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TECHNOLOGY

Artificial intelligence and digital transformation of insurance markets

CHRISTOPHER P. HOLLAND | ANIL S. KAVURI



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DEAR READER,

Welcome to edition 54 of the Capco Institute Journal of Financial Transformation.

In this edition we explore recent transformative developments in the insurance industry, through Capco's Global Insurance Survey of consumers in 13 key markets, which highlights that the future of insurance will be personalized, digitalized, and connected. Other important papers cover topics high on global corporate and political agendas, from ESG and climate change to artificial intelligence and regulation.

The insurance industry has been undergoing transformation in recent years, with insurers responding to the needs and expectation of tomorrow's customers, for products that were tailored, flexible, and available anytime, anyplace, and at a competitive price.

COVID-19 has accelerated such change, forcing insurers to immediately implement programs to ensure they can continue selling their products and services in digital environments without face-to-face interaction. New entrants have also spurred innovation, and are reshaping the competitive landscape, through digital transformation.

The contributions in this edition come from a range of world-class experts across industry and academia in our continued effort to curate the very best expertise, independent thinking and strategic insight for a future-focused financial services sector.

As ever, I hope you find the latest edition of the Capco Journal to be engaging and informative.

Thank you to all our contributors and thank you for reading.

A handwritten signature in black ink, appearing to read 'Lance Levy', with a stylized, flowing script.

Lance Levy, Capco CEO

ARTIFICIAL INTELLIGENCE AND DIGITAL TRANSFORMATION OF INSURANCE MARKETS¹

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ABSTRACT

Artificial intelligence (AI) is recognized as a strategically important technology because it has the potential to exploit human-like intelligence at machine scale and speed. However, the hype surrounding its business use masks the AI phenomenon and makes it difficult to analyze and evaluate in a systematic manner. Current approaches to defining AI tend to focus on its technical aspects and neglect the business, ethical, legal, and regulatory context. To remedy this deficiency, an AI systems approach is taken that defines AI within a broader systems framework. This is important because it provides a richer set of concepts that relate AI technology to business processes, business models, ethical considerations, and the legal and regulatory environment. A new framework of digital transformation is proposed, which is based on a synthesis of a new AI systems definition and business model concepts. The digital transformation model is illustrated with two global leaders in insurance markets, Ping An and Tesla insurance. In both cases, a similar causal model of digital transformation, continuous innovation, and rapid growth is identified that exploits the AI digital flywheel effect. The managerial and regulatory implications of the case study analyses and conclusions are described, and future research opportunities are outlined.

1. INTRODUCTION

Digital technology is transforming all types of businesses and markets [Schwab (2017, 2018), Brynjolfsson and McAfee (2016)] and these changes are having a profound effect on the insurance markets and the broader financial services [Naylor (2017), Alt et al. (2018)]. Digital technology is defined as the set of technologies that are used to process, analyze, store, move, and interpret data, which includes cloud computing, enterprise systems, data networks, computer hardware, software, social networks, mobile systems, and internet of things (IoT). The rate of improvement in the performance of digital technology is reflected in new artificial intelligence (AI) technology and business applications, and radically new business models [Holland (2019)], in what has been termed more generally as “Industry 4.0” [Schwab (2017)].

2. ARTIFICIAL INTELLIGENCE DEFINITION

A sample of recent AI definitions is provided to position the scope of this paper with relation to the insurance market.

“Artificial intelligence (AI) refers to systems that display intelligent behavior by analyzing their environment and taking actions – with some degree of autonomy – to achieve specific goals. AI-based systems can be purely software-based, acting in the virtual world (e.g., voice assistants, image analysis software, search engines, speech and face recognition systems) or AI can be embedded in hardware devices (e.g., advanced robots, autonomous cars, drones or Internet of Things applications)” [EC (2018)].

¹ This research is an output of the Technology and Next Generation Insurance Services TECHNGI project (www.techngi.uk) funded by Innovate UK and the Economic and Social Science Research Council (grant reference ES/S010416/1) as part of the £20 million Next Generation Services Research Challenge.

The European Commission [EC (2018)] has identified several important characteristics and properties of the AI system. The key point is that AI systems display “human-like” behavior, but unlike humans can be embedded into software, as well as the physical environment such as an autonomous car.

The Financial Stability Board (FSB) gives a very practical and high-level definition in their discussion paper on AI [FSB (2017)].

“AI is the theory and development of computer systems able to perform tasks that traditionally have required human intelligence. AI is a broad field, of which ‘machine learning’ is a sub-category. Machine learning may be defined as a method of designing a sequence of actions to solve a problem, known as algorithms, which optimize automatically through experience and with limited or no human intervention. These techniques can be used to find patterns in large amounts of data (big data analytics) from increasingly diverse and innovative sources” [FSB (2017)].

The key ideas that emerge from just this short sample of definitions is that an AI system can perform tasks that replace human intelligence and that the algorithms adapt in the light of new data, i.e., experience. The FSB also relates the definition to big data, and the interdependency of AI with big data is crucial in almost all application areas, including insurance, where an AI algorithm needs to be “trained” with a large volume of what is termed big data [Gandomi and Haider (2015)].

The Bank of England and the Financial Conduct Authority (FCA) define machine learning with a focus on the purpose of the model to identify patterns and to make predictions, and also highlight the fact that it can yield benefits for both businesses and their customers [Jung et al. (2019)].

