A Critical Success Factors (CSFs) Model for Next-Generation Artificial Intelligence (AI) Systems in Insurance Markets

Professor Christopher P. Holland Ph.D. FIoD
Loughborough University, UK
Email: c.p.holland@lboro.ac.uk

Introduction

The concept of CSFs in the Information Systems (IS) literature originates from Rockart [1], and was used to support the design of management information systems. The term CSF was defined by Rockart as a key activity or area of the business that must work well to ensure overall competitive success. The CSF concept has been widely applied to R&D and engineering projects [2], as well as Information Systems projects [3], [4].

In this paper, the Critical Success Factors (CSFs) for Artificial Intelligence (AI) implementation in insurance markets are identified and illustrated with examples from case study research conducted by Loughborough University as part of its Technology in Next Generation Insurance (TECHNGI) project. The emphasis is on identifying the organisational and strategic factors, in addition to the AI-specific issues that affect the overall success of AI projects. It is assumed that standard project management tools such as critical path analysis, allocation of resources, interdependencies between sub-projects, project schedules, project communication and troubleshooting are employed, and these standard technical project management elements are excluded from this paper to allow a clearer focus on the organisational, strategic, and digital factors that are necessary for new, contemporary AI projects.

Challenges for Next-Generation AI Systems in Insurance Markets

The broader context for AI projects in insurance is set out because it is important to understand the nature of AI systems and their strategic potential in insurance markets before considering the Critical Success Factors (CSFs) for successful AI project implementation. That is, a brief exploration of the context of AI systems is given, because this helps define the nature of the AI implementation problem, and therefore offers guidance on the AI-specific factors that are necessary for successful AI projects.

Definition of AI – A Systems Perspective

The importance of adopting a system perspective of AI has been identified widely in the technical, medical, insurance and business literature. For example, leading technical experts from Google show that the machine learning element is a very small part of the overall AI system in which it operates, and that technologists and business managers must therefore pay much more attention to the technical challenges and economic costs of the infrastructure that surrounds the adaptive algorithms that differentiate AI systems from standard IT systems [5]. The conclusion from the Google team is based on a huge variety of projects and extensive collective experience.

It has been widely cited by other researchers. This modern viewpoint on AI systems [5] has close parallels with much earlier work that identified the importance of IT infrastructure on advanced IT management systems [6].

The IEEE has recently published a report on the importance of ethical design of AI, which used a system perspective throughout to emphasise the contextual nature of the AI technology, and to emphasise the importance of factors such as data, personal well-being, the professional skills of developers, the transparency of AI systems and their effectiveness [7]. The concept of 'Software as a Medical Device' is well established in a medical and patient context, and the medical regulators have invested a significant amount of effort in defining the term [8]. However, the agreed definition focused only on the standalone features of a piece of software. It would be futile to attempt to regulate AI software as a simple medical device, because it would omit the contextual use. The context is relevant because the performance of AI medical software depends crucially on available data, human skills, links to other medical systems and generally, the digital, managerial and ethical context of the software [9]. Similar to the technical and medical literature, business researchers have also identified the crucial role of data and digital infrastructure to facilitate AI system deployment in a commercial context [10][11].

In an insurance-specific context, the European regulator EIOPA adopted a systems approach to evaluate and make recommendations on the ethical dimensions and consequences of applying AI technology in consumer insurance markets, and focus on the ethical and regulatory aspects of big data, which are used to train and evaluate AI algorithms [12], [13].

The approach taken here is to contextualise AI algorithms and big data within a digital and business context, and to include the regulatory and legal framework as part of the overall AI system – see Figure 1, source TECHNGI, Loughborough University [14].

