
3. Autonomous data driven AI that is on the horizon for early adopters

	Rules driven (attended)	Rules / Data (unattended)	Data driven (self-learning)
Product / Risk Prevention	Standard underwriting T&Cs to limit risk Auto rules manage legal/compliance risks	RPA can summarise exposures real-time Apps can alert insured of risk factors	Fundamental change to insured risk event e.g. driverless cars, PAYG insurance
Distribution / Quote to Bind	STP to improve efficiency and UX Includes auto release of documents	Use in-force data to deliver bespoke CX e.g. help determine client product needs	Internal/external data for auto decisions AI determines additional services to offer
Underwriting / Risk Pricing	Standard models (eg GLM) with software Legal/compliance using defined rules	ML model(s) replace standard models Discovery of unusual patterns	Use of real-time data (eg IoT,telematics) Deep learning models update algorithms
CX services / Sales/MTA/Claims	Automated processing upon approval Triage actions using defined rules	Automated processing across apps Use of predefined chatbots to record data	Self-learning chat bots for improved CX Auto-verify using IoT, audio, OCR etc
Claims / Approval Process	Claims triage using defined rules Automated processing upon approval	Automated processing for simple claims Use of predefined chatbots to record data	NLP aided decisions (repair vs total loss) Videos of damage fed into AI process
All functions / Reporting	Macros/reporting software create reports Process requires use of structured data	Create reports using multiple applications Reports delivered to pre-defined timetable	Use NLP to transform unstructured data Self learning for sentimental analysis

Product/Proposition

Through a combination of IoT, machine learning and RPA technology, the (re)insurance value chain is starting to better understand exposures and flag early warning signs to support risk prevention. The development of connected devices is enabling a real-time understanding of these risks across the value chain.

As an example, for motor insurance, telematics has fundamentally changed the understanding of risk and exposures. The technology has also enabled PAYG insurance as a new business model, and this supports other economic developments like the gig economy.

In the longer run, the application of deep learning will enable driverless cars. This will fundamentally change the nature of motor insurance; where the risk primarily now stems from the human behind the wheel, it will shift to the driving algorithm. Rather than a personal lines product, motor insurance may then become a third-party liability risk for the vehicle manufacturer or the algorithm provider, and perhaps one that would be largely retained rather than insured. Moreover, few people may choose to own personal vehicles if they can simply be summoned when needed. Although we can do that today, with taxis and Uber, we are also paying for the services of a human driver. Motor insurance makes up more than half of the total premium income for the global non-life insurance market, so this would certainly be a challenge for the industry.

Distribution

AI is enabling far greater Straight Through Processing and connectivity across distribution networks for data than has been possible in the past. This is driving efficiencies in the sales process for insurers; the AI can help solve underwriting, data validation and exception management issues that previously required manual intervention and therefore slowed down end-to-end transaction times.

Over the recent past, such change was difficult to achieve in specialty insurance lines. However, developments such as Lloyd's PPL and Blueprint Two is enabling greater efficiencies in aligning capital to risk by leveraging recent investment in digitisation and combining it with AI in various parts of the process.

The integration of AI with other technological developments like Blockchain, IoT and drones is likely to drive fundamental change to distribution of insurance products. The idea of embedded insurance – where insurance becomes a seamless integrated component of broader online platforms and services, rather than a product sold in itself – has a lot of attention in the insurtech space.

There is also potential for non-insurance companies (such as big tech) to compete with insurers and/or existing distribution channels, leveraging their existing relationships and deep data on their users and customers.

Underwriting/Pricing

For classes of business such as private motor and domestic buildings insurance, machine learning is – for now – more commonly used to enhance an existing GLM or GAM model, or to provide an alternative view, rather than directly as a model for setting prices. The overlay of human expertise remains important; deep learning and other 'data science' models are being explored, but issues of interpretability and transparency mean they are not being fully used. Insurtechs are better positioned to embrace this philosophical shift, but the advantage is offset by a lack of historical data.

For underwriting, software bots can collect data and provide initial screening of risks, with less focus on traditional proposal forms. More advanced intelligent automation can collect and analyse the data, add binding probabilities and allowing underwriters to manage resources more effectively. Fully automated underwriting from start to finish with instantaneous quotes now exists in some markets, with insurtechs being a major influence in this area.

Even in the more complex specialty markets, algorithmic underwriting 'smart follow' capacity propositions, like Brit's Ki and Canopius' Vave, are gaining traction. These should help to reduce the costs of placing coinsurance business in the London Market.

Claims management

Several (re)insurers are applying rules-based AI to help triage claims for process efficiency gains. Defined rules help separate the claims, and the subsequent process for straightforward cases may be automated – in full or in part – with RPA technology. Rules-based chatbots are being used by some insurers to record simple information and these can be extended with machine learning to become more dynamic.

Deep learning has the potential to enhance this process further, combining NLP, image, video, and audio data to support algorithmic decision making for lower risk claims.

Customer experience (Sales/MTA/Claims)

The application of AI here is similar to that described for Claims management. Rules-based AI has been deployed to triage different customer journeys for process efficiency gains. Human intervention occurs for higher risk/complexity issues, and otherwise processes may be largely automated. Rules-based chatbots are being deployed in a similar way and deep learning is a natural evolution to deploying the next generation of these chatbots.

Reporting (all functions)

The application of simple rules-based AI is prevalent throughout the insurance industry in reporting. Visualisation software packages have enabled most organisations to leverage this technology. Early adopters have started to create and deliver recurring pre-defined reports using RPA technology to materially reduce the required man-hours for generating reports.

Clearly this is an application that can directly benefit the actuarial function.

The next generation of automated reports are likely to combine AI with NLP to leverage unstructured datasets and deep learning for sentimental analysis from all electronic communications (e.g. customer feedback).

How are organisations leading this change?

AI change programmes are often complex in nature and fall outside the comfort zone of many insurers. During our market consultation, we wanted to understand the key learnings from AI development programmes in the (re)insurance industry to date.

The approach taken for implementing AI solutions depends on factors such as:

- Size of organisation
- Level of senior leadership buy-in
- Availability and quality of data

In our discussions, overall themes suggest that:

- Large composite insurers have the resources to set up dedicated AI / ML teams, however challenges faced can include integration across the business as well as IT / data issues from their existing platforms
- Small / medium firms exhibit less tangible evidence of successful implementations but may be more agile in their approach

- New insurtech entrants have attracted significant capital investment, as evidenced by recent high-profile IPOs in the sector. Many rely on existing insurers for underwriting capacity, though, and achieving scale is a challenge.
- Large tech players are perhaps the biggest disruption threat; they could more easily achieve scale from their existing user base and may have some built-in underwriting advantage from the in-depth data on user activity they can leverage. Currently they are mostly pursuing partnership or investment models (examples include Verily and Oscar backed by Google's parent Alphabet) rather than direct involvement.

Key considerations when designing an AI change programme

Internal vs. External

- Companies that are starting out on their AI journey will need to assess whether they have the resources available internally or if they will need support from other organisations.
- Most companies will probably use some form of external resource to kickstart their programme as they start developing their in-house data science capability.
- External support could include:
    - Working with consultancies to demonstrate value, especially to senior leadership. Small examples that can be built to scale, with clear handover to internal teams.
    - Collaborating with universities to learn from leading academics and researchers working on the latest innovations in AI and ML.
    - Partnering with technology firms who can bring platform and software expertise.
    - Incubating Insurtech start-ups or investing in them to build solutions both for the (re)insurer and their clients.
- The teams we spoke to also noted the importance of fully assessing available internal resources, especially in larger organisations, as there can be pockets of expertise, technical skills and software licenses that could be leveraged before going externally.

Delivery Model

- Traditional waterfall project structures are difficult to apply for AI change programmes given the level of uncertainty on outcomes.
- Agile approaches with small teams working in short development cycles (6-8 weeks) appear to work well for such projects. These can help show incremental value at each cycle and increase engagement from wider business teams.
- Proof-of-concepts are a useful way to engage with teams on a particular problem and help drive practical use cases.
- Companies also highlighted the need for tightly defined scope of AI projects to focus in on a particular process or target outcome. When defining this target, companies should consider how this would improve their customers' experience or improve their processes and reduce costs.
- IT and procurement teams will play an important role in the success of AI implementations and should be engaged early in the process. Design decisions around software and whether to use cloud platforms should be considered holistically as part of the organisation's wider IT and procurement strategy.

