DATA TECHNOLOGIES AND NEXT GENERATION INSURANCE OPERATIONS

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ABSTRACT

This article uses insights from knowledge management to describe and contrast two approaches to the application of artificial intelligence and data technologies in insurance operations. The first focuses on the automation of existing processes using robotic processing intervention (RPA). Knowledge is codified, routinezed, and embedded in systems. The second focuses on using cognitive computing (AI) to support data driven human decision making based on tacit knowledge. These approaches are complementary, and their successful execution depends on a fully developed organizational data strategy. Four cases are presented to illustrate specific applications and data that are being used by insurance firms to effect change of this kind.

1. INSURTECH – OPPORTUNITIES FOR DEEP CHANGE

Compared with the rapid pace of fintech implementation in other financial services – e.g., commercial banking, domestic and international payments, or capital market transactions – adoption of financial technologies by insurance firms (insurtech) is still at a comparatively early stage. There are many technologies and vendors courting the sector and some interesting examples of innovation and application by insurtech startups and established insurance firms. Nonetheless, there are as yet relatively few instances of new business models emerging based on the synthesis of new technologies in order to disrupt the market, either through new products/services or by offering existing products/services at substantially lower cost.

This article takes a knowledge management (KM) view to examine the data challenges that are slowing the adoption of new technologies in insurance. It asks: how might a new digital approach to insurance harness two different but complementary approaches; so-called 'lights-out' automatic processing and data-driven decision-making? Whilst many managers hold an idealized view of the potential of artificial intelligence (AI), along with a somewhat mechanical view of robotic process automation (RPA), our evolving project finds that a data-centric orientation, which can change both the modus operandi of a firm and its business model, cannot be achieved by focusing on ambitious transformative technology alone. The reality is more prosaic: real change starts by cleaning and curating the firm's underlying dataset before moving to more advanced challenges. Mundane as this might appear, advanced technologies are just as significant in this preparatory phase as we shall explain.

It is organized as follows. The following section discusses the issues involved and explains the 'knowledge management' perspective and how it can help. Section 3 then examines the associated challenges of data management. Section 4 highlights the role of insurtech in the data journey and section 5 reviews some examples drawn from our recent research. Section 6 concludes.

2. KNOWLEDGE MANAGEMENT AS AN ALTERNATIVE VIEW

There are many new data technologies that, in combination, have the potential to radically improve the operation and control of financial services [Maul et al. (2019)]. However, as Bohn (2018) notes, the insurance industry is something of contrast which "…faces a slow-motion parade of promise, possibilities, prematurity, and pared-down expectations." (p.76). Still, despite insurance being relatively less transactional than, say, banking firms with large insurance operations need to process myriad financial transactions efficiently and reliably. So, there is still great potential for using various insurtech applications to reduce operational costs and improve the assessment and mitigation of risk.

In terms of work presently performed by human agents, we can alternatively think of these two aspects as machine agent processes and machine cognitive agents respectively. Whilst, these terms might appear distinctive, in practice both are somewhat loose concepts. We will present our analysis in terms of a set of digital technologies positioned at various points on a continuum between two extremes, from the most basic automation (RPA) to the most sophisticated reliance on computerized decision making (AI).

The application of these technologies is supporting major and ongoing operational changes. But the relatively preliminary review that we have conducted so far in our research project, suggests that the key issues are rather more practical than many journalistic discussions suggest.

- First, on closer inspection, it is clear that there is considerable variety in AI technologies, and we are some way from consensus on what is and what is not included under the general AI label. Insurers are currently using some forms of AI technologies in several consumer and back office applications, including natural language processing by virtual assistants, image processing to evaluate the veracity and extent of damage, risk assessment, fraud detection, micro-segmentation, processing diverse unstructured data, and automating low-value tasks [Zarifis et al. (2019)].
- Second, as we emphasize in this article, automated data processing requires a substantial effort upfront to organize and standardize the underlying data. Insurance, even more than other financial services, is characterized by fragmented data. For example, every house and its contents are different. Consequently, the initial efforts at automation will likely continue to be patchy until these underlying data issues are more fully addressed.

