The Geneva Papers on Risk and Insurance - Issues and Practice (2022) 47:205–241
https://doi.org/10.1057/s41288-020-00201-7

The impact of artificial intelligence along the insurance value chain and on the insurability of risks

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Received: 22 July 2019 / Accepted: 7 December 2020 / Published online: 8 February 2021

Abstract

Based on a data set of 91 papers and 22 industry studies, we analyse the impact of artificial intelligence on the insurance sector using Porter's (1985) value chain and Berliner's (1982) insurability criteria. Additionally, we present future research directions, from both the academic and practitioner points of view. The results illustrate that both cost efficiencies and new revenue streams can be realised, as the insurance business model will shift from loss compensation to loss prediction and prevention. Moreover, we identify two possible developments with respect to the insurability of risks. The first is that the application of artificial intelligence by insurance companies might allow for a more accurate prediction of loss probabilities, thus reducing one of the industry's most inherent problems, namely asymmetric information. The second development is that artificial intelligence might change the risk landscape significantly by transforming some risks from low-severity/high-frequency to high-severity/low-frequency. This requires insurance companies to rethink traditional insurance coverage and design adequate insurance products.

Keywords Artificial intelligence · Insurance · Value chain · Insurability · Technology · Digitalisation

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Supplementary Information The online version of this article (https://doi.org/10.1057/s41288-020-00201-7) contains supplementary material, which is available to authorized users.

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Motivation and aim of the paper

There is a growing consensus on the potential of artificial intelligence to transform modern economies and societies (Abrardi et al. 2019; Bolton et al. 2018; Boyd and Holton 2017; Makridakis 2017) by enabling computer systems to carry out numerous tasks and activities that are typically considered to require human intelligence, thereby significantly improving efficiency and efficacy. At the same time, there is a controversial debate over the risks and limitations of artificial intelligence.[1]

The progress and popularity[2] of artificial intelligence results from the combination of two developments that enable its productive use. The first is that artificial intelligence has matured, thanks to recent advancements in machine learning and deep learning algorithms (Abrardi et al. 2019). The second is that the availability of big data combined with the rapidly increasing computation power of modern information technology systems accelerates the development and increases the accuracy of artificial intelligence applications (Allam and Dhunny 2019; Thrall et al. 2018). As a result, considerable progress has been made in the capabilities of artificial intelligence in the last few years.[3] There is a wide range of real-world use cases across industries. Among these are pattern and anomaly detection (e.g. for fraud mitigation, see e.g. Ahmed et al. 2016), speech recognition and natural language generation (e.g. for the development of chatbots, see e.g. Dale 2016), recommendation engines (e.g. for automated product suggestions, see e.g. Marchand and Marx 2020), image recognition (e.g. for improved public safety, see e.g. Zhang et al. 2016), and automated decision-making systems (e.g. for robo-advice, see e.g. Faloon and Scherer 2017).

While some industries such as banking,[4] healthcare,[5] manufacturing[6] and software development[7] have been investing in artificial intelligence for years (Bughin et al. 2017), industry studies note that the insurance sector is lagging behind in the worldwide and intersectoral artificial intelligence movements (Rangwala et al. 2020; Deloitte 2017). Nevertheless, it is likely that artificial intelligence will have a broad impact along the insurance value chain, from underwriting and claims management over distribution and customer service to asset management. Consequently, insurance executives must understand the new technologies that will contribute to this change and how artificial intelligence can help organisations create innovative

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[1] In 2014, Stephen Hawking stated that 'success in creating effective AI [artificial intelligence], could be the biggest event in the history of our civilization. Or the worst. We just don't know' (Kharpal 2017).

[2] Figure A1 in Appendix A in the electronic supplementary material illustrates the exponential growth in the academic interest of artificial intelligence by showing the development of published articles on the subject in Web of Science from 1980 to 2019.

[3] In 2016, the programme AlphaGo defeated a human professional player for the first time in the full-sized game Go (Silver et al. 2016). Only 14 years earlier, this was believed to be impossible due to the complexity of the game compared to, for example, chess (Müller 2002).

[4] See e.g. Jakšič and Marinč (2019) on the role of artificial intelligence in the banking sector.

[5] See e.g. Jiang et al. (2017) and Patel et al. (2009) for an overview of artificial intelligence in medicine.

[6] See e.g. Li et al. (2017) and Lee et al. (2018) for applications of artificial intelligence in manufacturing.

[7] See e.g. Kothari (2019) for an overview of artificial intelligence applications in software engineering processes.

products, glean valuable insights from new data sources, streamline business processes and improve customer service.

The intention of this paper is to support practitioners in understanding the potential benefits associated with artificial intelligence applications and to motivate academics to study this multifaceted, controversial and heavily under-researched topic. Towards this end, we establish a database of papers and industry studies on the use of artificial intelligence in the insurance sector and systematically evaluate the impact of artificial intelligence along Porter's (1985) value chain and on Berliner's (1982) insurability criteria. Based on the review results, we derive potential future work from practitioners' and researchers' perspectives. In this way, we provide practitioners and academics with a high-level overview of the most important research topics and promote future work in this field. To structure our discussion, the paper is organised into three core steps:

1. Description of artificial intelligence applications that will influence the insurance sector.
2. Analysis of the impact of these applications along the insurance value chain and derivation of benefits for insurance companies as well as insurance customers.
3. Deduction of the consequences for the insurability of risks.

The remainder of this paper is structured as follows. We begin with a short description of our research methodology (Research approach). Then, the literature on the three core research topics is reviewed (Survey of existing knowledge on artificial intelligence in insurance). Finally, the results are summarised and potential areas of future work from both the industry and research perspectives are discussed (Summary and derivation of potential future work).

Research approach

Literature review

The literature review consists of a structured search and identification process based on vom Brocke et al. (2009) and Webster and Watson (2002). We review the academic literature by using a search string that includes several keywords in combination with 'insurance' or 'insurer'. The selection of keywords is based on Niu et al. (2016), who conducted a keyword analysis drawing on 20,715 articles on artificial intelligence published between 1990 and 2014. The keywords include terms for disciplines, subdisciplines, techniques and application areas of artificial intelligence. However, as some of the keywords are vague (e.g. 'management', 'identification', 'optimisation') and research on artificial intelligence has developed over the past five years, we have amended the keywords accordingly.[8] The keywords used in the literature review are summarised in Table 1.

The literature search is conducted in the journal databases EBSCOhost (Business Source Ultimate, Computer Source and EconLit) and ABI/INFORM Collection.

[8] See Martínez-Plumed et al. (2018) for a discussion of the keywords provided by Niu et al. (2016).

Table 1 Keywords used in combination with 'Insurance' OR 'Insurer'

Artificial intelligence	Smart devices	Artificial neural network
AI	Genetic algorithm	Swarm intelligence
Machine learning	Analytics	Support vector machine
Deep learning	Data mining	Computational intelligence
Big data	Fuzzy logic	

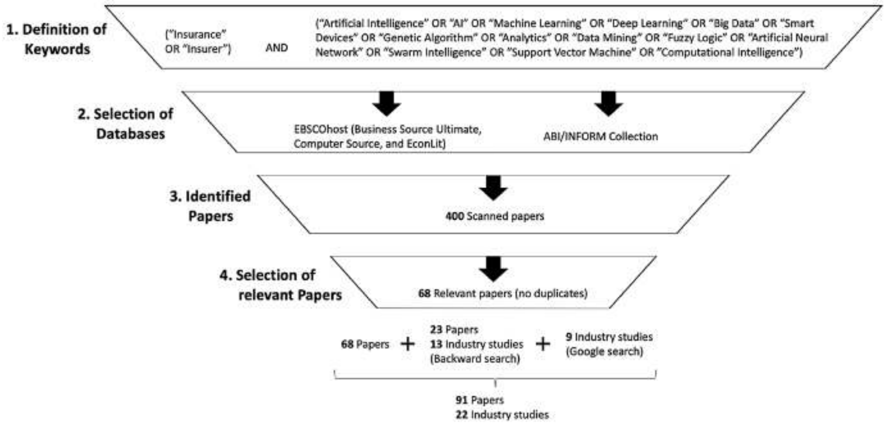

Fig. 1 Literature search process based on vom Brocke et al. (2009) and Webster and Watson (2002)

These databases were chosen because of their focus on business- and economic-related topics and because they include the relevant insurance-related journals.[9] The search process (1) was restricted to papers published from 2000 to June 2020, (2) focused on scholarly (peer-reviewed) publications and (3) searched for keywords in the abstract. The search process is displayed in Fig. 1.