“Machine learning (ML) is the development of models for prediction and pattern recognition from data, with limited human intervention. In the financial services industry, the application of ML methods has the potential to improve outcomes for both businesses and consumers” [Jung et al. (2019)].

These definitions have some important commonalities and omissions.

- They focus on the technical dimensions of AI, especially the algorithm and the use of big data to train algorithms.
- Machine learning is commonly identified as an important element of the algorithmic dimension of AI systems.

- Human-like behavior is taken as the key characteristic that defines AI systems, with no reference to other, new forms of intelligence that could exist, and which are unique to machines.
- The capabilities of AI systems are expressed in a limited manner, e.g., with respect to optimization and pattern matching, which is a narrow conception of human intelligence.
- There are no references to the business context of the AI application nor to its organizational scope, e.g., business application, functional area, and whether it relates to individual, group, or organization-wide systems, which are a crucial part of defining earlier generations of technologies, such as management information systems (MIS), including enterprise resource planning (ERP) systems that cover the whole organization and decision support systems (DSS) that are focused on the individual/group.
- There are no references to the ethical and regulatory contexts, which have become significant in market sectors such as health, insurance, banking, and e-commerce, where privacy, confidentiality, and data protection regulation are important factors in the design, use, and evaluation of AI systems.
- The notion of value is touched upon but is not described in any meaningful manner, for example to distinguish between simple cost savings from improved automation and strategic advantages from advanced data analytics and improved business models.

2.1 Technical properties of AI

The technical properties and attributes of AI systems are important to distinguish AI technology from existing management information systems. The emphasis on machine learning is relevant here because the capability to learn from data and, therefore, adapt is the crucial point. The current set of AI systems in business are termed “narrow” AI, which means that they have very limited intelligence that is applied to a single area or problem. There is an active debate in the literature about more general AI intelligence [Tegmark (2017), Bostrom (2017)], where the machine displays superior intelligence to a human [Penrose (1989)]. Taking this a step further, the singularity concept asserts that it is simply a matter of time, and continued exponential increases in computing power, when we will reach a singularity where machines overtake human intelligence and then continue to evolve into super-intelligent beings in their own right, e.g.,

Prometheus [Tegmark (2017)]. The idea of strong AI or general AI presupposes that intelligence is a function of algorithmic complexity and processing power, which is strongly disputed because it does not actually address the core definition of intelligence and the related philosophical and scientific models of consciousness [Penrose (1989)].

The concept of intelligent capabilities, whether they are very limited in their scope or attempt to have more general intelligence, leads onto the ability of AI to perform human-like behavior [Turing (1950)], i.e., to do tasks that would normally require humans to perform, such as complex classifications of data, predictions, assist in an online application process, optimize pricing, and voice/image recognition. Note that there is no effort here to define intelligence, but the approach is simply to state that the machine can perform tasks that previously required humans. This emphasis on humans in most of the definitions of AI raises an important question, which is that there may be other forms of machine intelligence that are not directly comparable to human behavior. The implicit assumption in these definitions is that the ultimate aim for AI is to emulate humans, rather than build a different form of intelligence. The point here is that there may be different forms of intelligence, and by concentrating on human-like capabilities we may miss other important development opportunities.

2.2 Business, ethical, regulatory, and legal context

The broader context is relevant when AI is considered from a managerial perspective, because it situates the technology within an organizational setting, with a business purpose or framework. For example, to assist someone in an online application, to identify a fraudulent claim, to estimate risk, or to organize policy documents. The key dimensions here are redesigned individual business processes that take advantage of AI and big data, new kinds of products and insurance services such as behavioral insurance and parametric insurance services, and the emergence of new types of insurance business models that are underpinned by AI processes and products. The use of sensitive personal data and the importance of insurance from a societal perspective create difficult ethical issues that are now receiving careful attention from regulatory bodies [Wood-Harper et al. (1985)]. The legal and regulatory context is crucial because it potentially affects all aspects of AI systems in insurance from their design principles, method of implementation, rate of adoption, and consumer rights over data, and appeal over automated decision-making.

3. PROPOSED DEFINITION OF AI INSURANCE SYSTEMS

In an insurance context, it is necessary to place these rather general AI definitions into a specific business or application context, which adds meaning to its relevance and helps in understanding the contentious strategic, ethical, social, and legal issues related to the implementation of AI systems in insurance. A socio-technical approach to AI systems is a concept that places the AI algorithms and machine learning technology into a broader business context [Wood-Harper et al. (1985)], which encompasses the digital technology of core insurance systems (data capture, GPS, cloud computing, internet of things, and software), big data, the insurance business processes or activities, people, and business models that are involved in a particular insurance product-market business example [Wood-Harper et al. (1985), Data Ethics Commission (2018)].