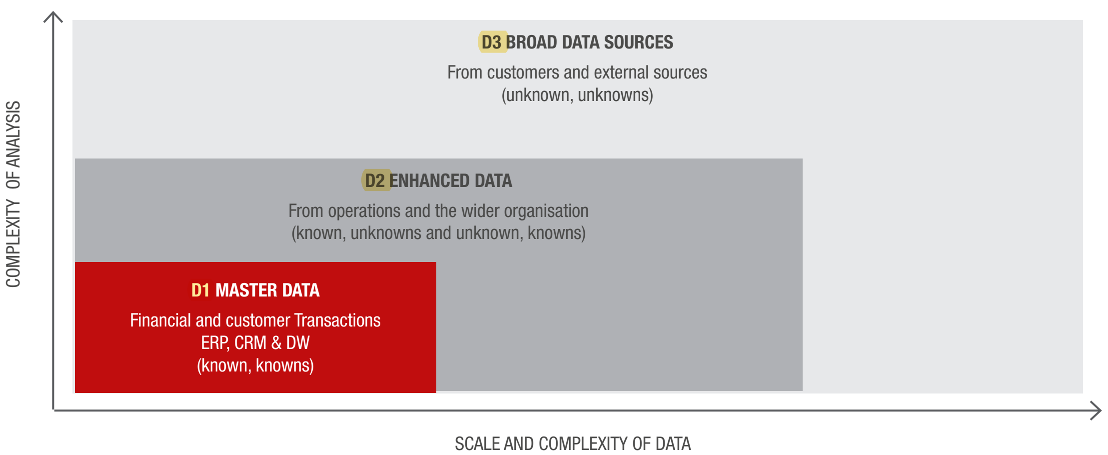
The 'lens' we use for examining this challenge of data management is the conceptual framework of "knowledge management" (KM). This avoids the trap of forced distinctions between data (as electronic representations of facts) and information (as processed data). Whilst the term 'data-centric' is useful for describing new organizational orientations towards data as a firm-level resource, it underemphasizes the role of the intelligent human and computer processes that turn data into useful information. Effective use of information technology in this role requires advanced computation – generically AI though this label covers a variety of technologies – complementing the data resources that have been gathered and curated using more mechanical approaches to data processing.

A KM approach challenges managers to see beyond data and information as, respectively, the raw material and outputs of computer systems, and alternatively, to reflect on the entirety of how an organization is able to think and do what it does. In its simplest sense, KM distinguishes between on one hand, tacit knowledge, arising from human activity and thought, and on the other hand, explicit knowledge derived from actions and events that have been codified and recorded [Polanyi (1962)]. Because explicit knowledge can be stored and further processed by computers, the ultimate aim is to turn all tacit knowledge into explicit knowledge.

Grant (1996) presents a very useful overview of knowledge-based theories of the firm in which he also elaborates tacit knowledge as 'knowing about' and explicit knowledge as 'knowing how', emphasizing that ease of communication is a fundamental property of the latter. Further, it can be argued that the new technology allows for machines to adapt by using tacit knowledge gained while the programmed algorithm is running whereas previously machines could only function as programmed with explicit knowledge.

[1] The analysis we report here draws on an initial review of the adoption of artificial intelligence and other insurance technologies, developed as the first stage of a current ESRC financed research project. This project, Technology Driven Change and Next Generation Insurance Services Grant Reference ES/S010416/1, is part of the broader Innovate UK/ RCUK Next Generation Services Challenge, https://bit.ly/2o2O0dB, that seeks to support the development and application of new data technologies in insurance, accountancy, and legal services. Our work can be followed on our project website at www.techngi.uk and on Twitter at www.twitter.com/techngi

Figure 1: Building the resource for data analytics



(adapted from CIMA, 2013, p.5)

Put simply, next generation insurance systems will render all the tacit knowledge embodied in people explicit so that it can be embedded in systems that can operate with much less need for human intervention. In so doing there will be intertwining of basic RPA processing used to gather and curate data from more advanced processing along the AI spectrum, to create insight from the new data and which will feed into the next round of RPA-driven operations.