In total, exactly 400 publications were found in the two databases. After their examination, 68 papers were identified as relevant for this literature review. A backward search,[10] as proposed by Webster and Watson (2002), was then conducted, where an additional 2056 sources were screened, and 23 relevant papers and 13 industry studies were found.[11] Another nine industry studies were identified by

[9] For example, *The Journal of Finance*, *American Economic Review*, *Journal of Risk and Insurance*, *Insurance: Mathematics and Economics*, *The Geneva Papers on Risk and Insurance—Issues and Practice*, *The Geneva Risk and Insurance Review*, *Journal of Insurance Regulation* and *Risk Management & Insurance Review*.

[10] A backward search is the process of screening the references of the initially identified papers.

[11] Moreover, all working papers from the annual meetings of the American Risk and Insurance Association (ARIA; for 2012 to 2019), the 2015 World Risk and Insurance Economics Congress and the European Group of Risk and Insurance Economists conferences 2011, 2012, 2013 and 2016 are examined. Surprisingly, no additional sources were identified through this examination, emphasising that there is still a lack of research on these topics in the risk and insurance community.

performing a regular Google search with the defined keywords. Based upon this selection process, a database of 91 papers and 22 industry studies (see Appendix B in the electronic supplementary material) is developed and the main results are extracted. The 91 papers consist of 86 journal articles and five trade journal articles. Based on their content, the papers were assigned to the respective stage in the insurance value chain (see Table B1 in the electronic supplementary material).[12] Industry studies could not be mapped to a single step of the value chain because they discuss the impact of artificial intelligence on the entire insurance industry and across the value chain, so for them a separate list (see Table B2 in the electronic supplementary material) has been created.

Conceptual frameworks: value chain and insurability criteria

Following Eling and Lehmann (2018), we use two conceptual frameworks to illustrate our results. The first, Porter's (1985) value chain, distinguishes a firm's primary from supporting activities in delivering a product or service; because Porter's (1985) value chain was not formulated for a specific industry and was intended to be a rather general concept, we adapt it using the insurance-specific value chain by Rahlfs (2007) (see Fig. 2).

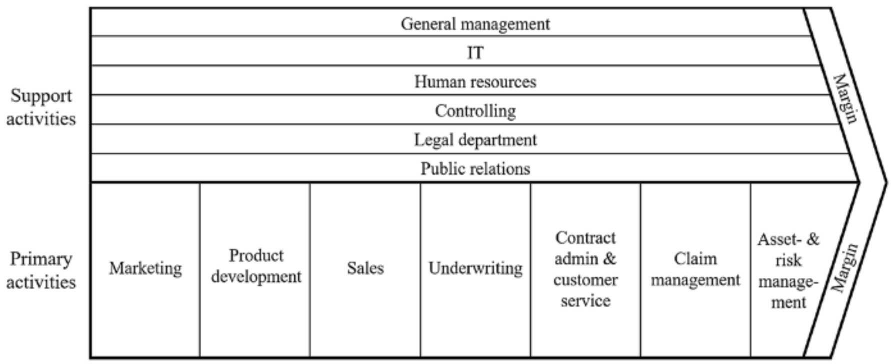

Fig. 2 Insurance-specific value chain based on Porter (1985) and Rahlfs (2007)

[12] The focus of research on artificial intelligence in the insurance sector is on claim management and underwriting and pricing. A quantitative examination of the number of identified papers per stage of the value chain shows that 38% of the 91 papers address the application of artificial intelligence in claim management, while 26% assess the usage of artificial intelligence in underwriting and pricing. The other value chain stages have a percentage share below 10%, indicating that the application of artificial intelligence in these areas is still heavily under-researched (see Table C1 in Appendix C in the electronic supplementary material for more details).

Table 2 Insurability criteria and related requirements defined by Berliner (1982)

		Insurability criteria	Requirements
Actuarial	(1)	Randomness of loss occurrence	Independence and predictability of loss exposure
	(2)	Maximum possible loss	Manageable
	(3)	Average loss per event	Moderate
	(4)	Loss exposure	Loss exposure must be large enough
	(5)	Information asymmetry	Moral hazard and adverse selection not excessive
Market	(6)	Insurance premium	Cost recovery (insurer) and affordability (policyholder)
	(7)	Cover limits	Acceptable
Society	(8)	Public policy	Consistent with social values
	(9)	Legal restrictions	Allow the coverage

We then analyse Berliner's (1982) insurability criteria, a frequently used and comprehensive approach for differentiating insurable and uninsurable risks. Nine insurability criteria cover five actuarial, two market-specific and two societal aspects of insurability (see Table 2). This approach has been used, for example, by Biener et al. (2015) to analyse the insurability of cyber risks, by Charpentier (2007) to scrutinise the insurability of climate risks and by Gehrke (2014) to evaluate agricultural production risks. We refer to Berliner (1982, 1985) and Biener et al. (2015) for further details on the criteria.

Survey of existing knowledge on artificial intelligence in insurance

The digitalisation[13] of the insurance industry is already quite advanced and has gone far beyond the transition from analogue to digital information processing (Stoeckli et al. 2018). Eling and Lehmann (2018) describe digitalisation as 'the integration of the analogue and digital worlds with new technologies that enhance customer interaction, data availability, and business processes'. Digital transformation is also driven by InsurTechs,[14] which have emerged in the last decade (Riikkinen et al. 2018). New technologies affecting the insurance industry include cloud computing,[15] telematics, the Internet of Things (IoT),[16] mobile phones, blockchain

[13] Digitalisation is often used interchangeably with digitisation (see e.g. BarNir et al. 2003). However, a clear distinction should be made between the two. While *digitisation* is the technical process of converting analogue data into digital forms, *digitalisation* describes the adoption of digital technologies in various contexts (Legner et al. 2017). These two developments lead to digital transformation, which triggers profound changes in business and society (Majchrzak et al. 2016; Vial 2019).

[14] InsurTech encompasses the emerging technologies, innovative business models, applications, processes and products that might transform the traditional insurance sector (International Association of Insurance Supervisors 2017). For an overview of the InsurTech landscape see e.g. Braun and Schreiber (2017).

[15] See e.g. Akhusama and Moturi (2016) who analysed cloud computing uses in terms of productivity applications, business applications, infrastructure on-demand, finance applications, core business applications and databases in insurance companies in Kenya.

[16] The Internet of Things can be defined as a 'collection of smart devices that interact on a collaborative basis to fulfil a common goal' (Sicari et al. 2015).

technology,[17] artificial intelligence and predictive modelling (Cappiello 2020). Digitalisation has already had a considerable impact along the insurance value chain and will continue to do so as new technologies emerge and mature (Eling and Lehmann 2018).[18] Key changes comprise enhanced process efficiency, improved underwriting and product development, reshaped customer interactions and distribution strategies and new business models (Albrecher et al. 2019). Bohnert et al. (2019) show in their study that digitalisation activities have a significantly positive impact on the business performance of insurance companies.[19]

At the beginning of the digitalisation wave, the main focus was on online and digital distribution channels (Garven 2002) and their impact on insurance agents (Eastman et al. 2002a, 2002b), customers (Kaiser 2002) and competition (Brown and Goolsbee 2002). In the ensuing years, the ubiquity of mobile and interconnected devices exponentially increased the availability of customer data.[20] The extensive amount of available data has opened up new opportunities for insurance companies to apply innovative technologies for their benefit. For this reason, access to the vast amount of customer data forms the basis for numerous artificial intelligence applications and can be considered a precondition for the implementation of artificial intelligence by insurance companies.

What is artificial intelligence and which technologies will influence the insurance industry?