Skills

- Within the implementation teams, it is important to have a balance of skillsets:
    - Data science vs. in-depth insurance and actuarial expertise
    - Pioneers (blue sky thinking) vs. Settlers (work on practicalities of the solution)

    - AI evangelists vs. Commercially driven
- However, the most important skillset is communication:
    - Ability to clearly communicate what can be achieved through these solutions to senior management and ensuring their buy-in will be critical to any AI programme
    - Working with business teams to engage and enthuse them on the potential opportunities so that they can share new ideas for application and provide feedback on solution designs
    - Being able to translate between different domains of expertise (e.g. IT vs. Machine Learning models vs. Actuarial modelling)
- Companies cited that integrating data scientists within their business teams was also an important aspect of successful implementations. The gap between understanding what AI/ML models can do and what would be the most commercially valuable model can sometimes be difficult to bridge if there are centralised teams that do not work closely with the business.
- For the actuarial profession, the opportunity presented by AI and ML techniques is a great way to expand our skillset by understanding the key concepts of this new field and being able to apply them within our technical areas of expertise.

Governance

- As with any new technique or change that can impact the key metrics of an insurance company, it is important that programmes consider risk management and governance and how these will be applied to the new AI models.
- Companies need to consider their own appetite for risk as well as ability to meet wider regulatory requirements.
- Complexity of AI models needs to be balanced with the ability to explain model outcomes and ensure that they are "fair" – this can be a tricky area given there is no definitive way to interpret algorithmic fairness.
- Approaches taken by companies include:
    - Setting up specialised Steering Committees to regularly review progress of AI solutions, with stakeholders from key teams such as Internal Audit and Risk Management
    - Support from consultancies to conduct independent AI ethics reviews
    - Education initiatives to raise awareness of this new area, the opportunities, and the challenges, so that business teams have a realistic view of what is possible and can provide more robust challenge.
    - Models and algorithms with risk monitoring thresholds incorporated so that risk management becomes a core part of their decision-making

AI use cases

In addition to the market consultation on a 'Chatham House Rules' basis, we have also considered public use cases on how AI technology has been deployed within the insurance market. The following examples showcase the deployment of AI.

Case study 1: Cognizant

Company brief background

Cognizant is an American multinational technology, consulting, and business process outsourcing company, with approximately 280,000 employees globally – around half of these located in India.

In 2019, Cognizant produced a report[9] describing how it helped a global reinsurance company examine how to make underwriting more efficient and productive, reducing the time underwriters spend on manual work and expanding the range of data that informs decision-making.

Proposition - what they do and how they do it

Specifically, Cognizant built an AI-driven solution to perform predictive, data-based underwriting analysis for the reinsurer planning to enter the U.S. flood insurance market.

The global reinsurer wanted to better understand and model flood risks, with a view to using this insight to ensure it could adequately price tranches of risk as reinsurance treaties as well as individual homeowner and business insurance policies.

Cognizant analysed flood maps developed and made public by the US NFIP (National Flood Insurance Program) in 2016 and combined it with other public census and housing data. They augmented this data further with the client's proprietary claims data and a GIS (geographic information system). This led to a database with resolutions accurate to full 9-digit ZIP codes as well as ZIP+4.

Finally, Cognizant used open-source R software to apply Natural Language Processing techniques on previously manually underwritten policy documents, combining this with their geospatial analysis of the flood data, to identify potential attributes that could predict whether a ZIP-4 postcode ultimately represented an underwriting opportunity or not.

In this way, the AI model was trained to produce risk scores that emulated the manual underwriting process to an acceptable degree of accuracy, allowing assessment of every US postcode at scale in an automated way.

While the report did not reveal details of how this was ultimately implemented by the client, a model such as this could be used to quickly examine the risk and profitability of underwriting portfolios based on the ZIP codes of the exposures. It could also be used for pricing and underwriting individual properties; depending on the complexity of the exposure, this may be fully automated, or may act as a pre-qualifying step for manual underwriting.

[9] Source: https://www.cognizant.com/case-studies/pdfs/ai-solution-for-flood-insurance-underwriting-codex3640.pdf

Benefits/ Other comments

Cognizant claimed the following results of the model:

- *Modelled a potential market with 83% accuracy.*
- *Generated a ten-fold reduction in throughput time in underwriting.*
- *Improved case acceptance by 25%*

Case study 2: Hollard Insurance and LarcAI

Company brief background

Hollard insurance is a privately-owned South African insurance group that sells both life and non-life insurance. Headquartered in Johannesburg, their website states they have more than 6 million policyholders across 18 countries on four continents. Hollard employs more than 4,000 people around the globe and posted R18.1bn ($1.25bn) in premium income in the year to June 2016.

Proposition - what they do and how they do it

LarcAI, a South African analytics and automation company, published a case study[10] detailing how they used robotic process automation (RPA) to streamline various parts of Hollard's customer operations using virtual assistants.

The case study details how LarcAI implemented solutions to reduce the time taken and increase the accuracy of manual processes taken by staff when processing broker submission emails, incorporating the following steps:

- *receipt of electronic communications, primarily email*
- *interpret the communication and attachments to identify the context and classify the content*
- *action to repetitive, non-human requirements and interact with humans where intervention is required*
- *maintain compliance content and traceability throughout the workflow execution*
- *resolve the instructions based on the content and context within the scope of the virtual assistant instance*

The process taken by humans was essentially abstracted into more discrete steps that are fulfilled by a different 'capability' of the robot:

- *Access the email source locations; initiate activities and processes to engage the content*
- *Interpret the context of the email and its attachments*
- *Interpret the instructions in the content supported by the attachments*
- *Classify and file the documentation*
- *Identify the appropriate workflow action and routing*
- *Extract, transform and populate data into information fields required for processing*
- *Interact with users and systems whilst actioning the instructions*
- *Provide outward confirmations of process concluded with documentary evidence where required*

[10] Source: https://larcai.com/portfolio/case-study-hollard/

A legitimate concern with this type of intelligent automation solution is that the decision-making may not be transparent, and as such difficult to audit and to demonstrate fairness and equity. It is true that some of these component capabilities are 'black box' solutions, and the reasons for the underlying decision or output from the robot's algorithms is difficult to trace precisely. However, the final process does provide an audit trail and documentary evidence of the output at each stage. If these decisions were being taken by humans, it is not clear that the discoverability of the rationale would be any greater.

LarcAI also noted that when the robot is unable to fully execute its processes – in other words, interpret emails, classify and extract instructions, identify workflows etc. – it sends an instruction to a human user, who can then complete process the email manually. Crucially, the outcomes to these exceptions are observed by the robot, enabling it to learn further and expand its capability to deal with different situations.

The report concludes with a brief statement about how the robot generally performed as expected on first release, but adjustments were made in further releases to improve accuracy.

Benefits/ Other comments

LarcAI claimed the following results:

- *Saved processing time of around 2,000 hours per month (projected)*
- *98% of cases (assuming a 'case' approximately translates to email) are managed autonomously*
- *Cost per transaction reduced by 91%*
- *Broker community have remarked on the improvement without being aware that the process is now supported with robotic intervention*
- *Staff sentiment has improved due to overall improvement in job satisfaction, as well as lower overall staff costs as they were not needed to be replaced after leaving*

Parametric Insurance

Parametric insurance differs from traditional indemnity insurance in that, rather than directly compensating the insured for a loss they suffer, payment is triggered based on some form of an index parameter that is correlated to, or acts as a proxy for, losses that might be suffered by the insured. A *measurable trigger* and *fixed compensation* are agreed in advance.

This approach is much more transparent, in general, than a traditional indemnity insurance, and should mean much faster pay-outs and lower claims administration costs. On the other hand, since the coverage is not directly linked to customer losses, it may not provide the right level of protection for the insured. This is termed 'basis risk'.