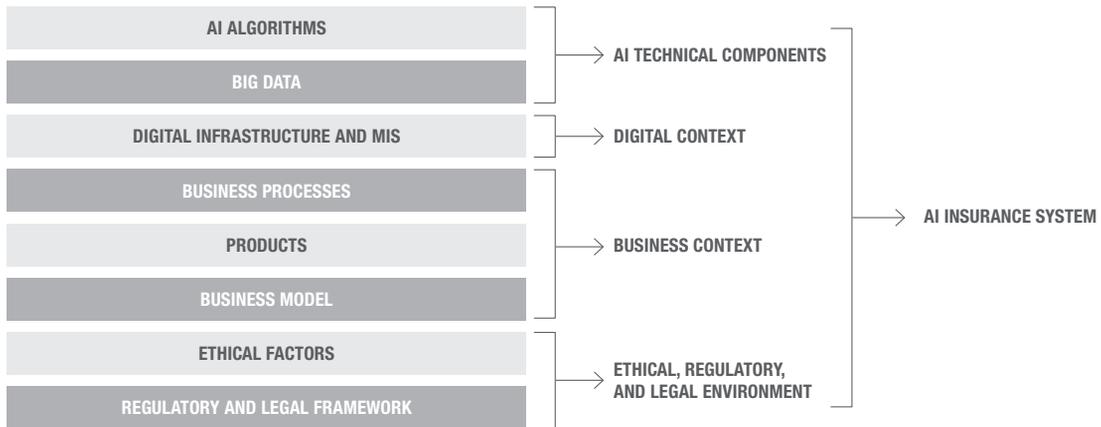
An AI insurance system is defined by the authors as:

“A set of inter-related elements of AI algorithms, big data, digital infrastructure and Management Information Systems (MIS), and the business context that encompasses business processes, products, and the business model of the firm, within an ethical, regulatory, and legal environment.”

For example, in a behavioral AI automotive insurance system, GPS and digital technology in mobile devices and/or the car itself capture telemetry big data that is shared with the insurance company. The data could be combined with other data types – e.g., historical loss data, weather patterns, route map information that contains speed limits, and data from other drivers – and analyzed using machine learning algorithms to derive a driving score, which is then used as an indicator of the risk of an accident and used to price the insurance premium. This approach is a fundamentally different approach to using what was historically used to model risk in car insurance, which was the demographic information about the driver, the value and type of car being insured, and the driver's history, in particular previous claims and convictions. A behavioral approach shifts the use of data from a periodic, typically annual exchange of summary data between the insurance firm and the customer, to a continuous exchange of real-time driving data, where risk is modeled on a continuous basis and is used to inform the insurance premium on a dynamic basis.

Expanding on this verbal definition and extending the systems approach by formalizing the identification of individual system elements, a revised model is developed in Figure 1. An AI

Figure 1: A framework definition of AI



insurance system perspective shows the inter-relationships between the technical components of the AI system – i.e., the algorithm, big data, digital platforms, core legacy systems, sensors, GPS, and other digital technology – and separates them from the business context, which includes the business processes, insurance product, business model, and insurance value chain [Data Ethics Commission (2018)]. This setting of the AI technical components within the broader business context is similar in concept to a socio-technical approach to systems design [Wood-Harper et al. (1985)]. The legal and regulatory context is then concerned with issues such as transparency, explainable AI, fairness, and ethical considerations. Regulatory issues are applicable to all types of AI and have particular relevance in those sectors where there are additional privacy, confidentiality, and data protection rules, such as in health, insurance, banking, and e-commerce.

The key feature of a systems approach to AI definition is that it allows a holistic approach and the consideration of each element separately, their relationships to each other, the natural groupings of the elements or components, and an appreciation of the overall structure of an AI system.

3.1 AI technical components

The natural starting point is the AI algorithm, because this is what distinguishes AI technology from MIS. In a traditional ERP system, the algorithm for managing the production and accounting systems is fixed and applied to a set of data to generate meaningful insights, information, and statistics. In an AI system, the algorithm has the potential to change, adapt, and “learn” as new information becomes available – it is this dynamic ability to adapt that is probably the most important characteristic of AI that sets it apart from earlier digital technologies and systems. Some researchers and

commentators emphasize the ability to make predictions as a key characteristic of AI, for example, to classify information, or to identify a pattern or anomaly, or to predict the likely probability of an outcome. While this is useful, it could be argued that many types of management information systems that have no claim to be AI systems, make predictions; for example, a weather forecasting system will predict tomorrow’s weather based on a causal model of weather patterns, a sales forecasting system will predict next week’s sales based on a simple regression model and prior information of historical sales, level of promotion, competitor reactions, and market confidence. An ERP system will predict the optimal time for ordering parts from suppliers based on a fixed material requirements planning system.

Big data is an integral technical component to all AI systems and is vital for the initial training of the algorithm, and then for its ongoing operations, evolution, and maintenance. Commercial AI systems are rarely standalone systems because they need to access new forms of big data and relate these to existing data in legacy MIS, such as enterprise and policy management systems. In insurance, new forms of big data are often related to physical and behavioral phenomena related to insured assets, such as data from health trackers, telemetry, IoT in buildings, and smart sensors. The inclusions of digital infrastructure as a general class of technology to capture, communicate, store, and analyze is, therefore, important.

3.2 Digital context

The digital infrastructure and management information systems link the AI applications to the broader organizational enterprise systems. In an insurance company, these include functional business areas such as HR, marketing, finance and

policy management, as well as regulatory compliance, and risk management. Almost all current AI applications in insurance are designed to support existing business processes within a functional area, typically following the customer lifecycle: digital marketing to acquire new customers and retain existing ones, AI behavioral risk assessment, smart policy management, ChatBots and online tools to facilitate e-service, voice recognition and natural language processing (NLP) to automate call center operations, a/b testing of new customer interface designs, and automated claims management from image recognition and machine learning to estimate the cost of claims. This means that the digital infrastructure and MIS remain as the core systems in an insurance company and that AI systems are in effect a smart wrapper to existing organizational blueprints defined by the existing enterprise systems and business processes.