The first developments concerning artificial intelligence began more than 60 years ago with the construction of the first 'thinking machines': computer systems with human-like intelligence equalling, and at some point, exceeding that of human beings (Baum et al. 2011; Lake et al. 2016). To test a machine's ability to exhibit intelligent, humanoid behaviour, the Turing test was invented (Turing 1950).[21] The first definitions of the term 'artificial intelligence' date from this time. However, as a result of the various conceptions and the rather vague nature of (human) intelligence, there is no widely accepted definition of artificial intelligence but rather a multitude of coexisting definitions (Wang 2019; see also Bhatnagar et al. 2018; Monett and Lewis 2018).[22]

[17] See e.g. Gatteschi et al. (2018) for a discussion on several blockchain use cases in the insurance sector.

[18] See also The Geneva Association (2018) for a discussion of the impact of digital technologies on insurance and the role of insurance in an increasingly digitised economy.

[19] See Bohnert et al. (2019) for an analysis of the relationship between the expression of a digital agenda in annual reports and the business performance of 41 publicly-traded European insurance companies for the time period 2007 to 2017.

[20] The collected data include traditional, structured, transactional data as well as contemporary, unstructured, behavioural data, commonly referred to as 'Big Data' and characterised by its volume, velocity, variety, veracity and value (Erevelles et al. 2016; Lycett 2013). Big Data might, for example, simplify the detection of insurance fraud (Bologa et al. 2013).

[21] Turing (1950) proposed that a machine has reached intelligent behaviour once a human evaluator cannot tell whether or not he or she was engaged in natural conversation with another human or with a machine.

[22] See Wang (2019) for a discussion of the difficulties in defining artificial intelligence.

McCarthy (2007), who played a leading role in coining the term artificial intelligence in 1955, describes it as the science and engineering of manufacturing intelligent machines. Barr and Feigenbaum (1981) describe artificial intelligence in more detail as the part of computer science concerned with designing intelligent computer systems, systems that exhibit characteristics associated with intelligence in human behaviour such as understanding written and spoken language, learning, reasoning or solving problems. A survey by Monett and Lewis (2018) asked professionals and experts worldwide to comment on hundreds of definitions of artificial intelligence. The most accepted definition was Wang's (2008): 'The essence of intelligence is the principle of adapting to the environment while working with insufficient knowledge and resources. Accordingly, an intelligent system should rely on finite processing capacity, work in real-time, open to unexpected tasks, and learn from experience. This working definition interprets intelligence as a form of relative rationality.' For the purpose of this paper, we base our understanding of artificial intelligence on Kelley et al.'s (2018) more comprehensive description of artificial intelligence as 'a computer system that can sense its environment, comprehend, learn, and take action from what it is learning'.[23]

The premise of artificial intelligence applications is to train computer systems with large amounts of data obtained through IoT and other big data sources to recognise patterns and apply their learned abilities to new data sets. The three types of artificial intelligence—categorised by their degree of intelligence[24]—are narrow, general and super (Kaplan and Haenlein 2019). Artificial narrow intelligence systems are trained to perform very specific physical or cognitive tasks; they operate within a limited context and a predefined range. In contrast, artificial general intelligence works on broader problem areas and has the capacity to assess its surroundings and give emotionally-driven responses comparable to those of humans. Artificial super intelligence systems, which exhibit the potential to outperform humans across a wide range of disciplines, have not yet been developed and are very likely still decades away (Jajal 2018). Table 3 summarises the three types of artificial intelligence.

Table 3 Types of artificial intelligence (Kaplan and Haenlein 2019)

Artificial narrow intelligence (weak AI)	Artificial general intelligence (strong AI)	Artificial super intelligence (conscious/self-aware AI)
Application of AI to specific areas only	Application of AI to several areas	Application of AI to any area
Inability to autonomously solve problems in other areas	Ability to autonomously solve problems in other areas	Ability to solve problems in other areas instantaneously
Outperformance of humans in a specific area	Outperformance of humans in several areas	Outperformance of humans in all areas

[23] See Appendix D in the electronic supplementary material for a summary of definitions of artificial intelligence.

[24] There are many definitions of intelligence. Grewal (2014) defines intelligence as 'a general mental ability for reasoning, problem solving, and learning'. The term intelligence generally refers to the ability to acquire and apply different skills and knowledge to solve a problem (Neisser et al. 1996).

Compared to classical rule-based systems, where data is strictly processed as initially defined through programming rules, artificial intelligence algorithms can learn and improve themselves independently based on past experiences (Kreutzer and Sirrenberg 2020). The method used to train these algorithms and thus realise artificial intelligence is machine learning. It consists of four types of learning: supervised, semi-supervised, unsupervised and reinforcement (Gentsch 2018; Kreutzer and Sirrenberg 2020). The most common type of machine learning is supervised learning, which requires humans to define each element of the input and output data. The algorithm is then trained to find the connection between the input and output variables of the data set, so that the answers are derived as precisely as possible. The second most common type is unsupervised learning, which does not include predefined output variables. The aim of the algorithms is to identify patterns and structures among the input variables independently. Semi-supervised and reinforcement learning are rather rare, and we refer to Kreutzer and Sirrenberg (2020) for their explanation.

Over the past few years, deep learning has gained increasing attention in artificial intelligence research. Deep learning,[25] which was not widely accepted as a viable form of artificial intelligence until 2012 (Krizhevsky et al. 2017), is a subset of (unsupervised) machine learning. While conventional machine learning techniques are limited in processing raw data, deep learning allows the processing of data from a wider range of data sources and requires less human effort to pre-process data (LeCun et al. 2015). Due to the increasing volume and complexity of data and the rapid development of modern computing, deep learning has recently become increasingly popular (Yu et al. 2018).[26] In the last decade, deep learning has made significant progress in numerous fields (Yuan et al. 2019) such as speech recognition (see e.g. Graves et al. 2013), image classification (see e.g. Rawat and Wang 2017; Yu et al. 2017; He et al. 2016), language translation (see e.g. Young et al. 2018), object recognition (see e.g. Krizhevsky et al. 2017) and detection (see e.g. Ren et al. 2017 and Redmon and Farhadi 2017), and has outperformed other machine learning techniques. Even though the predictive accuracy of artificial neural networks has greatly improved, the networks' internal logic often remains inexplicable and incomprehensible due to their inherent complexity (Knight 2017; Castelvecchi 2016).[27] Most of the discussions among insurance practitioners with regard to applying artificial intelligence for parts of their value creation still focus on conventional

[25] See e.g. LeCun et al. (2015). In a deep learning neural network, a digitised input (e.g. an image or speech) proceeds through multiple layers (typically from 5 to 1000) of connected 'neurons', of which each responds to a different feature of the input and an output is ultimately provided (Topol 2019). *Neural networks* are defined as 'neuron-like processing units that collectively perform complex computations' (Lake et al. 2016). As the name suggests, this artificial intelligence method originates in neuroscience. Initially, research on artificial intelligence was intertwined with neuroscience and psychology (Churchland and Sejnowski 1988; Marblestone et al. 2016). The first attempts to construct artificial neural networks that could compute logical functions were made in the 1940s (McCulloch and Pitts 1943). There are manifold types of deep learning neural network algorithms. For reviews see e.g. Goodfellow et al. (2016) and Yu et al. (2018).

[26] Unlike classical neural networks, deep learning applies more hidden layers, resulting in superior processing of complex data with manifold structures (Goodfellow et al. 2016).

[27] Due to these opaque decision-making systems, deep learning is often described as a 'Black Box System' (Guidotti et al. 2018).

machine-learning-enabled applications, as deep learning is still in the development phase and cannot yet be reliably deployed and implemented across a wide range of tasks (Panetta 2018). However, deep learning is expected to have a significant impact on the insurance industry as it requires very little human engineering to benefit from the increasing amount of available data and computation power.

To date, there is no common description of the different application fields of artificial intelligence. Some experts have created IT-related categories such as ‘machine learning’, ‘modelling’ or ‘problem-solving’ (see e.g. Görz et al. 2013; Russell and Norvig 2012). However, Kreutzer and Sirrenberg (2020) see machine learning and deep learning not as independent fields of application but rather as the basis of artificial intelligence usage. They define natural language processing, natural image processing/computer vision, expert systems and robotics as the four major application fields of artificial intelligence. They further note that many artificial intelligence applications, such as autonomous vehicles, represent a mixed form of these applications.