Another way of using the KM lens to 'see' into the problem-set of insurance is to distinguish between observable and embedded knowledge [Birkinshaw et al. (2002)]. The challenge being to identify the necessary knowledge of what actually happens and why and then embed this into computer operating systems as programmable routines and more responsive algorithms. Over time, the sum of a firm's knowledge resources might come to explain its existence. For simplicity, we will use tacit versus explicit knowledge along with the standard industry labels around data management and information processing.

3. THE KEY CHALLENGES: KNOWLEDGE AND DATA MANAGEMENT

Ideally, a KM approach starts by asking what business opportunities are available and hence, what knowledge is required? The reality for existing firms, however, will more likely be an iterative approach that works outwards from more basic considerations: what data and processes are already available? What is the quality of the data in terms of its correctness, completeness, relevance, etc.? What systems and people exist to produce useful information for decision-making?

Paradoxically, the lack of an existing dataset can present an advantage for a start-up insurance firm that can plan its data strategy from first principles: crucially, without the lure of using existing data that, although free, may also be flawed or redundant to future business orientations.

Figure 1 depicts how a data transformation journey might be envisaged for an existing firm as a progression from D1) developing an agreed set of shared master data that enables services to be delivered and recorded, to D2) enhanced enterprise data capturing wider contextual data about, say, customers, insured assets, claims, etc., and finally D3) the development of 'broader data sources' including vast quantities of structured and unstructured historical data, e.g., personal credit scores, climatic data, customer 'click-stream' data (as they make choices about products/services on the website), etc. and dynamic data emanating from social media, the internet-of-things, etc. The two axes indicate how, as the volume of data expands, analysis, storage, curation and retrieval become more complex, as does the complexity of the analytical techniques and computing resources necessary to make sense of the data. This journey of data transformation is in our view the key objective of the firm's data strategy and data governance.[2]

[2] Data governance covering inter alia (as identified by BI Surveys 2018) documents and content, data security, data storage and operations, data modelling and design, data architecture, data quality, meta-data, data warehousing and business intelligence, reference and masterdata, and data integration and interoperatiblity

From this perspective, it is suggested that rather than diving headlong into capturing broad data, insurance firms should envisage a journey comprising three phases as follows.

D1. Data phase 1: Obtaining clean master data

Master data is agreed upon information shared across an organization. It includes all those details about customers and products that are necessary to provide quotes to customers, administer policies and claims, along with recording amounts charged and paid. Master data may have been collected from within or from outside the organization. The significance for electronic data management and governance is that the data is shared across various functions (typically through an ERP system), each with editing rights but likely no overall responsibility for its correctness. For example, a customer only wishes to advise his/her new billing details once and will tell whichever function they happen to be dealing with at the time, say, claims processing but the next use might be for policy renewal.

Substandard data in the system may occur for many reasons, even with otherwise good systems discipline. For example, 1) inconsistencies between systems arising from acquisitions and mergers, 2) data gaps and corruptions during operating system upgrades, 3) transitions between hardware vendors when data fields may have been incompatible, etc. Furthermore, there may be certain sub-routines within the overall system that are not electronically integrated; indeed, the issues may be as much about management structures as information systems.

Allowing for such organizational aspects, the key activities of a master data cleansing operation might be as presented in Table 1:

Table 1: Key activities of a master data cleansing operation

STEP	ACTIVITY	INSURANCE EXAMPLES
1	Standardize all data fields, e.g., terminology, headings, descriptions, etc. and also standardize how these are interpreted by workers in practice.	Insurers like Wrisk are digitizing all their processes across the value chain, so the data is more readily available.
2	Digitize all data entries at source wherever possible. Note: this may require workarounds to codify external records and use technologies such as screen scraping and voice recognition software.	Tokio Marine use handwriting recognition to digitize documents in Japanese.
3	Automate customer and agent-led* data entry routines wherever possible. Use AI to check digital inputs in real-time – flagging up queries for workers to validate with customers.	CUVVA customers use their mobile application to enter their personal details and pictures so agents are only called in for special cases.
4	Ensure that all relevant data is captured by the master database and is subsequently stored off-line in a retrievable format.	Insurers are collecting data within milliseconds from internal and external sources and storing it so that it is ready for actionable insights on risk.
5	Automate all transactional routines in the front and back offices from the point of data entry.	FRI:DAY have a fully automated insurance process that creates benefits that are larger than the sum of its parts.
6	Use AI to identify errors/gaps in the historical master data and fill in automatically with reference to other databases, e.g., by comparing policy and claims data, etc., or flag for worker validation input.	Insurers such as Lloyd's of London use machine learning to audit their data. It is trained by internal data and external benchmarking data.**

* agents = workers in company or with third-party agents

** For more detailed case studies on how insurance is using new technologies we invite readers to follow the TECHNGI project; particularly the library of case studies that we will be curating.

D2. Data phase 2: Enhancing the dataset

The next stage is to ask how the master dataset might be enhanced and its scope extended? For example, what other data could be captured from within the organization and its customers? How might that data be stored, curated, and analyzed at scale to replace or augment human workers and further 'train' the RPA and AI algorithms. It may be that external databases could be accessed, such as credit scores purchased from specialist agencies and bank accounts to evaluate relationships between, say, changing financial patterns as a proxy for changing driving behavior and claims. For instance, are drivers whose finances improve or deteriorate rapidly more likely to have an accident, or even just make a fraudulent claim? Furthermore, new services may be created with the primary purpose of collecting new data on the consumer that will support the AI micro-segmentation [Fountaine and Saleh (2019)].

The quantity of additional data could be significant; for example, storing 'Google street view' images of a customer's home at the point of issuing the policy. This would capture the state of repair and existing property additions to validate the present proposal and set a benchmark against which a future claim for damage might be based.

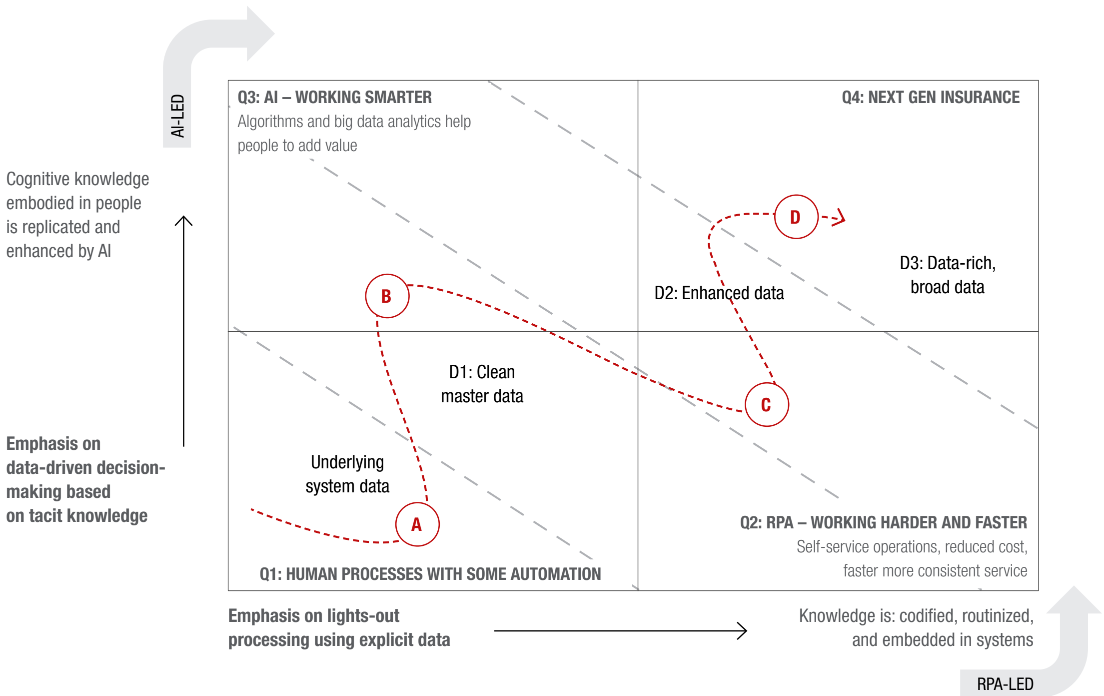
At this stage, management will have to make some fundamental decisions about data storage resources, e.g., own infrastructure or use of the Cloud, and what data to store given that individual sets of data may not make economic sense in isolation, but only when a critical mass of data is available that can be cross-correlated. In five years' time, the questions that top management may be asking in evaluating insurance risk will not likely be the same ones as today.