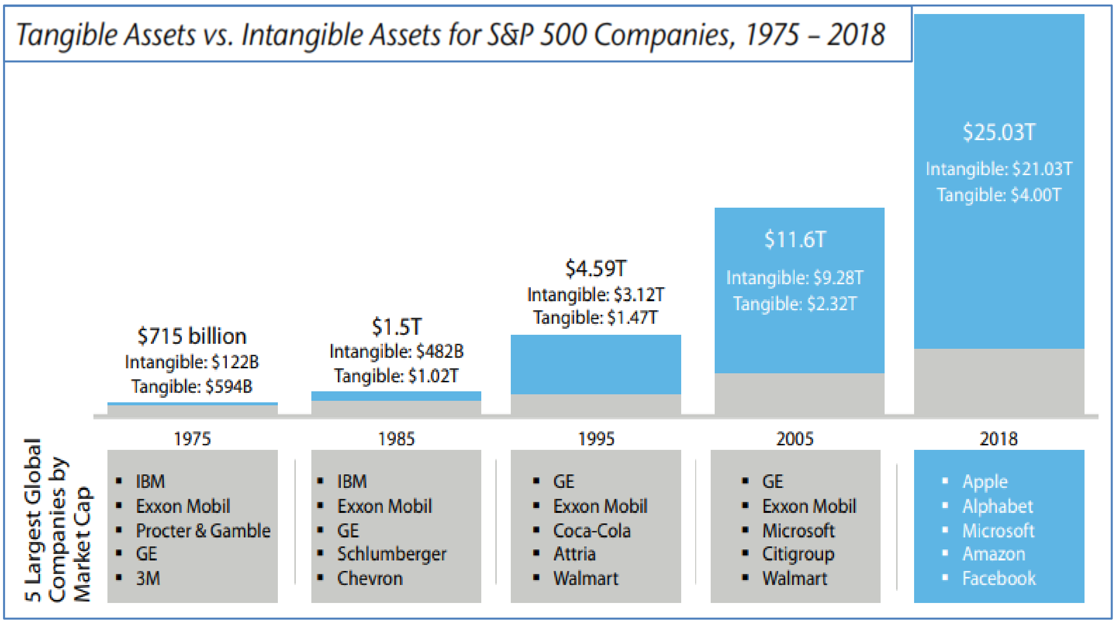
Parametric insurance is not new, with the first such deals written in the late 1990s, and the concept itself is not a technology-dependent idea. Nonetheless it forms an important strand of insurtech innovation. Until recently, parametric insurance has been limited mainly to large bespoke deals for natural catastrophe perils. Now technology is enabling a much broader range of offerings from two perspectives:

- The availability of new data sources allows for a much broader range of possible indices and triggers that can be used as a basis for parametric insurance, no longer limited to natural catastrophe risk.
- Digital delivery can also dramatically reduce the cost of delivering such products, so deals do not have to be large to justify the set-up costs.

As a result, a new breed of insurtech parametric propositions has emerged in recent year, offering 'off-the-shelf' products that address gaps in indemnity products and/or provide cover for intangible risks that may be difficult to insure on a traditional basis. And these can be targeted at much smaller scale markets – SMEs, individual customers, even microinsurance solutions.

Growing opportunity for parametric cover

One of the features of the third industrial revolution, and this is only likely to be accelerated with the advent of the fourth, is the shift in the risk landscape from physical, tangible assets towards virtual and intangible assets.



** Five largest Global Companies by Market Cap as of December 31, 2018*

Tangible assets refer to property, plant and equipment.

Source: 2019 Intangible Assets Financial Statement Impact Comparison Report, Aon / Ponemon Institute LLC (April 2019)

Traditional indemnity-based insurance may be ill-suited to protecting such assets, because directly quantifying the loss from an insured event, or even identifying that there is in fact a loss, may be difficult or effectively impossible. Pricing for such risks is even more challenging.

Parametric insurance products can remove this uncertainty and enable such risks to be covered, and priced, in a very transparent way.

In addition to the intangible risks, there are other protection gaps within the traditional insurance market. These may arise through explicit exclusions or terms imposed by insurers, or underinsurance by insureds. Parametric insurance can help to address these gaps.

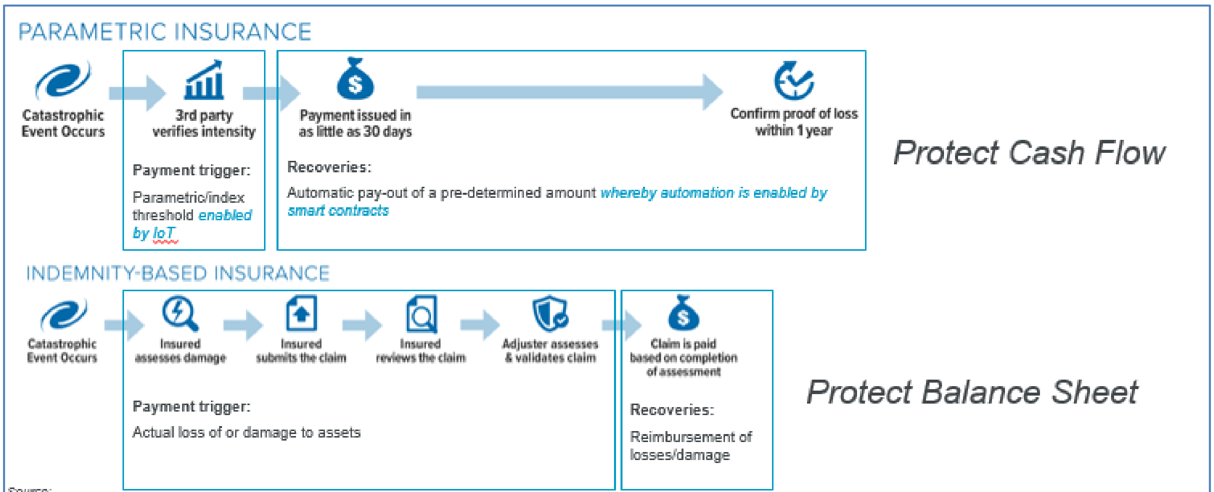
Parametric insurance has also been touted as a potential solution to certain systemic or non-diversifiable risks. With catastrophe risk, for example, use of parametric cover has increased the overall capacity available to cover large catastrophes. This is because alternative sources of capital can support a relatively simple parametric proposition, without the need for full analytical and underwriting capability that a traditional (re)insurance company would need to support an indemnity-based cover. Partly, though, these risks are attractive as a diversification investment for capital providers, because natural catastrophe events are not thought to be greatly correlated to global market returns.

However, this may be less true for other types of systemic risk that are more global in nature. Pandemic risk is one such risk that is clearly at the top of mind. You could argue that global market returns have not been depressed, despite the economic effects of Covid-19 and associated lockdowns, although they have at least been more volatile. Even so, given the sheer amount of the economic loss from such a global event, it would be extremely challenging to develop the capacity required. Even on the conservative basis of measuring the actual drop in world GDP against the 2019 figure, the loss is over $3 trillion in 2020 alone. This is several times bigger than the estimated $0.63 trillion of available reinsurance and non-traditional capital for natural catastrophe risk (and only approximately $0.1 trillion of that comes from non-traditional capital sources).

Nonetheless, parametric insurance could form at least part of a solution to global systemic risks.

Claims settlement

One of the main advantages in parametric insurance over traditional indemnity insurance is that claims may be settled much more quickly, and at much lower expense. Verification that a trigger has been breached is a necessary step, but that is generally a matter of checking an index value (and perhaps a validation check that nothing has gone wrong with the index). In many cases this can be automatic. Since the amount of pay-out is fixed in advance, the claim can then just be settled. Potentially, if a smart contract is used, this could happen almost instantaneously – before even the customer knew they had a claim.