Table 4 summarises insurance-relevant artificial intelligence applications based on a systematic assessment of all the 91 papers and 22 industry studies (see Appendix B in the electronic supplementary material), explains them and maps specific industry use cases. The applications cover the full process from accessing to processing data and from evaluating to deploying data for enhanced decision-making or process optimisation. Many high-level applications across the value chain, such as automated claims management, combine multiple artificial intelligence applications such as text analysis and natural language processing, image and video analysis, as well as pattern and anomaly detection.

The use cases show that most applications in the insurance industry, ranging from the analysis of images of customers through the use of algorithms for the estimation of contractual terms for life insurance policies to the optimisation of fraud detection, aim to realise artificial narrow intelligence (weak AI) as they solve very specific tasks. In light of today’s insurance markets, insurance companies are thus more interested in applications of artificial narrow intelligence than in mimicking human intelligence (strong AI). The impact of more human-like artificial general intelligence on the insurance industry remains unknown as the technology is not yet fully understood and developed. For now, insurance companies should focus on the implementation of artificial narrow intelligence while monitoring the technological developments of artificial general intelligence. Most applications focus on specific areas of the value chain and are used for customer and operations efficacy: scenarios where the computational advantage, speed and accuracy of artificial intelligence are mainly levered. Using artificial intelligence to generate new insights or to reveal previously unknown results is more difficult to realise from a technological point of view (Deloitte 2017). Today’s most prominent use cases in this category are telematics-enabled usage-based insurance contracts in the health, motor and property and casualty segment.[28] Start-ups such as Oscar[29] use machine learning algorithms,

[28] See e.g. Ayuso et al. (2019) for a discussion on improving automobile insurance ratemaking using telematics by incorporating mileage and driver behaviour data.

[29] https://www.hioscar.com/.

Table 4 Artificial intelligence applications and their implementation status in the insurance industry

Application	Explanation	Implementation status in the insurance industry
Panel A: Conversion of language or text		
Voice/speech recognition and natural language generation	Identification, understanding and interpretation of words and phrases in spoken language Generation of information in natural language from structured data sets (verbal and written)	Various insurers have developed chatbots* to respond to written or verbal customer requests (e.g. Lemonade, Allianz, PNB MetLife, AXA, Aetna, Geico) Allstate has implemented a virtual sales assistant (ABIe) to support agents in quoting and issuing products
Text analytics and natural language processing	Understanding, categorising and interpreting written text and and converting it into computer-readable structured data sets	Versicherungskammer Bayern has used natural language processing to increase the effectiveness of customer service by letting IBM Watson sort and classify incoming customer mails Anthem has used IBM Watson to coordinate medical data with specific patient factors to help medical professionals identify the most likely treatment options and provide evidence-based healthcare
Sentiment detection	Detection and analysis of emotions in written or spoken word	Some InsurTechs and established insurance companies have been experimenting with sentiment detection by detecting and analysing emotions in written or verbal customer feedback to improve customer satisfaction and retention Swiss Re has invested in digi.me, which aggregates social media data of consumers willing to exchange their personal information for personalised business deals
Panel B: Recognition of patterns, trends and preferences		
Pattern and anomaly detection in data sets (text and/or image)	Detection of patterns and anomalies/outliers in unstructured data sets to derive conclusions	Numerous insurers have increasingly employed pattern and anomaly detection for the automatic detection of fraudulent claims (e.g. Oscar, Fabric, Aegon, Ping An, AXA, Generali, Allianz)

Table 4 (continued)

Application	Explanation	Implementation status in the insurance industry
Predictive analytics	Making predictions about future outcomes based on the statistical analysis of big data	Many health and motor insurers have applied predictive analytics to data from connected devices and developed new innovative and personalised usage-based insurance products, (e.g. MetroMile, Progressive, State Farm, Allianz, John Hancock, Generali)
Recommendation engine	Interpretation of results and recommendation of appropriate data-driven actions	Recommendation engines have helped insurance sales agents to better identify cross- and up-selling opportunities; recommendations for clients to improve loss prevention Suggestion of risk categories for customers based on previous claims and events to prevent human errors in underwriting processes
Panel C: Content-based processing of information and data-driven decision making		
Image and video analysis	Interpretation and analysis of shown objects or persons	Lapetus Life: Risk assessment and underwriting processes with instant insurance quotes by analysing an uploaded picture of applicants (in combination with answering nine questions) Video and image analysis from satellite pictures to provide early warning systems for natural catastrophes (Swiss Re) or to provide index insurance (RIICE project)
Facial recognition and biometrics	Interpretation of human physical states from biological characteristics such as facial structures	ManuLife has introduced a biometrics authorisation application for the automatic identification of users
Automatic decision making	Derivation and automatic application of rules and logic in artificial intelligence systems	Basler Versicherungen (in cooperation with Deutsche AM) and Helvetia Versicherungen (in cooperation with MoneyPark) developed robo-advisors for automated asset management and asset allocation

*See Riikkinen et al. (2018) for various chatbot applications in the insurance industry for instance, to analyse claim data and make inferences about the frequency of certain activities and procedures doctors perform. Based on the results, Oscar is able to identify experts and specialists in certain treatments to refer policyholders to the most suitable hospital. As another example, Lemonade[30] is changing several links in the traditional insurance value chain by replacing brokers, underwriting agents, service employees and fraud detection experts with artificial intelligence systems.

What is the impact of artificial intelligence along the insurance value chain?

We continue our systematic assessment of all 91 papers and 22 industry studies to summarise the impact of artificial intelligence applications along the insurance-specific value chain (Table 5).[31]

There are three principal categories of change initiated by artificial intelligence systems (see Eling and Lehmann 2018). The first is the way in which insurance companies interact with their customers (e.g. sales, customer service) is being transformed. While customer services traditionally required personal interaction with an agent, broker or bank for customer queries and product information due to a lack of alternatives, the information available has improved significantly over the internet and/or via chatbots. Some products can even be purchased online via chatbots without any personal interaction. This enables insurance companies to deploy human sales and customer service agents more effectively as chatbots take over some of their tasks. The insureds benefit through the availability of customer service and product information at any time and at a higher speed. Further along the value chain, digital technologies, such as apps, offer assistance and support claims reporting. Especially important is the use of artificial intelligence in risk reduction and prevention, for example, by proactive customer outreach in a risky situation. This enables the insurance industry to evolve from a 'detect and repair' to a 'predict and prevent' mode (Kelley et al. 2018). If implemented, this might lead to a completely new business model: preventing losses through a comprehensive risk management solution rather than compensating losses (The Geneva Association 2018). Such a development has the potential to decrease overall losses, which would not only benefit insurance companies and insureds, but also economic welfare.

The second change is the automation of business processes (e.g. processing of contracts, reporting of claims) and decisions (e.g. underwriting, claim settlement, product offerings). While transaction-intensive industries such as health insurance are already using background processing, the use of big data and

[30] https://www.lemonade.com/.

[31] In Appendix E (see electronic supplementary material), we combine Tables 4 and 5 into a 'value chain and technology matrix'.

Table 5 Impact of artificial intelligence along the insurance value chain

Value chain stage	Main tasks	Impact of artificial intelligence along the insurance value chain
Marketing	Market and customer research for product development Analysis of target groups Development of pricing strategies Design of advertisement and communication	**Predictive analytics and pattern detection**: Improved prediction of customer lifetime value Enhanced customer segmentation for personalised customer outreach and tailored communication strategies **Recommendation engine**: Advanced insights about preferences in consumer purchasing behaviour for the identification of cross-selling potentials, target product propositions and the generation of new ideas for product innovation Development of sophisticated marketing strategies (e.g. live event marketing) for the improvement of customer experience and response rates
Product development	Configuration of products Verification of legal requirements	**Predictive analytics and pattern and anomaly detection**: More comprehensive insights from real-time analysis of big data collected from IoT devices enable the development of innovative insurance products (usage-based insurance) Establishment of add-on services such as early detection of potential risks and their prevention enables the development of new revenue streams in addition to risk coverage **Predictive analytics and image and video analysis**: Entry into new markets and development of ecosystems with business partnerships in artificial intelligence-driven markets (e.g. autonomous driving, real-time health and elderly care with nanobots, natural catastrophe management, smart home ecosystems)
Sales and distribution	Customer acquisition and consultation Sales conversations Product sale After-sales services	**Combination of natural language generation, predictive analytics and recommendation engine**: Support of human sales agents by offering advanced sales insights (e.g. cross- and up-selling opportunities) through smart data-driven virtual sales assistants (chatbots) for improved customer consultation and tailored product recommendations Proactive customer relationship management and improved after-sales services through increased client transparency **Voice/speech recognition and natural language generation**: Chatbots for automated product consultation and sale of standardised insurance products