3.3 Business context

The business context is described in terms of changes to business processes, products, and insurance value chains and business models. The digital transformation process can be analyzed by considering the interactions and causal effects of AI technology and applications on business processes, which are the basis for product innovation, value creation, and the emergence of radically new business models in insurance.

3.4 Ethical, regulatory, and legal environment

Beyond the boundary of the insurance firm, the regulatory and legal environment is particularly important in areas such as transparency and explainability of AI systems, and ethical issues associated with its implementation. Regulatory [EIOPA (2019)], governmental [EC (2019)], and consumer organizations [BEUC (2020)] all agree that there needs to

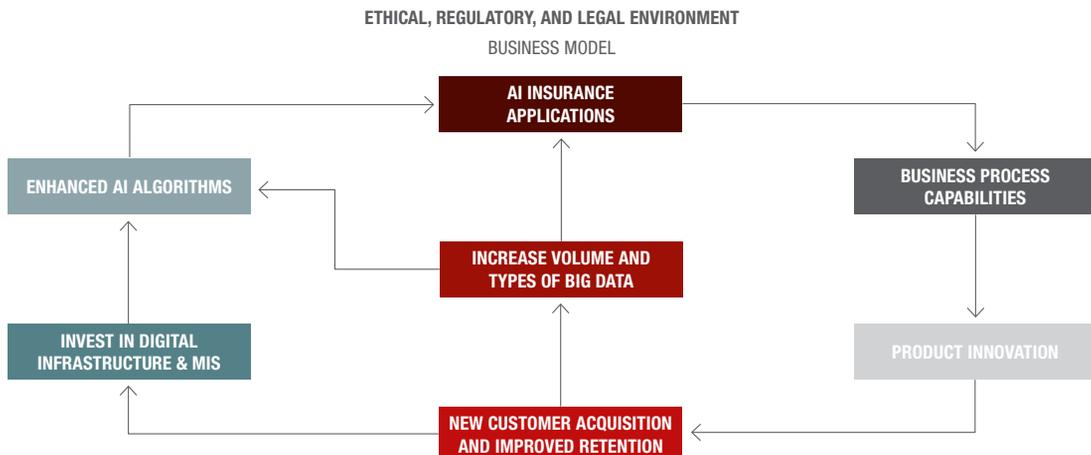
be oversight and regulation so that insurance firms abide by relevant legislation and more generally protect consumer rights. There is also a more general argument that societal norms and ethical considerations should also be considered. In addition, the regulatory environment must also be balanced against maintaining the need for innovation [Keller et al. (2018)] and to enable profitable and sustainable insurance companies. There are significant benefits to consumers from AI systems in insurance, including ease of use, extending insurance to previously non-insured groups through improved targeting, new products such as cyber risk, reduced premiums from administrative lower cost insurance operations, consumer analytics to mitigate and reduce risks, learning systems from the behavior of large networks of consumers, and early warning systems [Keller (2020)].

4. A STRATEGIC MODEL OF TRANSFORMATION IN INSURANCE MARKETS

The framework definition in Figure 1 identifies the elements of an AI insurance system and this is used as the basis for developing a causal model of AI transformation in insurance markets, which is shown in Figure 2.

This is a simplified description of the mechanisms of digital transformation from the novel application of AI and digital technologies. Starting with customer acquisition, new customers generate increased levels of big data that is used to personalize the AI insurance applications and to train and enhance the existing AI algorithms. New customers create revenue, which is invested in digital infrastructure and MIS, which links the AI systems into the organization's enterprise systems. AI-enabled insurance applications create high-performance business process capabilities in areas such as

Figure 2: AI and digital transformation in insurance markets



customer interaction, risk assessment, claims handling, and digital marketing. These business process capabilities are the direct result of a set of narrow AI applications, and provide the basis for product innovation, which is used to attract new customers and improve the retention of existing ones. A virtuous circle is created that leads to increased data and customer growth, which is termed the AI data flywheel effect.

4.1 AI insurance systems focused on individual business processes

Business and technology examples of contemporary AI systems are used to illustrate the digital transformation model. All the AI examples given in this section have the common feature of focusing on a single business process, and this is termed “narrow” AI. This is a characteristic of almost all current business examples of AI systems and is a result of the current state of maturity of AI technology, which can handle narrowly defined problems, based on extensive training of the algorithm to solve a very specific and tightly defined problem. Conversely, the machine learning technology that provides the mathematical algorithms for today’s AI applications is poorly equipped to handle more general problems, where the organizational scope and/or the number of parameters and interdependencies between different aspects of the problem domain are significantly higher.

Starting with big data, which is at the center of the model, a recent survey report by European Insurance and Occupational Pensions Authority [EIOPA (2019)] identified a clear transition in the use of data to assess and evaluate risk, which is a core part of all insurance markets. The data transition is from the use of traditional data sources to new forms of big data that are enabled by digital strategies that embrace and encourage customer involvement in the value creation process. Traditional data sources to assess risk include demographic, exposure, loss, hazard, and medical data. Big data sources include behavioral data, IoT, images, personal data from smart watches, and genetics data.

Taking risk assessment in motor insurance as an example, insurance carriers are utilizing telematics technology from technology partners to fundamentally redesign the risk assessment process, which enables the development of new kinds of innovative insurance products, such as personalized behavioral insurance, pay per use, dynamic risk assessment and pricing, and to create customer value with new services such as data analytics on driving performance, risk mitigation, and driver advice based on a large network of other insured drivers. Behavioral insurance has been adopted quickly by

market leaders in the U.K. (Aviva), Germany (HUK-COBURG), the U.S. (Geico), and China (Ping An). What emerges from these examples is that the innovation process and changes to the business model do not stop at risk measurement based on driver behavior. The data collected to assess driver behavior is also used to create additional services such as analytics and driver performance dashboards, dynamic pricing, and risk mitigation.