Source:
(Image) How Parametric Products Benefit Catastrophe-Driven Risk Transfer, AmWINS Group, Inc. (19 March 2020)
What is parametric insurance?, Swiss Re Corporate Solutions (01 August 2018)

Basis risk

The main disadvantage of parametric insurance is that the pay-out is not directly linked to the amount of loss suffered by the insured, rather it is determined by measurement of an index. This 'basis risk' means that parametric insurance may be less effective at protecting the customer's balance sheet than traditional indemnity insurance, since the pay-out may not compensate for the lost assets.

In their simplest form, parametric triggers and pay-outs are binary – either the pay-out is zero if the trigger is not met, or the full amount is paid out if the trigger is met. This may mean the customer receives nothing even though they have suffered a substantial loss, and it may also mean the customer receives a large pay-out even though they have not suffered any loss.

More complex designs, that respond to different triggers or apply a formula to the pay-out based on the actual index values, are of course possible. If the underlying index is not a close proxy for the actual risk, though, some basis risk is inevitable.

Basis risk does sometimes lead to the question of whether parametric products can really be described as insurance. This is one of the key concerns often raised by regulators during the approval of new parametric products. Clearly basis risk may also make the product less attractive to the insured.

Basis risk can be divided into some key categories as follows:

- Design Risk: A weak relationship between the value of the index and the outcome for the insured
- Spatial Risk: Distance between the location of the risk and the measurement source for the index
- Temporal Risk: Differences between the incidence of risk in time and the timing of the measurements for the index.

For example, consider a parametric crop insurance that is based on a rainfall index. Such a product might exhibit all three of the risk categories above: design risk (if the crop yield is not particularly sensitive to the amount of rainfall at the trigger point(s) of the insurance), spatial risk (if the measurement of rainfall is taken from a location that has different conditions from the crop location), and temporal risk (if the triggers are based on rainfall during times that are not linked to the crop growing season).

Careful selection of the proxy index and triggers is important to help to mitigate these issues and to develop a more compelling customer proposition.

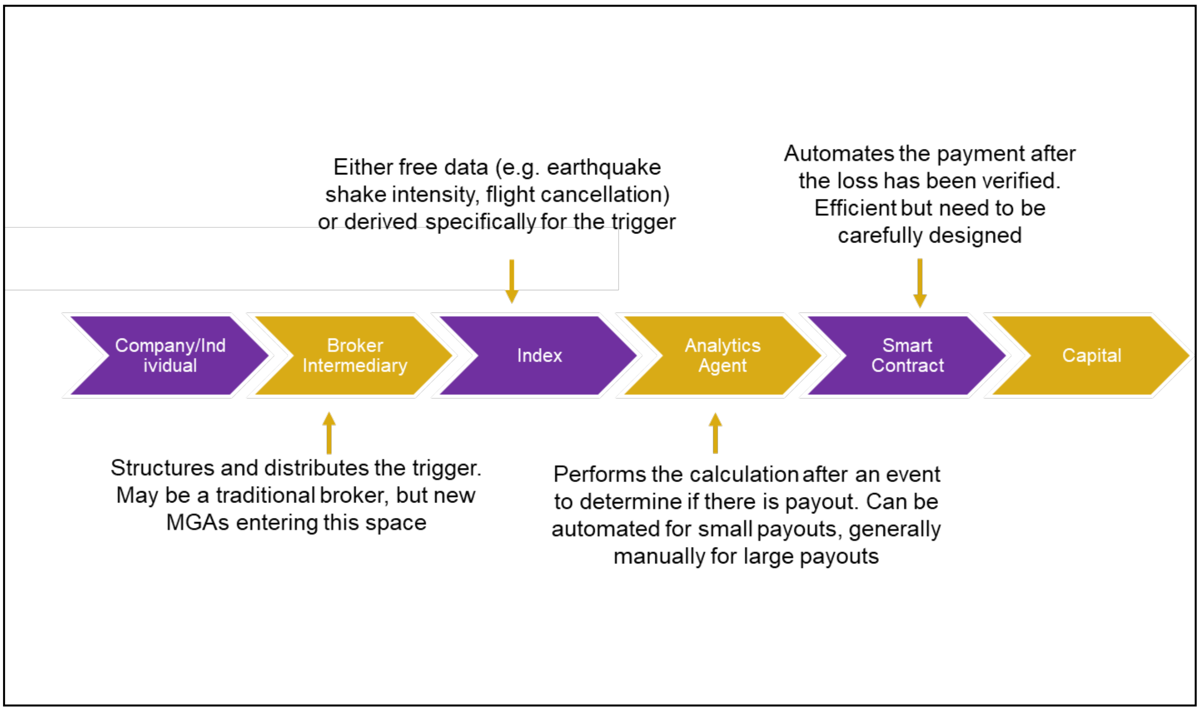
Complementary Solutions

Because of the speed of pay-out, parametric insurance is often said to be effective at protecting cash flow – making emergency funds available when the insured needs them most.

Indemnity insurance, in contrast, is said to be effective at protecting the balance sheet – because it reinstates the insured to the same position it was in before the loss.

In this sense, the two types of insurance may be complementary, rather than seen as competing against each other. The parametric insurance can make a rapid pay-out – not covering the full amount of the loss, but sufficient to cover any emergency costs or cash flow issues until the indemnity pay-out can be assessed and agreed.

Parametric insurance value chain



Some insurtechs are looking at the left end of the value chain – distributing the products direct to consumers or, more usually, through a B2B2C connection. In most cases, the capital is still being supplied by traditional (re)insurance carriers – backing the insurtechs through MGA coverholder relationships or similar arrangements. However, there are insurtechs also looking at the right-hand side, creating a marketplace or other mechanism for a broader range of capital providers to support individual deals or portfolios of parametric business. This is not unique to parametric business; the goal is to connect risk to capital as seamlessly as possible.

However, the focus of insurtechs – and the area where actuarial interest most clearly lies – is in the middle of the value chain above: developing the indices and triggers that constitute the product design, and the analytics agent to determine when a claim occurs.

The Technology Angle

As mentioned previously, advances in technology are increasing the breadth and potential of parametric insurance, both through the expansion of data sources and indices, and the automation of operations to lower cost and speed up claims processing.

At the extremes, IoT devices can allow for products based on indices from live streamed data direct from the source of risk. And smart contracts – which can be built on distributed ledger technology such as Blockchain – can potentially enable fully automated claim payments.

Indices and IoT

A trusted data source is required to form the index for a parametric policy. Until recently, parametric insurance has mainly been used to provide weather or disaster-related coverage. The indices are constructed from datasets sourced from national organisations or companies that collect data for non-insurance purposes.

There are over 10 billion IoT devices currently being used to capture and transfer data, and these can provide a vast amount of data to insurtechs. To date, the insurance industry has made only limited inroads into making use of this data, and it can take time to collect sufficient data to identify patterns of behaviour associated with losses. However, there have been some successes in this area.

For example, Blink Parametric has recently launched a platform to cover IoT-supported domestic appliances. If there is a fault, automatic alerts are issued to the insurer, which triggers actions such as a service call or a cash pay-out to the insured's bank account.

Another example is Parsyl, which uses smart sensors to determine if marine cargo has been spoiled by temperature. Their parametric product automatically analyses data and informs customers of temperature breaches. If the trigger is met, payments are made within 72 hours.

Smart contracts

One of the attractive features of parametric insurance is the automation and speed of payment to insureds when the terms of the parametric trigger are met.

Smart contracts can be used to enable this efficiency as they are contracts that are partially or totally automated by computer code. This makes them ideal for parametric insurance as a claim can be triggered and a payment made automatically when the trigger is met. Smart contracts offer the possibility to reduce costs and enhance the experience for customers.

The first major smart contract product was launched by Axa to cover flight cancellation in 2017. However, this was withdrawn after a trial period – there was a lack of appetite from the travel and airline industry. This underlines that parametric insurance can enhance a customer proposition but is not an end in itself; it needs to meet an underlying customer need for coverage.

Expectations of take-up and which lines/types most likely to be affected

The areas in which parametric insurance could be offered is wide-ranging, provided that a suitable trigger can be defined. So far, it has primarily found success with coverages where traditional insurance is too expensive or just unavailable.