Table 5 (continued)

Value chain stage	Main tasks	Impact of artificial intelligence along the insurance value chain
Underwriting and pricing	Product pricing (actuarial methods) Application handling Risk assessment Assessment of final contract details	**Combination of image analysis, natural language processing and pattern detection**: Automated application handling, underwriting and risk assessment processes enable accurate insurance quotes within minutes New data and insights allow the formation of small and homogenous risk pools, reduction of adverse selection and moral hazard in risk assessment **Predictive analytics**: Real-time data evaluation from IoT devices for individual and continuous premium pricing in usage-based insurance products
Contract administration and customer services	Change of contract data Answering customer requests regarding the contract or other purposes	**Voice/speech recognition and natural language processing and generation**: Development of chatbots for automated answering of written and verbal customer queries Offering advice about health and fitness goals or improved road safety to promote loss prevention **Predictive analytics**: Proactive customer outreach and regular customer engagement **Recommendation engines**: Development of customer services from a service-only business division towards offering product recommendations
Claim management	Claim settlement Investigation of fraud	**Combination of natural language processing, image analysis and pattern and anomaly detection**: Automated claims management leading to decreasing claim settlement life cycles and increased payout accuracy Improved fraud detection reduces fraud-related loss positions

Table 5 (continued)

Value chain stage	Main tasks	Impact of artificial intelligence along the insurance value chain
Asset and risk management	Asset allocation Asset liability management Risk control	**Combination of predictive analytics, pattern and anomaly detection, natural language processing and video and image analysis**: Automated investment research with more accurate and detailed market data enables portfolio managers to make better informed decisions due to new insights and more sophisticated analysis of data Automated risk reporting **Automated decision making**: Development of robo-advisors for automated asset management Automated trading systems improve asset allocation
Support activities	General management IT HR Controlling Legal Public relations	**Combination of predictive analytics, pattern detection, video and image analysis and natural language processing:** More efficient and effective recruiting processes by identifying and analysing suitable candidates based on various data sources Improved understanding of laws, regulations and norms in different countries and regions through better analysis of local data allows international insurers to localise the services offered and thus ensure compliance with legal requirements Enhanced data architecture as artificial intelligence can populate and improve data quality in the context of the increasing amount of data available through IoT devices, social media and other big data sources **Automated decision making**: Simple, low-value administrative tasks such as rearranging data can be automated and carried out by artificial intelligence

artificial intelligence will stimulate a further wave of automation. The biggest benefits of automation for insurance companies are potential cost savings. Furthermore, a higher accuracy for administrative repetitive tasks can be achieved by eliminating human errors and skilled employees will have more time to concentrate on truly value-adding tasks. Automation in the reporting and settlement of claims will accelerate business processes, leading to greater customer satisfaction. As artificial intelligence applications can process and analyse large amounts of data generated by telematic devices, social networks or other internet sources (e.g. customer feedback, pictures, videos) in, for example, the underwriting process, insureds may have to answer fewer questions, which increases their satisfaction and hence has a positive impact on customer retention. One major challenge with the use of big data and artificial intelligence in this context is the accompanying ethical and legal issues. These include discussions about the extent to which insurers are allowed to use all of the generated data for decision making, how long the data has to be retained and which actions insurers must take to protect the data against, for instance, cybercrime (Hussain and Prieto 2016).

While the first two categories of change are closely related to the impact of artificial intelligence along the insurance value chain, as discussed in Table 5, the third category includes fundamental changes in insurance markets, which have not been discussed so far. The development of artificial intelligence will not only create new insurance markets and new risks but also cause certain existing markets to disappear (The Geneva Association 2018). One obvious example is autonomous driving, which changes the nature of liability in the automotive industry. Who is liable in case of an accident: the passenger, the car manufacturer or the software developer of the artificial intelligence algorithms? This development questions whether traditional car insurance, as we know it today, will still exist in the future. Cyber risks arising from the use of artificial intelligence technologies are also generating new market opportunities, with some industry studies predicting that cyber risk insurance might become the largest non-life segment in 2032 (e.g. KPMG 2018).

In addition to the impact of artificial intelligence in each single stage of the insurance value chain, the combination of these changes will have profound implications for the entire insurance landscape. The increasing prevalence of digital technologies in society causes traditional industry borders to blur. The resulting ecosystems will significantly influence the future of the insurance industry.[32] Ecosystems can be understood as 'an interconnected set of services that allow users to fulfil a variety of needs in one integrated experience' (Catlin et al. 2018). The most relevant ecosystems for the insurance industry include

[32] Catlin et al. (2018) expect the emergence of 12 major ecosystems which will account for approximately USD 60 trillion in revenues by 2025. This highlights the significant impact of ecosystems on the global economy.

the mobility, home and health ecosystems. These ecosystems offer insurance companies the opportunity to not only enter new revenue streams by reconsidering their traditional roles in the economy but also to integrate their insurance products into seamless customer journeys (Lorenz et al. 2020). While insurance companies currently have a passive and limited relationship with insureds, the emergence of ecosystems might cause significant changes in the way they interact with customers and how they distribute their products and services. In the mobility ecosystem, for example, insurance companies face the opportunity to expand their services to areas such as the purchase of vehicles, parking, traffic management and car sharing (Catlin et al. 2018). The potential benefits of ecosystems for insurance companies further include increased customer retention, improved loss prevention to reduce claims and lower distribution costs (Lorenz et al. 2020).

Table 6 summarises the major benefits of artificial intelligence applications for insurance companies and customers along the value chain. The results in Table 6 are derived from our findings in Table 5. As previously mentioned, the reduction of insurance costs—whether through decreasing loss payments or transaction costs—is beneficial both for the shareholders of insurance companies and for the insureds. Lower insurance costs will increase the insurer's profitability, leading to a higher shareholder value, but will also reduce premiums if passed on to the insureds (which can be assumed in competitive markets). Regardless of which case occurs (depending on the competitive situation), the reduction of insurance costs ultimately leads to an increase in economic welfare.

Table 6 Benefits of artificial intelligence applications for insurers and customers along the value chain

Value chain stage	Major benefits for insurers	Major benefits for insurance customers
Marketing	Artificial intelligence analyses vast amounts of customer information to create more accurate customer profiles and to target customers with individualised marketing campaigns, ultimately increasing response rates More concise customer segmentation allows for better understanding of individual customer needs	Insurance customers receive more personalised and meaningful product offerings that ensure beneficial insurance coverage for their individual life situation
Product development	Innovative insurance products (e.g. usage-based insurance) have the potential to address new customer groups and cover emerging risks Analysis of customers' buying behaviour, feedback data based on customer interaction with chatbots and reactions to product recommendations allow insurers to improve current offerings and create more tailored products Innovative products offer opportunities for add-on services to create new revenue streams in addition to risk coverage in areas such as early risk detection and risk prevention	New insurance products reward and thus encourage risk mitigating behaviour, ultimately leading to fewer losses (e.g. promoting safe driving leads to fewer accidents; fostering a healthy lifestyle implicates fewer health issues) New insurance products become more equitable and transparent from the customer's point of view (e.g. lower premiums for safer driving habits)
Sales and distribution	Cost savings through less active involvement of human sales agents as chatbots are implemented Vast amount of data available from various sources allows insurers to proactively reach out to customers with product offers tailored to the individual's risk profile and coverage needs, which also improves cross-selling Faster and more effective product recommendation process as artificial intelligence matches individual customer profiles with available product offerings	Automated processing of customer orders (e.g. reviewing various types of data and facts such as credit analysis) accelerates the purchasing process and improves customer experience Customers receive personalised recommendations on insurance products and pricing
Underwriting and pricing	Majority of underwriting is automated, leading to cost efficiencies Increased amount of data allows insurers to make more accurate decisions regarding underwriting and pricing prior to contract conclusion	Seamless underwriting process reduces the number of questionnaires and information to be provided by customers which leads to time savings and higher customer satisfaction Individualised premiums reward risk mitigating behaviour and actions, for example careful driving or health-conscious lifestyles in usage-based insurance products