D3. Data phase 3: Gathering and curating broad data

The possibilities to interrogate a massive dataset to provide new insights into customer and asset profiles are endless. In fact, a popular phrase that captures something of the whole intangibility of big data is that it gives users the ability to "see the shape in the shadows". For example, telemetric "black boxes" are primarily intended to improve driver behavior but these can also produce a massive stream of contextual data in real-time, the full uses of which may yet to be discovered.

A further example might be analysis of social media feeds such as Twitter and Facebook. For example, activity on peer-to-peer networks might indicate rising perceptions of crime in a certain area and such an insight, if correct, will be some way in advance of actual claims to insurance companies and official police statistics; in which case premiums may need to rise to reflect the new reality.

Figure 2: Moving to next generation insurance



4. THE ROLE OF INSURTECH IN THE DATA JOURNEY

In moving towards the top right of Figure 1, some actions will be based on RPA, reducing routine human activity and, in the process, automatically recording all transaction and human decisions digitally. Some activities will require more cognitive-based AI algorithms to, say, identify (and even infill) gaps in the data structure. It sounds attractive to 'throw' both aspects at the data problem simultaneously. However, our research suggested that each will be used iteratively as depicted by the dashed line in Figure 2.

As RPA cleans up and improves the gathering of new master data (to Point A), AI can cross-check the files with additional data sources, for example, extending the evaluation of risk from, say, only basic asset and demographic characteristics to the consideration of many other variables, e.g., facts about a customer's lifestyle and financial behavior, Point B. The eventual objective might be to offer the same degree of policy customization as the firm might also offer to, say, the owners of an oil tanker. As AI helps create new insights from the growing database, RPA will generate queries to customers, either on renewal or during the policy, Point C. Perhaps the customer is underinsured and could be encouraged to increase cover or take action to mitigate their exposure. Swiss Re estimate that 70% of insurable assets are under insured [Swiss Re (2018)] and AI can help a firm secure more business and be socially responsible.

Indeed, the development of predictive algorithms at a micro-level might enable an independent insurance company to stay ahead of the 'consolidator' insurance websites. These tend to work on a minimum set of data points entered by potential customers so as to be able to offer comparable quotes across the market.

In achieving Point D, AI can be used to evaluate forward risks and validate claims. For example, voice and handwriting recognition software can be used to detect fraud in association with analysis of claims in the way that large organizations use algorithm-based software to check employee expense claim patterns.

In the case of motor insurance, for example, one might hypothesize that the use of 'satellite navigation' (satnav) devices may distract drivers and thus, increase the risk for some drivers/vehicle, but data on whether customers have actually fitted these and what make/model they have may not be being captured at present or historically. Perhaps such devices reduce risk but only for those 'professional' drivers (e.g., delivery vans) who use them frequently. Rather, it is those drivers who only venture outside their familiar territory occasionally and, say, use a map or the navigation app on their phones that cause the problems? There are many such questions but, nonetheless, this data may be worth capturing for future use. AI could 'backfill' the dataset for those vehicle models that have factory fitted systems, and cross-correlate with G.P.S. tracking data from black boxes, annual mileages, driver's age, gender, occupation, etc. Again, what to capture needs to be driven by an almost 'blind faith' in a future data-centric business model rather than by today's needs.