Farming and agriculture

Global agricultural production is worth $1.3 trillion a year, but only 25% of this is insured. 80% of crop losses are caused by droughts and extreme weather conditions. Agritech is an important area of technology development as well, and the crossover with insurtech creates many new possibilities; it is expected that agriculture and fisheries will be one of the key growth areas for parametric insurance.

As an example, Arbol has used high-resolution aerial imagery and highly localised datasets, accessed using IoT sensors and satellites, to create bespoke parametric cover at an individual field level. They have partnered with Global Parametrics recently to provide insurance to coffee farmers in Costa Rica.

Microinsurance

Parametric insurance is ideal for providing insurance to third-world countries where there is a necessity for the entire transaction from collecting premiums through to claims collection to be achieved at a low cost. This type of microinsurance is normally offered by partnerships between governments, aid agencies, insurance and other financial companies. An example is UAP Insurance in Kenya, which has collaborated with Safaricom, Kenya's biggest mobile phone operator and the Syngenta Foundation for Sustainable Agriculture. Farmers can pay 5% extra when purchasing seed and fertiliser to protect against crop failure. Policies are registered with UAP using mobiles to scan the barcode on the product and the policy is registered at the nearest weather station to the farmer. When weather conditions deteriorate to the extent that the trigger on the index is satisfied, payments are made directly to the mobile phones of the farmers using Safaricom's M-PESA mobile-money service.

SMEs

SMEs make up 95% of companies in the UK and underinsurance has been highlighted as a major concern by the UK regulator. These companies tend to not have a risk manager so simple to understand parametric insurance is ideal for them. Examples of parametric insurtechs in this sector include Parametrix and Qomplx, who both offer cyber business interruption insurance to SMEs, and FloodFlash, who cover flood risk – even in high-risk zones where it is often difficult to get standard flood cover. Educating brokers on the advantages of parametric insurance is key as SMEs mostly rely on brokers to purchase insurance.

Corporate buyers

Larger corporates are more focused on risk management than SMEs but are increasingly exposed to losses from intangible assets such as intellectual property, cyber or reputational risks, where traditional insurance is limited in scope. There has been a small number of corporate parametric transactions that are comparable to catastrophe bonds in deal sizes, but demand to date has not proved to be significant. This is due to the challenge of overcoming basis risk and other uncertainties relating to pay-out.

COVID-19 has exposed an obvious coverage gap, since clearly the insurance industry has not offered comprehensive protection for its customers against the business interruption from the pandemic. There are solid reasons for this – insurers need to manage their own risk, and pandemic has long been a known systemic issue, even if the scale of the global lockdowns was unanticipated. It is also true that specific pandemic insurance products were available in the market before COVID-19 struck, but the take-up rate was low. Lack of clarity in the policy wording over what is or is not covered, though, has undoubtedly eroded confidence in traditional insurance.

This situation has offered an opportunity for parametric insurers to step up with a more transparent solution, and insurtechs like Machine Cover are planning to launch a business interruption parametric cover in 2021 as an add-on to a commercial policy.

Personal lines

Parametric insurance could gain a foothold in personal insurance by being embedded in purchases where the operation of the parametric cover is invisible to the buyer. For example, Blink has launched a platform for insurers to sell flight cancellation insurance when a flight is bought. This works because data is robust and free to access, and consumers are used to buying flight insurance. Other examples are Jumpstart which covers earthquake risk and uses technology to track real-time data. The trigger is a quake that reaches a peak ground velocity of 30 centimetres per second and in such an event, an automated text message is sent to the insured to start the process of paying the $10,000 of cover. Another insurtech, Assured Risk, sells a parametric hurricane insurance policy in Florida and follows a similar claims process. It provides coverage of up to $60,000 and the trigger is based on the strength of the hurricane and the distance of the insured home from the storm.

Insurtech – the Actuarial Context

Opportunities and Threats

Insurtech represents a tremendous opportunity for actuaries. The abundance of new data and complex analytical tools should put this firmly in the actuarial wheelhouse; we are the recognised scientists, engineers, and technicians of the insurance industry.

Automation too represents an opportunity. Actuaries currently spend a disproportionate amount of time on relatively straightforward tasks like data manipulation; automation can save a lot of time with such activities, as well as reducing error rates. This should free up actuaries to spend time on actual analysis and value-adding work.

We can also leverage insurtech to broaden our skill set and our reach. Areas of the insurance value chain that have not traditionally been in the actuarial domain should now come onto our radar, as analysable data becomes more pervasive. And these newer areas – such as marketing, individualisation of product offerings, operational optimisation – are less insurance-specific than the traditional actuarial fields. This may then lead to opportunities to cross over into new industries.

And yet there are threats here, too, for our profession. Many of our traditional approaches and methodologies do not translate well to this new world of high-dimensional, high-velocity data. We will need to evolve our skills to maintain our position.

Automation may be a threat. The need for actuarial headcount may reduce dramatically, and some actuarial tasks may be automated out of existence almost completely. And if the more straightforward actuarial applications no longer require junior actuaries, a valuable source of training in the fundamentals of actuarial work is lost.

Just as actuaries may broaden skill sets to move into other domains, as analytics and data science use cases expand in other industries and other parts of the value chain, people outside the actuarial profession will be picking up these skills and may encroach on our current ecological niches in insurance.

Healthy competition is not a bad thing and bringing in diversity of perspectives is helpful to solve the insurance issues of the future. There are some things we need to work on as a profession, but we have a lot of strengths, too. We should not be too defensive about this – if we embrace change, creativity and collaboration, we can be confident about our contribution to the digital era.

Opportunities	Threats
New data and analytical techniques • Enhance actuarial contribution to existing fields – pricing / underwriting, reserving, capital / exposure management • Expand actuarial contribution into new parts of the value chain • Increased breadth of skills provides a platform for expanding into wider industries and fields	*New data and analytical techniques* • Lack of capability in dealing with these, or encroachment of analysts from other fields / industries with fresher ideas, leads to reduced role for actuaries in existing fields
Automation • Reduce time spent on low added-value tasks • Reduce error rates in data processing • Free up time to spend on analytical work and value-adding business contribution	*Automation* • Reduced need for actuarial headcount • Fewer opportunities to 'learn the craft' • Some actuarial activities may be completely automated out of existence
Education and regulation • Opportunity to learn new and interesting skills that reposition actuarial science back at the cutting edge of analytics • Proportionate professional standards give business users (and regulators) additional comfort in using analytical results with actuarial involvement	*Education and regulation* • Education becomes outdated and fails to equip student actuaries with the skills needed to succeed in future • Over-regulation imposes additional burdens, relative to other professionals, that renders actuaries unable to contribute effectively on a commercial basis
Seizing the opportunity • Openly embracing the changes that insurtech makes possible, actuaries become innovation leaders taking the insurance industry forward into the digital future	*Circling the wagons* • Defensively seeking to protect its existing positions, the actuarial profession succeeds only in carving out a compliance or second line oversight niche

Strengths and Weaknesses

<table>
<tr><th>Strengths</th><th>Weaknesses</th></tr>
<tr><td>Data and analytics
Foundation in analytics
Experience with structured real-world insurance data
Excel / SQL
Professionalism and regulation
Professionalism
Ethical considerations
Domain knowledge
Insurance and risk
Finance and regulatory
Collaboration and creativity
Technical skill to interface between business and tech/analysis
Ability to innovate within the actuarial method
Perceptions
High levels of technical knowledge
Valuable skills for taking concepts to market reality</td><td>Data and analytics
Breadth of technique
Experience with differently structured ‘5 Vs’ data
NoSQL / Spark / Python / Big Data tools
Professionalism and regulation
Burdensome regulation
Commerciality, agility
Domain knowledge
Technology
Risk engineering
Collaboration and creativity
Communication skill to interface between business and tech/analysis
Collaborative approaches to create innovative solutions
Perceptions
Conservative and regulatory-focused
Not seen as innovation leaders or creators of new concepts; sometimes sceptical of the new and untested, closed-minded</td></tr>
</table>

Data and Analytics

A clear strength of actuaries is our foundation in analytics, rooted in maths and statistics. We are also strong at dealing with insurance data, with the experience to understand the flaws and avoid the pitfalls.