Table 6 (continued)

Value chain stage	Major benefits for insurers	Major benefits for insurance customers
Contract administration and customer services	Artificial intelligence matches customer queries with the most qualified available agent Chatbots offer automated customer service within seconds for certain queries which allows insurers to reduce labour costs	Chatbots can assist customers 24/7 and increase customer satisfaction by delivering a highly personalised experience No long waiting times at call centres as chatbots will always be available; if a human agent is still required, the faster redirection to the most suitable agent improves the customer experience
Claim management	Automated claims processing increases accuracy and efficiency while decreasing human involvement, leading to labour cost reduction (e.g. computer vision allows chatbots to examine the evidence and assess the loss amount) Claims processing time can be shortened significantly, leading to higher customer satisfaction and to lower customer churn Improved fraud detection decreases loss payments of insurers and increases profitability Employees are able to focus on complex claims and value adding activities rather than repetitive and standard tasks	Automated claim processing reduces the time to settle a claim which speeds up claim payments and hence increases customer satisfaction Facilitation of claim reporting for insurance customers through standardised processes (e.g. send a picture of damage to the insurance company via an app on the mobile phone) Improved fraud detection decreases loss payments of insurers and enables lower premiums
Asset and risk management	Fast and detailed analysis of a vast amount of market data improves investment result (by reducing transaction costs and by exploiting market inefficiencies) Implementation of robo-advisors increases efficiency and leads to cost reduction	Improved returns (after transaction costs) on certain life insurance products (e.g. unit-linked life insurance)
Support activities	Optimisation of talent acquisition as artificial intelligence applications take over time-consuming tasks, such as screening applicants, leading to cost savings and support finding the best employees Cost reduction and improved data quality as artificial intelligence takes over repetitive administrative tasks in data management	n/a

How does artificial intelligence influence the insurability of risks?

Table 7 summarises the expected influence of artificial intelligence on the insurability of risks structured along Berliner's (1982) insurability criteria. The results in Table 7 are deduced from our results in Tables 4 and 5. The assessment distinguishes between (a) the application of artificial intelligence by insurance companies themselves and (b) the changes in the risk landscape triggered by artificial intelligence. The results show that the application of artificial intelligence by insurers does not compromise but rather improves the insurability of risks. The only exception is criterion 8, public policy, which remains unclear as the application of artificial intelligence implies increased transparency of policyholders' sensitive data, which potentially raises ethical and moral questions. However, the change in the risk landscape as a result of the increasing implementation of artificial intelligence poses many challenges to the insurability of risks and raises numerous questions for all insurability criteria.

The heterogenous results underline that a clear distinction between the application of artificial intelligence by insurers and the changes in risks triggered by artificial intelligence is of utmost importance. For this reason, we divide our subsequent discussion into these two categories.

Application of artificial intelligence by insurers

In light of today's insurance markets, the application of artificial intelligence by insurance companies shows three major effects in the context of the insurability of risks. The increasing availability of detailed risk-relevant information about policyholders through historical and real-time data sets will change traditional actuarial risk assessment and pricing models. The granular analysis of texts, images and videos from internal and external databases, as well as from connected devices (i.e. telematics devices and health wearables), allows insurance companies to more accurately estimate and predict loss probabilities and loss amounts on an individual level. This enables insurance companies to distinguish good and bad risks more precisely and thus reduce adverse selection. Additionally, it might even give those with bad risks an incentive to increase loss prevention efforts or to change their behaviour; hence, it also reduces moral hazard (e.g. usage-based insurance products). It further allows insurance companies to form small and homogenous risk groups with accurate and adaptive premium pricing schemes for each policyholder as risk-relevant behaviour, including prevention effort, is transparent and directly measurable. Consequently, bad risks will pay a higher and good risks a lower premium. This, however, raises questions related to the affordability of premiums for bad risks, which potentially contradicts insurance criterion 6.

In addition, the acquisition, processing and storage of sensitive customer data by insurance companies must be compliant with data privacy and security laws, as well as with moral and ethical considerations. Sensitive customer data is the basis of numerous artificial intelligence applications and it is thus crucial for insurance companies to ensure compliance with legal frameworks (e.g. GDPR). For this reason,

Table 7 Impact of artificial intelligence on the insurability of risks

Insurability criteria	Main findings	Assessment
Randomness of loss occurrence	(a) Application of artificial intelligence by insurers Smaller, more homogenous risk pools can be created More accurate prediction of loss probabilities and risk exposures	Does not contradict insurability as loss occurrence remains independent
	(b) Changes in risks triggered by artificial intelligence Increasing dependencies of risks through connectivity with possibly interacting chain reactions and simultaneous occurrence of loss events (artificial intelligence system breakdowns as, for example, in autonomous vehicles)	Problematic as independence of losses seems to be at risk due to increasing interconnectedness of losses
Maximum possible loss	(a) Application of artificial intelligence by insurers Availability of vast amount of data and predictive analytics enables a more accurate estimation and prediction of maximum possible losses	Improves insurability
	(b) Changes in risks triggered by artificial intelligence Accumulation risks (from connected devices and use of the same software and data transmission architectures) can lead to high maximum possible losses that exceed capital capacities due to highly skewed loss distributions If dependency increases, some risks might be transformed from high-frequency/low-severity to low-frequency/high-severity as majority of losses happen simultaneously	Problematic: needs to be flagged as potential barrier (depending on adequate reinsurance options and cover limits)
Average loss per event	(a) Application of artificial intelligence by insurers Decrease in average losses per event for the following reasons: Reduced claim settlement cost and sharply declining payout rates for fraudulent claims Increasing incentives for policyholders to engage in risk-mitigating activities (e.g. usage-based insurance) Changed portfolio composition of risks with larger share of good risks	Improves insurability

Table 7 (continued)

Insurability criteria	Main findings	Assessment
	(b) Changes in risks triggered by artificial intelligence Artificial intelligence has the potential to significantly reduce the number of loss events but if a loss event happens, severity can be expected to be high due to the increasing interconnectedness of losses (e.g. autonomous vehicles reduce number of accidents but a system breakdown can cause highly severe losses)	Problematic: risk transfer to capital market might be more attractive for increasing number of high-severity risks
Loss exposure	(a) Application of artificial intelligence by insurers Decreasing importance of adequate risk pools for the application of the law of large numbers as individual loss probabilities and risk exposure can be predicated more accurately	Does not contradict insurability as overall loss frequency remains high; problematic if insurance becomes unaffordable for high-risk customers
	(b) Changes in risks triggered by artificial intelligence High-frequency and low- to medium-severity risks in motor and health segments might be significantly reduced due to safety and prevention features of smart artificial intelligence assistants	Problematic as risk transfer to capital markets for the remaining low-frequency/high-severity risks might prove to be more attractive
Information asymmetry	(a) Application of artificial intelligence by insurers Increased transparency of policyholders closes the gap between available and risk-relevant information and reduces information asymmetry and the risk of error resulting from imperfect information Adverse selection is reduced due to the evaluation of more and better data available prior to contract conclusion Moral hazard is reduced due to better aligned interests in terms of ex-post risk-relevant behaviour and prevention efforts (usage-based insurance products)	Improves insurability, given one important precondition: liberal data security and privacy standards regulation
	(b) Changes in risks triggered by artificial intelligence Decision-making by artificial intelligence is highly complex and has the potential to introduce adverse selection (e.g. in autonomous vehicles, the insurer might not be able to access and understand the underlying decision-making process)	Problematic: new forms of adverse selection could be introduced if insurer is not able to access, understand and analyse the involved artificial intelligence applications

Table 7 (continued)