Relating behavioral motor insurance to Figure 2, new forms of big data are used to develop AI driver apps that monitor and evaluate driving behavior, which generates new risk processes that enable product innovation to create personalized driving insurance pricing. This improves new customer acquisition and retention, which supports further investment into digital infrastructure and related MIS, and crucially generates a larger big dataset of driving behavior. The combination of better digital technology and larger datasets make it possible to enhance and refine AI algorithms, which is reflected in more effective AI behavioral insurance apps. This is a dynamic model and is a typical example of the data flywheel concept in action, where a growth in customers results in better data and AI systems, which creates a virtuous circle that is focused on the commercial use of more relevant data. A similar logic applies to health behavioral insurance, which uses personal data such as weight, physical activity, exercise, heart rate, and blood sugar levels.

Continuing with a focus on the business process as the unit of analysis, AI systems can be mapped onto a customer lifecycle model, starting with sophisticated A/B testing to score new website designs, machine learning for the automated evaluation of digital marketing campaigns, the use of virtual assistants to facilitate the sign-on process for new customers and also in e-service, AI for image recognition and claims handling, and machine learning techniques for market segmentation based on statistical clustering techniques using search and buying behavior through online channels.

4.2 Ping An – an ecosystems and technology-driven business model

4.2.1 AI TECHNICAL COMPONENTS AND DIGITAL CONTEXT

The Ping An group started as a traditional insurance firm and has expanded into four main ecosystems: (1) “Finance +”, (2) healthcare, (3) automotive services, and (4) smart cities. In 2020, the company had 598 million online users across its platforms, and four apps with at least 100 million users. The focus of this case vignette is on its telematics insurance app because this illustrates Ping An’s use of AI and

technology strategy to automate internal and customer-facing business processes, within a broader business model context [Larsen (2019)].

The AI algorithms that form the basis of its AI applications are developed in-house and are part of a technology-driven strategy that uses digital technology to improve all aspects of business performance. The origin of its technology strategy was to use digital technology to improve existing products and services and then expand the digitalization process into ecosystems for specific product markets such as finance, and invest in connecting with economic partners that play important roles in that market. The company realized that to avoid the legacy systems problems associated with long-established banks and insurance firms, it should build technology platforms that have inherent flexibility and scalability, and continually invest in new technology. Four technology pillars underpin its digital strategy, which are AI, cloud computing, security, and emerging digital technologies such as blockchain and internet of things (IoT).

Customer growth and behavior generates huge amounts of big data, and this is tracked to capture salient characteristics and properties, which is then used to improve customer understanding, cross-sell services, and to inform product innovation. Important technologies that cut across all ecosystems are customer identity, CRM data, cloud infrastructure, AI knowledge and expertise, and security. Investment into AI, digital infrastructure and MIS, therefore, benefits from huge economies of scale and scope.

4.2.2 BUSINESS CONTEXT

AI and digital technology are used to automate business processes in a comprehensive digitalization program. For example, to automate customer-facing business processes, especially to enhance the user experience in areas such as new customer acquisition, policy e-service, and online claims management, and internal processes such as risk management, digital marketing for cross-selling within and across ecosystems, and coordinating B2B relationships with economic partners such as automotive dealers and workshops. In automotive claims, 70% of claims involve superficial damage, and the insurance app uses a picture to estimate the damage and offer an immediate settlement into the e-wallet of the customer.

The business model of Ping An is hugely complex but can be described in a meta-model and then by a series of more detailed sub-models for each ecosystem. The meta-model is to treat data as the core element in the creation of value, and

most business activities generate vast amounts of big data, e.g., search and buying behavior, customer profiles, telematics data, responsiveness to advertising, and customer financial profiles. Long-term capital is invested to exploit the big data resources from each ecosystem, and continuous investments are made into talent and the generation of patents, or more generally, intellectual property (IP). At the level of an individual product, the business model for the telematics insurance app is described.

4.2.3 PING AN'S TELEMATICS APP

In 2019, the telematics application had 9.5 million monthly active users, and captured detailed driving behavior in the form of physical behavior, such as acceleration, deceleration, cornering speed, centripetal force, and use of phone while driving. An AI algorithm combines the driving and customer big data to create a unique customer profile, which is used to automate the assessment of crucial insurance business processes, personalized risk, and pricing. The insurance service benefits from the general AI applications to support standard customer lifecycle business processes such as new customer acquisition, security, customer identification, policy management, customer renewal, and cross-selling. Insurance-specific AI applications are also used to support claims management.

The MIS and digital infrastructure connects the AI technical components with other services, including links to thousands of dealerships, automotive workshops for repairing vehicles, and garages for maintenance.

4.2.4 ETHICAL, REGULATORY, AND LEGAL ENVIRONMENT

Although not the focus of this case, it is relevant to note that Ping An has benefited enormously from the historical legal framework in China, because it invested early in ensuring that it had a comprehensive range of business licenses to operate in a range of financial markets as a non-government insurance and banking organization. In addition, it could be argued that the Chinese market has been less restrictive in the use and exploitation of personal data in AI applications such as facial recognition, customer identity, and customer profiling across different served markets, when compared with the U.S. and especially with European GDPR legislation [Allen and Masters (2020)] and ethical frameworks [EIOPA (2021)].