The corresponding weakness is that we may be too schooled in certain techniques, and less open to newer ways of looking at data and analysis.

Many actuaries do have a strong interest in data science and have been proactive in investigating the techniques; the profession too is providing a degree of support with this through various initiatives.

On the analytics side, though, some of the paradigms of data science and machine learning techniques are difficult to reconcile with actuarial ‘best practice’ inclinations, and in some cases our technical standards, to understand what is going on under the hood. Increasingly, data science frameworks do include some tools for helping with this, but even so there is a lower level of transparency that we must learn to live with.

The data side of the equation is at least as important. The claims and exposure data we typically deal with is not always clean, but it is usually quite structured into neat tables.

We are much less experienced in the type of data, though, that flows through the insurtech data funnel. It would be unfair to label this completely unstructured, but it is at least differently and more loosely structured. The serial data from IoT devices, free text data, graph type databases – where it is the relations between datapoints that is important rather than the datapoints themselves, for example. As well as structure, we need the means to deal with what are referred to as the '5 Vs' of big data – velocity, volume, variety, variability, and veracity.

The focus to date with data science education and skills development among actuaries has been on the analytics side. This is understandable, as it represents incremental improvement in our core areas of work. It is reasonably straightforward, for example, if you are well-versed in GLM or GAM, to learn how to fit a Gradient Boosting Machine, or a Random Forest, or a Neural Net, to the same dataset – and that may be immediately useful in pricing analysis.

To ready ourselves for the future that insurtech is bringing, though, we need to break out of that comfort zone. There will need to be a greater focus on the data wrangling, feature engineering, and dimensionality reduction steps of the process. And on the toolkit and technology stack we need to use for this (hint: it's not Excel. Or even SQL Server). These are the real new frontiers of analytics.

Professionalism and Regulation

The professionalism of actuaries is a strength, both for our 'brand' and for the actual quality of our output. Putting a framework of standards and ethics around AI and big data is a good thing. External regulators recognise this point, even if actual regulations may struggle to keep pace with developments. Things like acting in the public interest, treating customers fairly, are part of the actuarial mindset – whereas they perhaps do not feature so much as a consideration in data science more generally.

On the other hand, we do not want to overburden ourselves with self-regulation baggage such that our role – if it exists at all – is limited to policing the analysis, rather than leading it. Some compromises on notions of transparency and explicability may be needed – these do not always translate well to the machine learning world. We may need to rediscover the ability to be agile and embrace a spirit of experimentation in how we execute analysis. Above all, we need the ability to be commercial. Otherwise, we will exclude ourselves from a lead role in these developments – on grounds of both cost and effectiveness.

Domain Knowledge

A clear strength of actuaries is that we combine insurance business domain knowledge with the analytical skill set. And we do have the ability to innovate outside established products and coverages through broader risk knowledge and visualisation, finding proxy data and drawing parallels, thinking about risk from first principles, for example.

There are two halves to insurtech, though, and we are lacking in domain knowledge on the technology side.

In addition, given that IoT and other rich data sources are giving much more detail about risk than has been available before, risk engineering domain knowledge may also be important.

Collaboration and creativity

The range of skills needed – across technology, analytics, and domain knowledge – is so broad that it is impossible for any individual to be thoroughly expert in every single aspect. This speaks to the need for a collaborative mindset – working with data scientists, engineers, IT experts – to deliver effectively in the insurtech space and create the solutions to the risk landscape of the future.

Actuaries have, of course, always worked with other functions – but in general have been quite self-contained on technical analysis matters.

This has implications for actuarial education too. There has been a focus on learning a relatively narrow set of core methodologies but in considerable depth. In the future we may need at least awareness of a much broader set of methodologies.

Consider, as an example, the convolutional neural networks (CNNs) used for image analysis, described in the Image, Video and Audio section. It may be important for some actuaries to understand this type of analysis in depth, but that is unlikely to be a core skill requirement for most actuaries. For others, an understanding of the basic concept and how it can be deployed is likely to be sufficient – then if leading a project where a CNN would be the right solution, the actuary could still identify that and have sufficient knowledge to collaborate effectively with someone else who did have the expertise.

Perception

Actuaries are perceived – at least by some people within the insurtech community – as being conservative, not transformative; driven by regulation, not innovation. Too often we are described as blockers of progress rather than enablers.

It would be hard to deny that actuarial work in general insurance has become more regulatory in nature, but this does seem unfair as a general characterisation. Actuaries are almost universally in favour of better data and automated workflows that together lie at the heart of the digitalisation effort. Resistance to change does not, in general, come from actuarial sources.

Perhaps, though, there is an element of scepticism that runs through the actuarial psyche. This can be healthy, but it may also mean actuaries can appear closed-minded – dismissive of new, untested ideas where there is no track record to work with.

This is something we should guard against. An open-minded approach to the actuarial method does work for new and innovative products – yes, we may need some data to work from, but actuaries are adept at finding proxies and building things up from first risk principles.

There has been some movement in the perception of actuaries in insurtech as well. As insurtechs move from concept to market reality, they have recognised the value of the actuarial skill set. We have seen Elon Musk at Tesla hiring actuaries as a key part of their insurance development plans; Julian Teicke – CEO at WeFox – who recently raised $650m in funding, also mentioned actuaries specifically as a key focus of their recruitment strategy to develop products founded on IoT data.

Impact on Core Actuarial Fields

Pricing and product development

Pricing is likely to be the actuarial field most affected by insurtech.

The additional data available from IoT, image, video and audio, and other 'big data' sources is the primary change here. The exposure data we use should be more accurate and enriched with new exposure factors. Making sense of all this additional data is the key new skill that will be required, and that will be a combination of both data and analytics skills. We have some experience of this already from dealing with motor telematics information.

In lines of business with relatively sparse claims experience, the traditional approach of claims frequency and severity modelling may not help us get much additional value from this extra data. While there are analytical approaches to dealing with the 'curse of dimensionality', which we will need to have in our toolkit, we may need to look a bit deeper into the data. Rather than focusing on the actual claims that happened, we may be able to find information on near misses, or leading indicators of problems.

This then leads into the product development aspects. One of the benefits, certainly of IoT data, is the real-time monitoring of the risk indicators. This can allow us to shift from pure insurance models – where the insurer pays out after something bad happens – to risk prevention and mitigation services. These could include, for example:

- providing the insured with information about behaviours that are increasing risk
- identifying preventative maintenance measures
- taking action to prevent losses before they happen, or to mitigate losses as they happen

This should be heavily data-driven so represents an opportunity to expand actuarial contribution.

For portfolio management purposes, the exposure data should become much more dynamic and tracking the portfolio changes will become more complex but also much more accurate and objective.

Parametric insurance pricing and product development

Parametric covers are in theory easier to model than indemnity products, as the uncertainty around claim severity is removed (or certainly reduced). If the historical data for the index is available, then determining the loss cost may be relatively straightforward – although trends may need to be factored in, such as climate change for weather-related indices.

In some cases, the historical data may exist but in a more complex form than traditional sources of claims data, so some data science skills may be needed to reconstruct the historical index information.

On the other hand, parametric covers are often more focused on lower-frequency type events, so the historical data may not give a full picture. And for newer types of risk, there may not be as much 'soft' experience and knowledge about the general nature of the risk that might complement or help to interpret the data. So modelling frequency is not always straightforward.

The other aspect is the design of the index and triggers to limit the basis risk. While – regulatory product approval issues aside – the basis risk is effectively the insured's problem and not the insurer's, clearly the product design must meet the needs of the customers to be an attractive and saleable product.

This is often the most complex aspect of the whole proposition; in a sense, consideration of the actual loss frequency and severity may just be shifted from being a pricing problem to being a product design problem. The question of moral hazard also needs to be considered in the design process.

This may depend on the specifics of the product, though, and it is true in most cases that a parametric cover should be a more actuarially tractable problem than an indemnity-based cover for the same type of risk.