Insurability criteria	Main findings	Assessment
Insurance premium	(a) Application of artificial intelligence by insurers Net premiums will more precisely match expected losses Individual and adjustable premiums might eliminate cross-subsidisation between risk classes Increased returns on capital and better cost recovery for insurers are possible through efficiency gains across the value chain, which reduce cost loadings leading to lower premiums	Improves insurability as insurers are able to better balance the trade-off between adequacy and affordability of premiums. Problems might arise with regard to premium affordability for high-risk customers
	(b) Changes in risks triggered by artificial intelligence Shift from high-frequency/low-severity towards low-frequency/high-severity risks (e.g. system outages or hacking attacks in autonomous vehicles) leads to very high required premiums	Problematic: insurers are required to charge very high premiums to achieve an adequate return on capital which might not be affordable for the insureds
Cover limits	(a) Application of artificial intelligence by insurers Loss probabilities and amounts can be predicted more accurately and support insurance companies in selecting adequate cover limits	Improves insurability
	(b) Changes in risks triggered by artificial intelligence Cover limits will be needed less to reduce moral hazard, but rather to provide adequate insurance solutions in the motor and health insurance markets of tomorrow (e.g. autonomous vehicles, health nanobots) and maintain security levels for new kinds of risk exposures and loss amounts Shift towards high-severity risks requires cover limits to be very high in order to attract customers	Problematic: cover limits could reach levels that are not acceptable for insurers

Table 7 (continued)

Insurability criteria	Main findings	Assessment
Public policy	(a) Application of artificial intelligence by insurers Increased transparency of policyholders can raise ethical and moral questions Policyholders' willingness to share sensitive information remains unclear (consent declarations of individuals are required) Potential negative impact of full transparency on the solidarity principle of the social insurance system (cross-subsidisation between risk classes) Insurance corporations have the opportunity to reshape their public perception and brand image by becoming enablers of social goods such as increased longevity, public safety and reducing hunger	Critical: compliance with societal and public policy aspects are crucial for a successful application of artificial intelligence in the insurance industry
	(b) Changes in risks triggered by artificial intelligence Decision-making by artificial intelligence (e.g. autonomous vehicles) in negative scenarios such as saving the passenger or two pedestrians can raise ethical questions	Problematic: new risks require new types of insurance coverage (e.g. protection of car manufacturers from controversial decision making by artificial intelligence systems)
Legal restrictions	(a) Applications of artificial intelligence by insurers The introduction of new data privacy laws in the European Union (GDPR) places the development of artificial intelligence in insurance under closer scrutiny: Clients have the right to demand a human employee to review artificial intelligence-enabled decision making in automated business processes Insurers need to provide full insights about anti-discriminatory practices (i.e. training of algorithms to avoid discriminatory outputs) Regulators demand full transparency about data acquisition, processing, storage and deployment to verify compliance with data privacy, ownership and security laws	Does not contradict insurability; however, legal compliance can be considered a precondition and must be set as a priority by insurers

Table 7 (continued)

Insurability criteria	Main findings	Assessment
	(b) Changes in risks triggered by artificial intelligence Advancements in artificial intelligence will enable the development of autonomous vehicles and health nanobots; regulation around important legal aspects like liability is not available yet	Does not contradict insurability; however, a clear legal framework is required in order to offer insurance coverage for new risks

responsible data management can be considered a precondition for a successful implementation of artificial intelligence. Another critical precondition is public policy, especially social and ethical considerations. The problem of discrimination caused by artificial intelligence was recently demonstrated by Amazon's recruiting algorithm; its rating of candidates for software developer jobs showed bias against women.[33] Hence, a transparent and anti-discriminatory application of artificial intelligence is crucial to gain the willingness of insureds to entrust their sensitive data to an insurer.

Finally, new risks become insurable with the implementation of artificial intelligence. Automated and continuous underwriting reduces transaction costs and will enable the extension of On-Demand insurance for various assets. Examples could include additional insurance coverage for personal belongings against theft or damage,[34] travel insurance and by-the-mile car insurance. Insurance coverage can thus be purchased for a wide range of low-severity risks for the time the asset is actually used and 'at risk'. Additionally, loss assessments of an insured event can be significantly accelerated by artificial intelligence, which accelerates the claims management process and the corresponding payments. Thereby, the most severe risks, such as crop insurance against natural disasters, can be covered by insurance companies.[35] Consequently, artificial intelligence applications by insurers push the boundaries of insurability as several low- and high-severity risks become insurable.

Changes in risks triggered by artificial intelligence

The insurance market of the future will be shaped by numerous everyday artificial intelligence applications. For example, self-driving vehicles and healthcare with proactive, real-time and data-driven analysis of health status will emerge. This development will have a significant impact on the risk landscape and has two major implications for the insurability of risks. Artificial intelligence applications have the potential to transform the nature of loss events. Given the example of autonomous driving, the total number of accidents is likely to be considerably reduced, implying much lower loss probabilities (contradicts insurability criterion 4). However, a breakdown of the underlying artificial intelligence system or a hacking attack can cause a cascading series of accidents resulting in a considerable increase in the maximum possible loss (contradicts insurability criterion 2). Hence, loss events are not independent due to increasing connectedness (contradicts insurability criterion 1) and the shift from high-frequency/low-severity to low-frequency/high-severity risks. Similar concerns are discussed by Biener et al. (2015), who concluded that

[33] See e.g. Dastin (2018).

[34] Insuring certain assets against theft with an On-Demand insurance product could be especially attractive during a short vacation.

[35] An example is the RIICE project, which provides satellite-based crop production monitoring. The assessment of an insured event can be completed more quickly and at relatively lower costs than the previous process of loss assessors travelling to the area and assessing the damage on site. See http://www.riice.org/about-riice/about-riice/.

accumulation risk[36] poses a major hurdle to the insurability of cyber risks. A potential way to reduce accumulation risk and ensure sufficient independency of loss events could be the diversification of applied artificial intelligence systems, which would improve insurability. High-severity risks also require very high cover limits and premium payments, which could contradict insurability criteria 6 and 7. Hence, insurance companies are challenged to revise traditional insurance coverage and design innovative insurance products.

In addition, ethical and legal aspects of artificial intelligence arise whenever algorithms have to make difficult decisions (e.g. whether a malfunctioning autonomous vehicle should strike a child or a group of adults, i.e. Foot's trolley problem, see e.g. Nyholm and Smids 2016), thereby raising liability issues (see e.g. Jarrahi 2018). Autonomous vehicles can demonstrate the potential safety problems related to artificial intelligence applications in everyday life. A fatal collision between an artificial-intelligence-controlled Uber vehicle and a pedestrian in Arizona in 2018 exemplifies this statement (see e.g. National Transportation Safety Board 2019). Furthermore, the data processed in artificial intelligence algorithms and the obtained insights raise questions regarding data security and protection (i.e. data access and usage). The need to regulate companies that develop and use artificial intelligence is evident. The use of algorithms ranges from autonomous vehicles to decision support systems in the health sector, as well as in artificial-intelligence-powered weapon systems. National and international institutions are responsible for developing guidelines for a fair and appropriate handling of artificial intelligence applications. However, the demands for transparency, non-discrimination and fairness clearly show the limits of the application of artificial intelligence as some principal dilemmas cannot be resolved. For example, the way in which machine learning arrives at the respective conclusions has never been—and due to the technical peculiarities will never be—completely transparent. Another ethical dilemma arises in the context of the fairness of artificial intelligence. An activity that a company or public authority considers fair might not have to be fair from the perspective of the consumer or citizen.

Despite all these concerns, the enormous potential of artificial intelligence must not be ignored. There still has not been an appropriately broad discussion of the limitations and concerns that reflects the relevance of the topic. However, as the technology is already being implemented and will have a profound impact on our everyday life, urgent action is required.

[36] Accumulation risk is the problem of emerging dependencies of risks through increasing interconnectedness. Given the scenario that all self-driving vehicles were manufactured by a few industry leaders and use the same software, algorithms and data infrastructure, a system breakdown, software malfunctions due to data transmission problems or cybercrime activities can paralyse city traffic and lead to simultaneous loss events in which all risks are dependent.

Summary and derivation of potential future work

We provide an overview of various artificial intelligence applications within the insurance industry and analyse their impact along the insurance-specific value chain based on Porter (1985) and in light of the insurability criteria developed by Berliner (1982). Table 8 summarises the results of the three core topics discussed in the previous section. Based on these results, we identify potential areas of future work from both an academic and practical perspective.