4.2.5 PING AN CASE DISCUSSION

The telematics app is primarily an insurance app, which is part of the Finance + ecosystem [Economist (2020)], but also incorporates important aspects of the automotive ecosystem.

It is, therefore, an example of synergies across ecosystems in areas such as cross-selling of insurance to customer buying vehicles, and cross-selling of vehicle repair services to insurance customers.

Ping An has built a range of digital platforms for specific products and services that host a set of narrow AI systems. These platforms form the basis of the four broad ecosystems of customers, Ping An services, and economic partners of Ping An, for financial services, health, automotive, and smart cities [Ngai (2018)]. Each ecosystem has a close focus on the customer so that it can cross-sell products within the ecosystem, e.g., insurance to a bank customer or vice versa, and across ecosystems, e.g., insurance to an automotive customer based on brand affinity, customer value, and ease-of-use.

The key individual, “narrow” AI applications follow the customer lifecycle model from AI robots in market surveys, AI agents to sell products, service policies through automated e-service robots, and claims management. The company claims that 82% of total service interactions with customers were managed by AI systems, which represents an impressive level of e-service automation and significantly reduces the cost to serve customers [Ping An (2021)]. AI robots are being used for inbound and outbound calls and sales. In claims management, automated AI systems account for 83% of all consumer claims. There may be a law of diminishing returns here, and human oversight to handle exceptional or unusual cases will always be needed. However, the norm is already that customer interaction takes place via AI systems.

Ping An’s strategy starts with a technology-driven business model for AI insurance, which generates an AI data flywheel effect and leads to rapid customer growth. The huge amount of customer behavior data is used to train AI algorithms and improve business processes, which in turn lead to further product innovation and improved customer acquisition and retention. This creates economic and data scale, which is then exploited further by expanding from insurance into insurance-related activities in what it terms an ecosystem that includes economic partners such as automotive repair workshops and sales outlets [Catlin et al. (2018)]. The ecosystem strategy creates significant barriers to entry for new competitors, e.g., the database of customer behavior and associated insurance knowledge, sophisticated AI systems, and relationships with economic partners that may be difficult to replicate. In addition, economic scale confers further advantages because there are clear technology economies of scale in the development of AI systems that can be shared across ecosystems – such

as security and digital marketing, and the hosting of the technology infrastructure and MIS on data platforms – and significant marketing economies of scale, particularly in reducing the unit cost of acquiring new customers.

4.3 Tesla – behavioral insurance in practice

4.3.1 AI TECHNICAL COMPONENTS AND DIGITAL CONTEXT

Tesla is a market pioneer and leader in electric vehicles and autonomous driving. AI algorithms, big data, and digital technology are in its core DNA, so it makes sense to enter a related market, which is fundamentally about handling data and in particular risk assessment. The shift from traditional sources of data to behavioral risk assessment is a market discontinuity and, therefore, creates an opportunity or opening for new entrants [EIOPA (2019)].

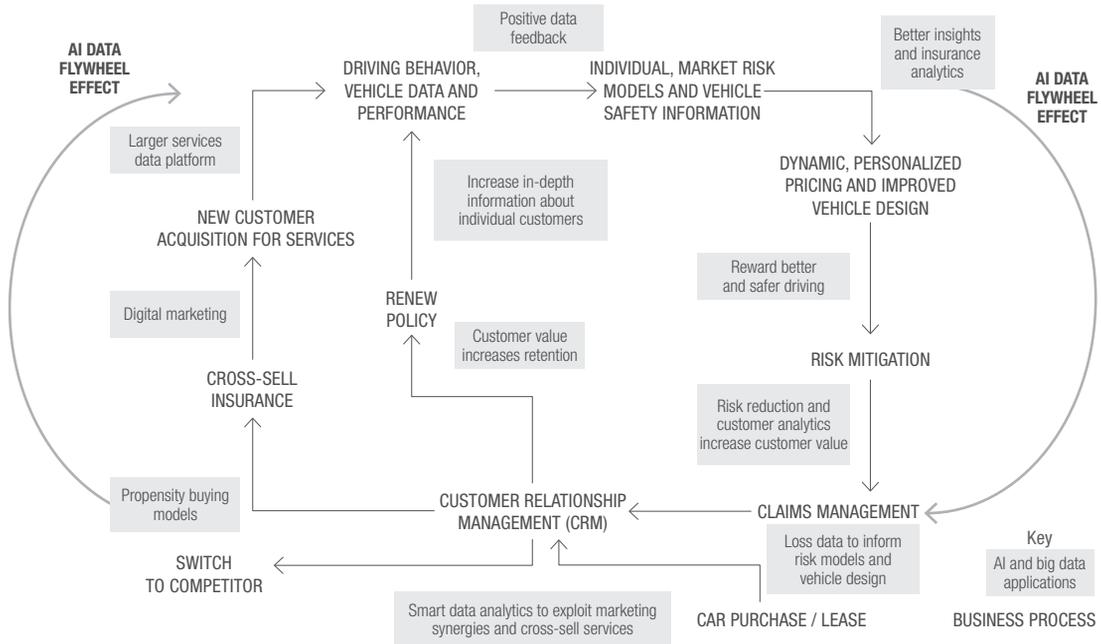
In existing, traditional insurance markets, established insurance carriers use their historical datasets, digital infrastructure and MIS, and knowledge of risk and claims as significant barriers to entry – knowledge and data effectively block or at least impede the launch and growth of new entrants. However, these datasets are based on traditional demographic information, and legacy digital infrastructure and MIS, which have much less value, perhaps even negligible value, in a behavioral risk market. The new digital technology, especially vehicle telematics, vehicle safety, accident data, and claims losses for electric vehicles are all brand new, which means that the behavioral insurance market for e-vehicles has the characteristics of a new technology market rather than an established, mature, insurance market.