Reserving

More detailed data about claims and the surrounding circumstances may be available through new data sources such as IoT and image, video and audio. The data may also be available much more quickly after the claim event than in the past.

These should help to increase the accuracy of case reserves and speed up settlements. This may create some short-term transition issues as the claims development patterns shift over time to reflect these changes.

If insurance products do morph into hybrid 'risk as a service' type products, blending elements of insurance with risk management services, the impact may depend on the accounting basis. Under IFRS-17, at least, these service components may be treated in a similar way to the actual insurance so there would need to be a reserving process for them as well.

With parametric covers, actuarial loss reserving may not be required at all. At the extreme, pay-outs may be instantaneous and automatic with smart contract technology, so there is zero outstanding claims reserve. Even if that is not the case, the pay-outs typically depend only on the objective index value so there should be no doubt over the claim amount.

Unexpired risk, or liability for remaining coverage in the IFRS-17 terminology, may be more interesting with certain types of parametric cover. If the triggers are based on accumulated values of an index, or the index itself is not 'memoryless', in theory this may need to be dynamically updated. Derivative accounting treatments may be more appropriate for such risks.

Intelligent automation and AI may also have a big impact on reserving. Actuarial judgement is still important, but it may be that large parts of the process can be automated, and the actuarial involvement is reduced to the final review process.

Capital

As with reserving, intelligent automation and AI may help to streamline many processes. The complexities and uncertainties of capital modelling – and the absence of hard data about tail risk (in many cases) to 'learn' from – is likely to mean that the human element remains significant.

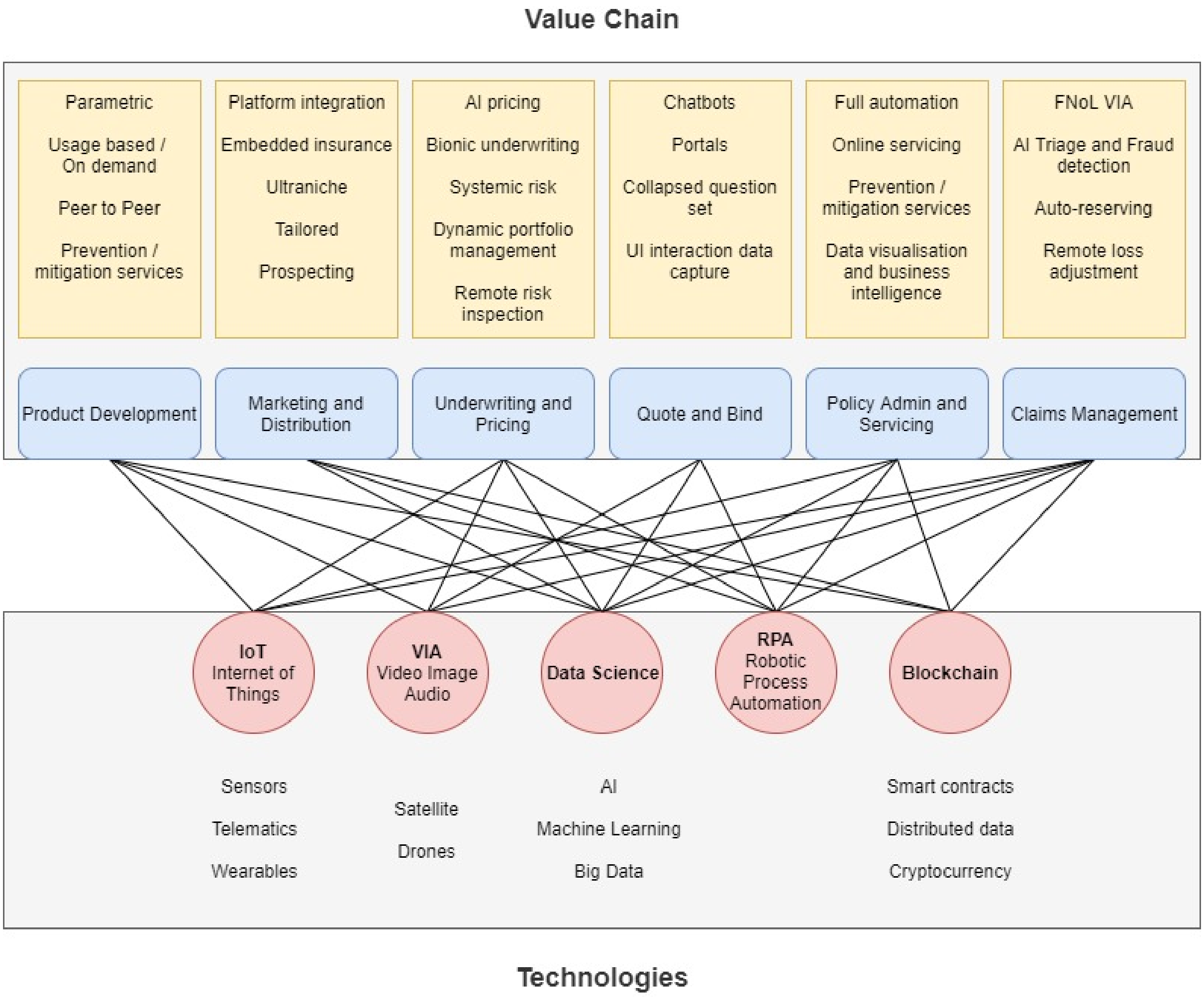
One possible consequence of IoT devices being used to prevent risk may be that the insurance element becomes more volatile and catastrophe-related than before. IoT may be more effective at preventing or mitigating smaller attritional losses than large, unexpected events. However, there should also be income streams from the IoT risk services that are less volatile than the attritional element of insurance that they effectively replace.

With parametric covers, uncertainty around severity of individual losses is reduced, but these also may tend to be more catastrophic and / or systemically correlated than traditional insurance risk.

As noted above, reserves may become less uncertain so that the reserve risk element becomes less significant.

Looking beyond…

Insurtech will change actuarial work in our existing fields, and there are plenty of opportunities for new and interesting analysis. Perhaps the most interesting opportunities with insurtech, though, are the opportunities to break out of these existing fields.



With new sources of data pervading throughout the value chain, actuaries should be looking for opportunities to become more involved in a wider variety of business activities – product, marketing, distribution, customer interface, administrative operations, claims, supplier interface, compliance – anywhere there is data, there may be a role for actuaries.

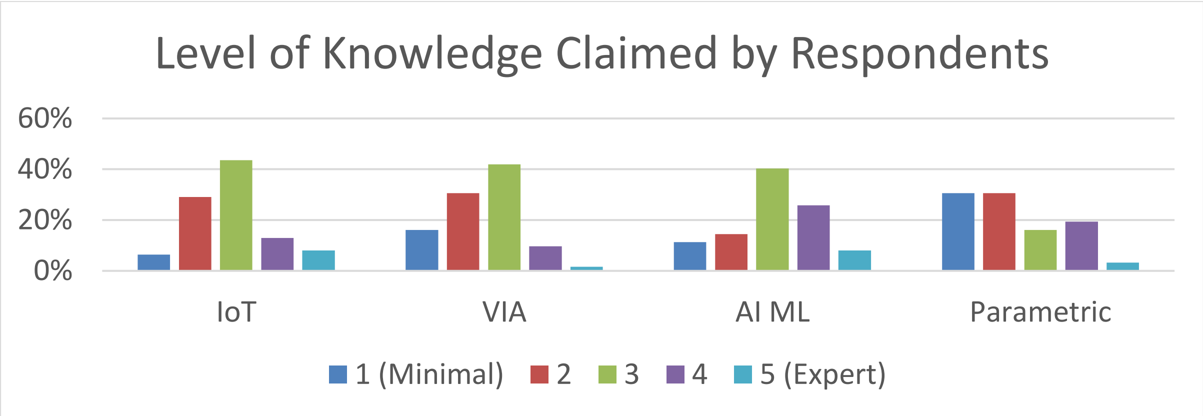
Many of these activities are less insurance-specific than the traditional actuarial fields, so a further potential for actuarial growth would be to leverage experience that we gain here to expand into other industries.