As governments try to wean their citizens off the culture of car use, 'green' insurance firms could play a larger role by offering pay-per-mile, or pay-per-day/week/month policies? Such policies are already available through companies like CUVVA, FRI:DAY, Wrisk, and Huddle. This might provide a marketing edge and also generate a lot of data that could feed into future data analytics for insurance firms. The data could even be sold to local authorities for transport planning. This would be an opportunity for insurance firms to demonstrate their environmental credentials. The TECHNGI project is developing a library of cases and the next section illustrates some examples of data management and application.

A final point in relation to this data journey is that most companies in insurance and in other industries still have a long way to go. This perception is corroborated by Leandro Dallemule, the chief data office of the global insurer AIG. "More than ever, the ability to manage torrents of data is critical to a company's success. But even with the emergence of data-management functions and chief data officers (CDOs), most companies remain badly behind the curve. Cross-industry studies show that on average, less than half of an organization's structured data is actively used in making decisions—and less than 1% of its unstructured data is analyzed or used at all. More than 70% of employees have access to data they should not, and 80% of analysts' time is spent simply discovering and preparing data. Data breaches are common, rogue data sets propagate in silos, and companies' data technology often isn't up to the demands put on it." [Dallemule and Davenport (2017)]

5. EXAMPLES FROM OUR RECENT RESEARCH

There is a wave of 'data hungry' technologies transforming insurance, such as AI, big data, IoT, and blockchain. AI has a role in the relationship of all these technologies and the insurer's data. There are many examples of current implementations of AI in insurance. Firstly, there are voice assistants that apply machine learning for the natural language processing used to communicate and the analysis related to insurance. These voice assistants are utilized by both the customer and the employee [Kannan and Bernoff (2019)]. AI is also utilized for image processing, such as handwriting recognition and evaluating damage from accidents. The images can be submitted by the customer or collected by IoT devices including drones. For audit, conforming to regulation, and fraud detection, machine learning is used to review many cases and identify a subset of unusual cases for an employee to check [Maul et al. (2019)]. Four cases are presented that reflect the four quadrants of Figure 2. The first two rely mostly on explicit knowledge and the last two utilize tacit knowledge also.

Change via route A – emphasis on using explicit knowledge by RPA

CASE 1. Q1: HUMAN PROCESSES WITH SOME AUTOMATION (FUNCTIONAL, CLEAN MASTER, AND ENHANCED DATA)

Manulife already uses AI in several ways including underwriting.

This insurer uses AI-enabled automation to handle the simpler cases that can be evaluated based on explicit knowledge and historical master data. This allows humans to focus their time on the remaining cases that need specialized data and tacit knowledge. The underwriting tool, called AIDA, is trained with machine learning and is allowed to underwrite life insurance with up to 1 million Canadian dollars of cover for the age groups of 18-45 without human involvement. A decision algorithm that utilizes machine learning can process the consumer application in a few minutes and make the final decision. Beyond the sophistication of the learning algorithm, success is dependent on the data in Manulife's systems being accurate, relevant, and available. This implementation illustrates the insurer's strong understanding of the strengths and weaknesses of current AI applications, their current data, the skills and tacit knowledge of their employees, and their ability to rewire their business processes gradually.

CASE 2. Q2: RPA – WORKING HARDER AND FASTER (CLEAN, ENHANCED, AND BIG DATA)

CUVVA provide hourly vehicle insurance.

This new entrant uses technology in a similar way to other online insurers like Lemonade, Huddle, and FRI:DAY. The consumer makes an initial monthly subscription payment and then makes an additional payment based on the hours they drive. CUVVA uses a mobile app that utilizes AI, automation, and vast, diverse data. The consumer uploads their picture and enters their vehicle number plate to receive a quote. Their systems check the database of the U.K.'s Driver and Vehicle Licensing Agency to identify any problems with the car and the license. CUVVA's system also checks the credit history and whether the prospective consumer has a criminal record. These checks are made automatically in a few seconds and the insurance is issued. This case illustrates how data is brought together and analyzed in an automatic way, supported by machine learning. The service offered is simple and requires explicit knowledge with limited tacit knowledge. More complex and challenging insurance services are not offered. As an insurer that was not only 'born digital' but also 'born AI enabled' the model fits the current capabilities of AI well.