4.3.2 BUSINESS CONTEXT

The brand advantage and market position of insurance carriers, especially in distribution, operations, compliance, and access to secondary markets for capital and risk, are extremely valuable. However, Tesla will exploit its global brand strength and particularly strong affinity with its customers to cross-sell insurance services, in much the same way that technology companies such as Apple sell services and software in addition to the phone and computing hardware. It will also take a digital first approach in designing operational systems and e-service capabilities, which may have significant advantages over insurance carriers’ legacy systems. Tesla’s scale and access to capital funding mean that the financial barriers to entry into insurance markets are not a significant consideration.

An expanded version of the simplified business model concept from Figure 2 is used to illustrate Tesla’s use of AI technology

Figure 3: Tesla's insurance business model and use of AI technology



to create a disruptive insurance business model – see Figure 3. Starting with a new car sale or lease, data analytics are used to create cross-selling opportunities for insurance services, typically based on propensity buying models. Tesla has adopted a typical new entrant strategy by offering high-value insurance services, claiming to undercut competitors by 20-30%. Their initial efforts were assisted by the fact that established insurance carriers had very little knowledge and data on which to base the potential exposure resulting from claims to fix e-vehicles. New insurance customers increase the volume of data and improve the accuracy of risk assessment from driving behavior. There is also a network effect because insights about road safety, routes, and safe driving can be shared across the community of Tesla drivers.

The telematics data from the car provides insights into both the performance of the driver and the vehicle, which can then be related to geographic location, weather information, driver profile, and road position and layout. The potential for generating rich insights to mitigate risk, improve driver behavior, reduce future claims, and offer personalized pricing that rewards better and safer driving, adds significant value to customer interactions and is likely to improve customer retention. The overall effect is to create a positive growth cycle where growth in data improves AI applications and business performance, which in turn attracts new customers

and continues to increase the volume and range of big data. This has been termed the “data flywheel” effect [de Véricourt and Gurkan (2020)] and is shown in the diagram as a positive direction of change, which stimulates a continuous growth cycle.

4.3.3 ETHICAL, REGULATORY, AND LEGAL ENVIRONMENT

Insurance firms in Europe and U.S. need to ensure that their data management practices and privacy policies conform to the strict data protection regulations in both countries. In Europe, the General Data Protection Regulation (GDPR) regulations require firms to protect privacy and personal data of all E.U. citizens. GDPR defines personal data as any “information relating to a person who can be identified, directly or indirectly” [Keller et al. (2018)]. Consequently, any data that enables identification of an individual is subject to strict GDPR rules.

Lawyers have argued that big data analytics are in many cases incompatible with GDPR, e.g. Zarsky (2017). However, insurance firms must somehow balance innovation with regulatory compliance, which is difficult at the cutting edge of practice, e.g., Tesla’s leadership in autonomous driving and personalized services for individual customers. For example, Tesla Model 3 cameras monitor the surrounding environment and record vandalism, which has come under scrutiny by the

State Commissioner for Data Protection because it may be an infringement of GDPR [Andernach (2021)]. Tesla's use of customer data to personalize its insurance products in the U.S. has also received attention and is subject to individual U.S. state laws [Bellon (2019)].

Under the regulatory patchwork model in the U.S., each of the 50 states have different definitions of personal data, which is likely to lead to high compliance costs [Bayley (2020)]. The situation in China is also changing and the Personal Information Protection Law (PIPL) will come into force in 2021. KPMG's analysis shows that it has similarities with Europe's GDPR and is likely to lead to a stricter regulatory environment in China concerning the use of big data and AI systems [KPMG (2020)].

4.3.4 TESLA CASE DISCUSSION

By entering the behavioral insurance market early, Tesla gains several distinctive advantages: it builds skills and knowledge associated with the new telematics technology and associated data analytics problems, it places the company in a favorable position as behavioral insurance becomes mainstream, and it gives the company important insights into new forms of risk differentiation, and an associated understanding of how to actively reduce claims and accidents. The data from the insurance business could also be used to improved vehicle safety and is likely to influence the design of future vehicles.

5. CONCLUSION

A framework definition of AI is proposed in Figure 1 that captures the key technical dimensions of an AI system and places these in a broader business and regulatory context. This approach is important because it provides a more nuanced perspective on how to analyze and evaluate AI technology by relating AI to business and regulatory themes, i.e., a socio-technical or business system. Big data is already recognized as a crucial input for the design and operation of AI technology, and it is shown that links to the existing MIS and digital infrastructure are also crucial in the successful deployment of AI systems.

Most AI systems in insurance are focused on individual business processes, which are the basis for product and service innovation. The combination of AI business process capabilities and product innovation have significant effects on the overall business model, whether this is to improve its performance through reduced costs and improved service, or to radically change the nature of the offering, which then

creates a brand-new business model that has the potential to disrupt the market, e.g., behavioral insurance. AI technology should, therefore, be viewed in a broader digital and business context to make sense of how AI technical components and the business context influence, and are influenced by each other, in a reflexive relationship.