Appendix 1 – Survey Results

We carried out a survey in 2020 of 62 people – mostly actuaries (there were 8 respondents who were not actuaries). The respondents were solicited via LinkedIn so the sample is clearly self-selecting and biased. [11]

The survey asked a number of questions about the four main workstreams of the working party – IoT (Internet of Things), VIA (Image, Video and Audio), AI ML (Artificial Intelligence and Automation), and Parametric.

The respondents in general felt they were moderately knowledgeable about these four topics:



The proportion of respondents keen to increase their level of knowledge exceeded 90% on all the topics, with AI ML generating the most interest at 97%.

On the other hand, only 18% of respondents felt the IFoA currently offers sufficient education and training in these areas.

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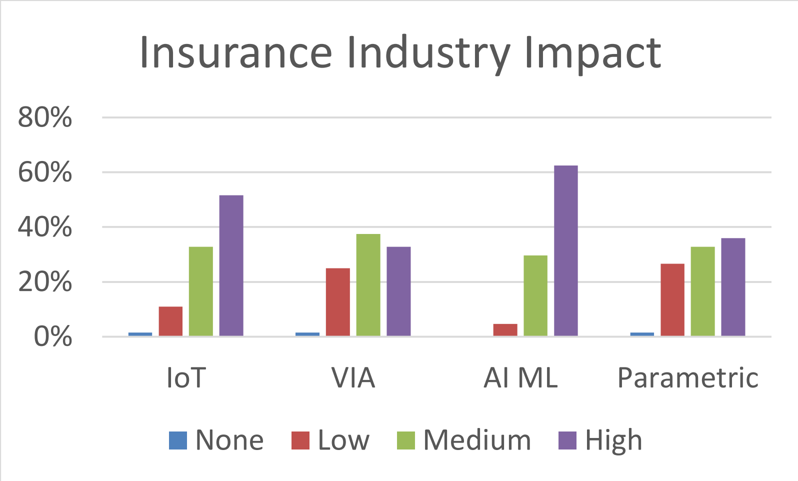
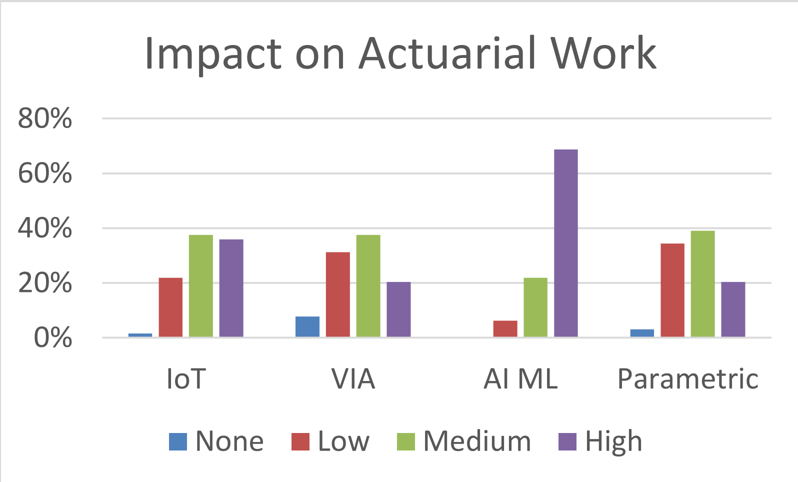
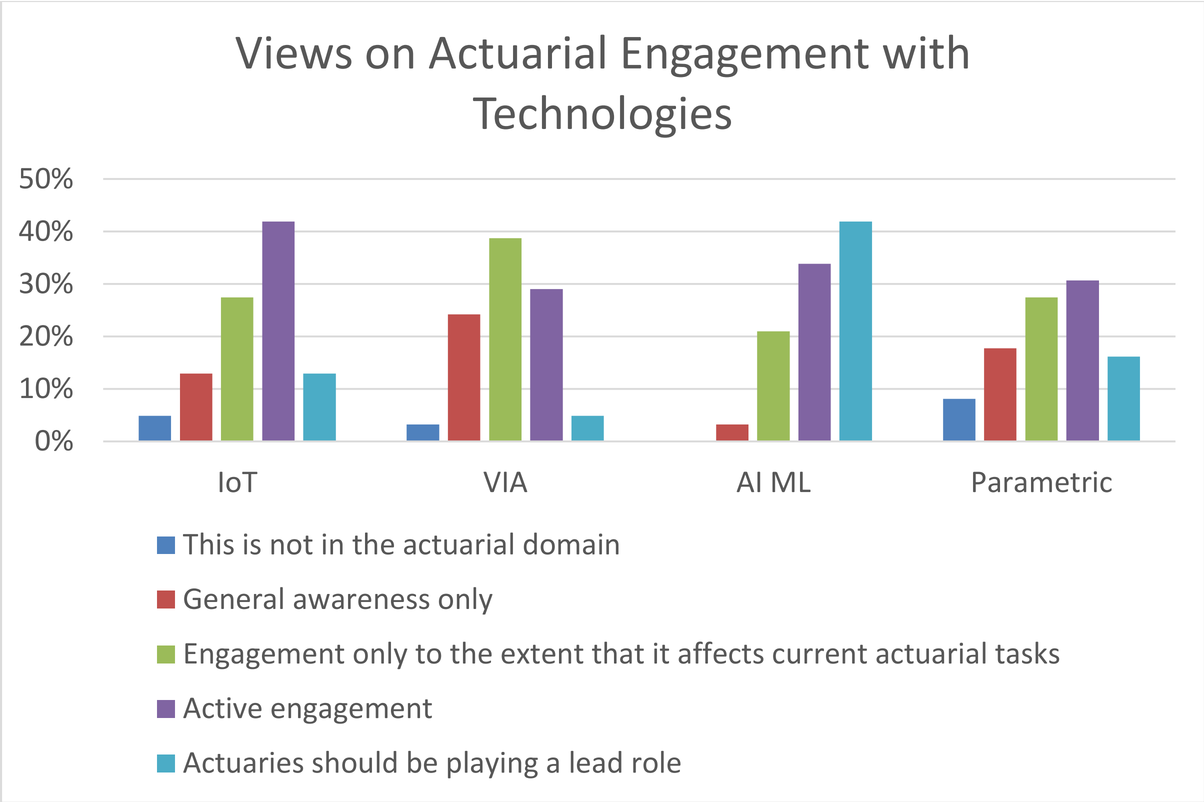
[11] The working party would like to acknowledge the assistance of Freddy Brofman in the initial design of the survey





There was a range of opinion expressed on how much impact the respondents expected the four areas to have on both the insurance industry and on actuarial work over a 5-10 year time horizon. AI ML in particular is expected to be high impact by a majority of respondents, both for the insurance industry and for actuarial work.

There were some differences observed between responses from pricing actuaries and from reserving/capital actuaries. Pricing actuaries typically felt all 4 areas would be medium or high impact on all 4 areas. Reserving/capital actuaries agreed with this assessment on AI ML, but for the other 3 areas were more typically suggesting low or medium impact.



There was again a range of opinion on the extent to which respondents felt that actuaries needed to be engaged with these technologies. A majority of respondents felt that actuaries needed to at least actively engage with IoT, and especially AI ML.

Rank	Functional Impact	Most Significant Benefit
1	Pricing, UW, Risk Selection	Better Customer Experience
2	Product and Service Design	UW / Pricing Competitive Advantage
3	Risk Prevention and Mitigation	Product and Service Differentiation
4	Claims Management	New Business Models (e.g. P2P)
5	Sales and Distribution	Reduced Acquisition Cost
6	Exposure Management	Reduced Operating Cost
7	Reserving	Claims Process Efficiency
8	Capital and Volatility Management	Reduced Claim Cost

Respondents were also asked to rank the above 8 functions and 8 potential benefits of insurtech generally by the expected size of impact over the next 5-10 years. Answers were heavily skewed towards pricing, underwriting, and product design aspects of the value chain; however, this is likely to be a function of the respondent sample, which is also skewed towards these areas.