Change via Route B – Emphasis on using tacit and explicit knowledge by AI

CASE 3. Q3: AI – WORKING SMARTER (CLEAN, ENHANCED AND BIG DATA)

LITA – Natural language capture allows AI supported advice.

From late 2017 to early 2019, Lloyds International Trading Advice (LITA), a service provided across the Lloyd's insurance market, worked with their technology partner Expert System Ltd. to develop a natural language processing solution for automated retrieval of legal and regulatory for insurance contracts around the world. Expert System provided an initial natural language processing (NLP) solution using their cognitive computing application Cogito, which was then trained on the Lloyd's regulatory database, Crystal, and employed for retrieval of relevant documentation.

Development from initial proof of concept (PoC) to business implementation required around ten rounds of iteration involving sometimes quite substantial manual intervention and reorganization of the data fed to Cogito. The first two iterations required especially substantial changes, with the development of a tailored taxonomy covering key insurance terms (many of which are specific to the Lloyd's market 'Lloyds'isms').

During the testing phase the output to a query was compared to what was produced without Cogito support by an experienced member of the LITA team to assess the accuracy of the output of the system. An initial 50% success rate, retrieving what the experienced members of the LITA team confirmed as the key required documents, was increased to 75%. Further subsequent 'tuning' raised the success rate to the current 88%.

The project has automated much of the work of the Lloyd's International Trading Advice (LITA), the small team within Lloyd's that provides members with legal and regulatory information required for underwriting business around the globe. The key lesson though is that the successful automation of this kind requires not only data technology but also the development of an explicit supporting data framework.

CASE 4. Q4: DATA-CENTRIC (DATA RICH AND BIG DATA)

TESLA offer insurance directly for their vehicle drivers.

TESLA do this for several reasons including reducing the cost to insure their cars. TESLA vehicles are usually quite expensive to insure because of their high purchase cost, high complexity, the additional dangers large batteries bring, and the fast acceleration that can lead to accidents. TESLA offers insurance at a lower cost by utilizing the data collected in the car that is processed by AI. Consequently, the TESLA vehicle is part of the Internet of Things (IoT) with several sensors including GPS, cameras, and accelerometers. The real time stream of huge volumes of data is utilized by machine learning to understand the risks and adapt to changing risks. This data cannot be fully utilized by humans, so machine learning leads in understanding it. New models of risk and how to manage it can be created by machine learning. Both the behavior of the driver and the vehicle can be influenced proactively. This current, customer specific, knowledge enables them to measure, predict, and influence behavior better. However, they still collaborate with existing insurance providers and benefit from their data and knowledge also. This illustrates both the advanced uses of data and AI but also the limitations, as TESLA is still not capable of offering all its driver's insurance and stills needs traditional insurers.

6. ASSESSMENT AND CONCLUSIONS: KEY ISSUES

We suggest that there will likely be a point of inflexion in the adoption of new data technologies, that will cause a 'domino' effect across the insurance industry. We can only speculate about the nature or timing of such a tipping point, but rather we note just one example of a recent potential for disruption. Tesla cars have a particular challenge in pricing their cars attractively as they ramp up production to a critical market mass. Their response is to reduce the total cost of car ownership by offering cheaper insurance directly to their customers on the basis that, as the CEO, Elon Musk put it, "We essentially have a substantial…information arbitrage opportunity where we have direct knowledge of the risk profile of customers and basically the car." [Tesla (2019: p1)].

This focus on AI captures both the widespread aspiration employing computers to take on a wide range of responsibilities that currently rely on human intelligence, but also the associated concerns about the ethical and economic implications of such a shift of responsibility from synapses to silicon.

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