There are some important common characteristics to both Tesla and Ping An. Both companies have developed a technology and data-driven business model approach, where digitalization and big data are taken as the starting point for the design of business processes, product innovation, and customer interaction. In the late 1990s, at the height of the internet boom, Charles Schwab described itself as a technology company in the brokerage business. This is also true of Tesla and Ping An – they are technology companies in the insurance market. Both companies still enjoy the enormous benefits of the internet for distribution to support new sales, delivery of the insurance service, and to offer e-services to existing customers. The key difference between today's AI systems and the digital leaders of the 1990s are network effects in marketing, which are combined with rapid data growth and evolution of AI technology from improved training, which has been termed the AI data flywheel effect [de Véricourt and Gurkan (2020)].

Their strategies and business models resemble those of fintech companies rather than an automotive company and an established insurance carrier. The technology strategies of the two firms follow a digital first approach because it is viewed as the natural way of improving business models, by adopting AI and achieving improvements in business performance through digital transformation. Technology is developed in-house, and emphasis is placed on fast prototype development and evolution of systems that are built on modern technology platforms that can exploit open technology and embrace new advances in areas such as image recognition, machine learning, security, data analysis methods, and computing innovations generally. The strong funding of both companies through shareholder investments mean that they can adopt a long-term approach to technology investment where the focus is on building market share and data scale rather than short-term profitability concerns, again, a feature of fintech markets rather than a mature insurance market.

The Tesla business model diagram in Figure 3 is a clear illustration of the causal model of digital transformation and it shows the roles and effects of individual AI applications on business processes, product innovation, customer value

and experience, and business benefits. Big data is essential for AI systems because it is required to train and improve algorithms, and to offer personalized services based on individual customer data. In parallel, customer growth is important because it funds continuing investments into the broader digital and MIS infrastructure that links individual AI applications together to form an insurance enterprise system.

Tesla has exploited the market discontinuity in the transition from traditional risk models to behavioral risk and its natural advantage regarding access to personal and vehicle behavioral data. It has then extended its offering to include vehicle repair, which in turn, provides important insights into future design improvements. Ping An has followed a similar path by exploiting its data analytics capabilities and access to a large number of customers to offer a behavioral driving app, and has extended beyond insurance services to offer an enhanced claim and repair service through close B2B relationships with automotive dealers and repair workshops.

Some parallels exist with the implementation of ERP systems in the 1990s and a brief comparison with Cisco, a widely recognized digital leader of that era, illustrates the point. Cisco's digital strategy was to build business capability by embracing digital technology throughout its operations and it focused on closing the loop on all its business processes. Cisco focused on automating all business transactions to create a common information blueprint for its enterprise, which then gave it strategic advantages, in particular the ability to integrate newly acquired companies extremely quickly.

The key difference between Cisco's ERP system and today's AI technology are that Tesla and Ping An are building intelligent business processes that increase the scope of automation to activities that required human intelligence in the past. The second-order implications of these AI systems are that AI leaders are enjoying data scale effects, which accelerate business growth, and big data in a symbiotic manner. They may also create new economies of scope by enabling companies to diversify beyond what were traditional market boundaries, such as automotive and insurance, or insurance and banking.

The insurance industry is evolving and developing novel and sometimes radically different business processes, products, and business models that take advantage of new technologies, in particular big data and AI systems [Naylor (2017), Holland (2019)]. Innovation in the insurance market has the potential to

create significant benefits and structural changes to individual firms and insurance value chains, as well as changing the nature of relationships between insurance firms and their customers. While these innovations should be encouraged, a laissez-faire approach to the regulation of AI technology would be a mistake because the risks associated with AI systems in insurance – e.g., unfair discrimination, exclusion, loss of privacy, and unfair distribution of benefits from innovation – are too important to neglect or ignore.

The regulation of AI systems should distinguish between legal norms such as GDPR, social justice and fairness [Rawls (1999)], which is of particular relevance regarding the distribution of the benefits from AI systems [Schwab (2018)], and ethical and regulatory frameworks. A risk-adapted approach is vital to ensure that regulation is focused on those areas that matter most to each stakeholder. In an AI context, the problems of opacity and lack of explanations on how AI systems operate mean that there are significant risks to consumer confidence and the regulation of insurance markets. Time is, therefore, of the essence in designing suitable approaches to manage this new wave of business models and AI insurance products that considers the different and sometimes competing needs and requirements of insurance firms and their customers, and regulatory and government bodies.

Future research opportunities include the analysis of the interactions between AI systems and business models and to explore the topic in different organization and market contexts. There are two broad trajectories for AI systems in insurance over the next decade: (1) better narrow algorithms and (2) broader algorithmic scope. Improved algorithms are almost inevitable with the growth of big data and access to cloud computing. The managerial question is how quickly will these improvements be realized and what are the limitations of these technologies? The other avenue to be explored is broader algorithmic scope, and it seems likely that if AI technology follows MIS theory, then it will evolve into an organization-wide technology and extend into the insurance value chain.

The regulatory aspects of AI need to be balanced with the need for innovation, otherwise customers may not reap the rewards of AI technology or gain trust in its use in insurance. The role of AI startups also deserves closer attention because they play a crucial role in facilitating incumbent insurance firms to implement novel AI solutions and as new entrants into the insurance market with disruptor business models.

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