The numerous entry points illustrate that artificial intelligence has the potential to change many activities across the insurance value chain. The main opportunities for value generation will evolve around process automation (leading to cost savings and thus margin expansion) and the use of additional customer insights for entering new revenue streams, acquiring new customers and more personalised interactions with existing customers (leading to revenue growth). Today, the adoption of artificial intelligence within insurance markets is in its earliest stages and the academic research on the implications of artificial intelligence on the insurance business model is still limited. However, the topic is attracting increasing attention and interest from practitioners worldwide, as illustrated by the rapidly growing and generously funded InsurTech sector.[37] The present paper helps practitioners navigate their organisations to take full advantage of the benefits of artificial intelligence, and motivates academics to pave the way for a successful adoption of artificial intelligence by answering important research questions and running empirical analyses that go beyond the scope of this paper.

Today's artificial narrow intelligence systems are trained to perform only very specific tasks (e.g. a chess computer cannot play poker). Of course, weak artificial intelligence is not the ultimate goal of the tech companies that are investing billions of dollars in the development of the technology. They try to develop artificial general intelligence systems that are capable of abstract and creative thinking and making judgements under conditions of uncertainty (Uj 2018). Without knowing if the development of these artificial intelligence systems is actually possible, experts expect the first system to be ready in the next 10 to 30 years (Uj 2018). Given this vague time horizon, insurance managers, policymakers and regulators need to focus on the technology that is in place now (i.e. artificial narrow intelligence or weak AI). At the same time, it is important to track technological development and to continuously update potential management and regulatory frameworks in this dynamic field of research and practice.

From a scientific point of view, the changes in asymmetry of information and the associated economic welfare effects are intriguing. Linked to this is the question regarding the value of data from the customer's and provider's points of view. Thus, in the face of a latent fatalism in dealing with data, it is not quite clear what privacy is worth from the customer perspective (Biener et al. 2020). Positive effects of artificial intelligence applications on economic welfare can also be found in the

[37] Total InsurTech funding volume has soared from USD 869 million in 2014 (94 deals) to over USD 6.3 billion (314 deals) in 2019 (CB Insights 2020).

Table 8 Summary of results

1. What is artificial intelligence and which applications will influence the insurance industry?
Due to the complex nature and various perceptions of (human) intelligence, a commonly accepted definition of artificial intelligence does not exist; this paper follows the definition by Kelley et al. (2018) and understands artificial intelligence as 'a computer system that can sense its environment, learn, and take action from what it is learning'; the three types of artificial intelligence, categorised by their degree of intelligence, are narrow, general and super. Artificial narrow intelligence constitutes the status quo of machine intelligence; the method used to train algorithms and thus realise artificial intelligence is machine learning; in recent years, deep learning, as a subset of machine learning, has gained increasing attention
Key application fields: (1) conversion of language or text (voice/speech recognition, natural language generation, text analytics); (2) recognition of patterns, trends and preferences (pattern and anomaly detection, predictive analytics, recommendation engines); (3) computer vision and content-based processing of graphical information (image and video analysis, facial recognition and biometrics); (4) data-driven decision making (automatic decision making)
The status quo of artificial intelligence in the insurance industry is largely dominated by industry use cases, where artificial narrow intelligence is used for the (semi-)automation of routine and standard tasks across claims management, customer service and risk assessment; the impact of today's artificial intelligence applications in insurance can be mainly classified as 'operations efficacy and efficiency' investment cases; only a few insurers and InsurTechs are already using artificial intelligence for innovative discovery processes ('customer and operations discovery') to seize value creation opportunities with new products, in new markets, targeted to new clients
2. What is the impact of artificial intelligence along the insurance-specific value chain?
Today's artificial intelligence applications impact the entire insurance value chain from marketing through underwriting and pricing to asset and risk management. There are three major categories of change by artificial intelligence applications: (1) the way insurance companies interact with customers; (2) the automation of business processes and decision making; and (3) new markets and new risks that emerge with artificial intelligence
Insurers can profit from increased operational efficiency (cost reduction through artificial intelligence-enabled process automation mainly in underwriting and pricing as well as claim settlement, including improved fraud detection) as well as from revenue growth (artificial intelligence improving existing products and allowing the development of new, more personalised product offerings)
Insureds benefit from an improved customer experience through a more personalised and efficient interaction with the insurance company; more transparent and tailored product offerings; individualised premiums in innovative insurance products; a faster purchasing process; a seamless underwriting process reduces time and effort spent by insureds; 24/7 available customer service through chatbots; more convenient claim reporting; faster claim assessment and claim payment; lower premiums due to cost reduction by the insurer
3. How does artificial intelligence influence the insurability of risks?
The assessment of the impact of artificial intelligence on the insurability of risks requires a clear distinction between the application of artificial intelligence by the insurers themselves and the changes in the risk landscape triggered through the implementation of artificial intelligence in insurance-related fields
The application of artificial intelligence by insurers not only has the potential to generate value in multiple dimensions across the value chain but also improves the insurability of risks. Major improvements include a more accurate estimation of loss probabilities and loss amounts, more accurate risk assessments and continuously re-evaluated personalised premiums and the reduction of asymmetric information
However, expected advancements in artificial intelligence and their integration in insurance markets contradict several insurability criteria as they might transform some risks from low-severity/high-frequency to high-severity/low-frequency due to the accumulation risk as a result of increasing interconnectedness, which might negatively affect insurability (randomness of loss occurrence, maximum possible loss, loss exposure)
Increased policyholder transparency, constant monitoring and the availability of new sensitive customer information raise numerous legal and ethical questions about, for example, discrimination, safety, liability and data protection

field of prevention at the collective level when it comes to better understanding large amounts of data and using them for the benefit of customers. On an individual level, however, welfare effects are not negligible, because there may be both winners and losers in digital monitoring by artificial intelligence systems.

Several shortcomings of this paper might motivate future research. One is the generalisation of the analysis to the entire insurance sector. This offers both practitioners and academics a sense of the scope of the topic, but it lacks accuracy and applicability, because insurance segments and product lines are heterogeneous. Consequently, a detailed analysis of artificial intelligence on single steps of the value chain for each major type of insurance or the evaluation of upcoming artificial intelligence trends (e.g. neural networks that pave the way to the development of artificial general intelligence) on the insurance sector could be interesting. Moreover, we show some future scenarios where insurers could become enablers of social good, like increased longevity and improved public safety. It would be interesting to analyse the role of the insurance sector in combatting significant societal challenges in health and elderly care. For example, a steadily increasing number of elderly people are living with chronic diseases and require personal care services. However, the number of care professionals and doctors is not keeping pace with the growth of this population. Research can include the role of artificial intelligence applications, such as health nanobots, tracking devices and chatbots, to support health and elderly care.

A second shortcoming is the analysis of insurability criteria, which are somewhat vague because of missing empirical evidence. Consequently, our assessment serves as an indicator of whether or not single criteria are likely to be contradicted by the implementation of artificial intelligence. So far, no academic studies have directly analysed the effects of artificial intelligence on important actuarial metrics such as adverse selection, moral hazard and risk pooling or market criteria. From a practitioner's perspective, the question is still open as to whether better risk-based calculation of premiums will lead to lower combined ratios as both losses and the collected premiums are expected to move in tandem. It might lead to better insurance products with higher customer value, but it is not entirely clear if artificial intelligence is Pareto-optimal in the sense that every client will profit from the increasing use of artificial intelligence. From a general welfare point of view, we would expect to profit if artificial intelligence reduced the number of claims, but there is no overall assessment yet. The paper also highlights the importance of societal insurability criteria, but a detailed analysis goes beyond the scope of this paper as several external factors are likely to be relevant.

Further thoughts have led us to the following open questions: What is the role of insurance companies when technology firms dominate access to data? How will insurance companies react if data and privacy regulation become more restrictive and prohibit the use of policyholders' personal information? Will self-driving vehicles and health nanobots transform risks to the extent that the traditional idea of insurance comes into question? Will the public perception and brand image of insurance companies suffer as people become uncomfortable with constant surveillance? Will increased transparency and usage-based pricing lead to less solidarity in the context of social insurance? Will this lead to social unrest if high-risk policyholders can no longer afford insurance? Or will good risks try to opt out of traditional insurance pools with cross-subsidisation across risk classes (e.g. in social security schemes)? These questions will have a direct impact on insurance corporations over the next few years, so it is important for insurance executives to start thinking about these scenarios today.

Funding Open Access funding provided by University of St. Gallen.

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