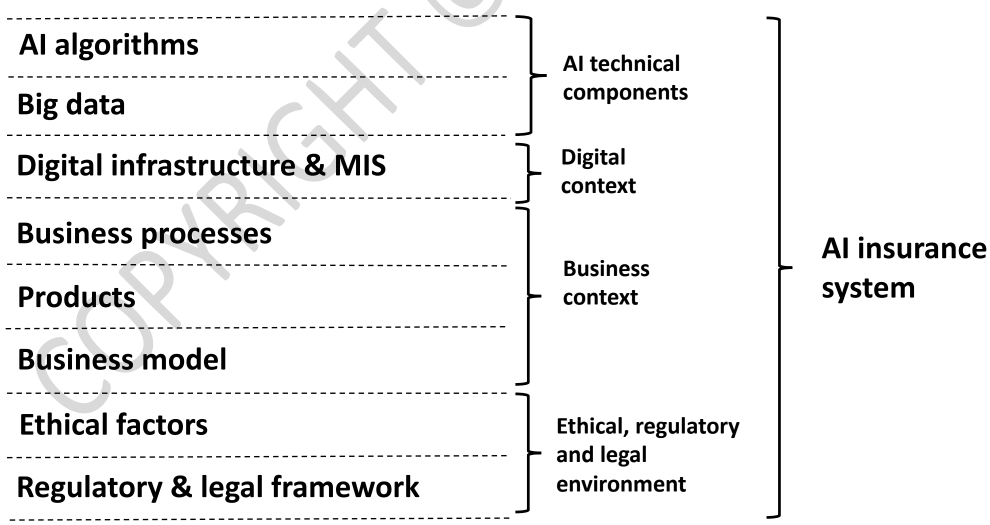

Figure 1. AI Insurance System Definition

The Strategic Potential of AI Systems in Insurance

Many articles in the business press assume that AI systems will have a disruptive effect on insurance markets. For example, the analysis of the new entrant 'Lemonade' in Forbes describes how AI is combined with behavioural economics to create a radically new form of insurance company that is based on trust and transparency between the insurance firm and its customers [15]. In a similar vein, the Chinese insurance company, Ping An, is described as a 'fintech super-app' in *The Economist*, an economics journal not known for hyperbole [16]. The rise of Ping An has been attributed in large part to its innovative use of AI and related digital technologies to disrupt insurance markets in health, automotive and smart cities [17]. Both examples are typical of InsurTech disruptors, i.e., they are designed to upset the status quo. The consultancy firm McKinsey sets out in detail the general disruptive effects of AI, deep learning, machine learning and big data on every functional area of insurance including pricing, risk assessment, distribution and claims management [18].

Disruptive change implies significant changes to the overall logic of insurance business models and this is certainly true in the cases of TESLA's insurance offering and Ping An's transition to a tech-driven company where digital technology, AI and big data permeate every aspect of its business operations, processes and interactions with customers and economics partners [14]. However, there are also other forms of digital transformation that should be considered because of their prevalence and the insights that they offer into the nature of digital transformation.

Disruptive change can be considered as a polar form of digital transformation, where the scale of business process change, use of digital technology and resulting business model are radically different to the business models and use of digital technology by incumbent market leaders [19]. At the other end of the spectrum is the use of AI to automate existing business models, using existing insurance data and retaining most of the existing set of business processes and overall business model logic [20]. Between these polar forms are business models that exhibit significant innovation, e.g., by exploiting new forms of big data, but which are better described as strategic augmentation or enhancement of existing business models, rather than something that is a brand new approach [21]. This nuanced approach to digital transformation recognises that there are distinctive types of change and transformation, which range from incremental innovation to big-bang approaches, and that the type of change will naturally affect the scale and difficulty of the implementation process, and therefore needs to be considered and included in a Critical Success Factors (CSFs) model.

Ethical Dimensions

The ethical dimensions of AI systems pose critical challenges to commercial insurance firms in the areas of data privacy, transparency and explainability of algorithms, avoiding algorithmic bias and building trust with consumers that AI systems can be trustworthy partners rather than adversaries in the insurance market [22]. Insurance is fundamentally a data-driven business [13], and the novel use of AI throughout the insurance customer lifecycle relies on new forms of big data and the novel use of existing data sets, to train and operate AI systems [12]. The pervasive nature of AI in insurance, where customer data is used at every stage of the customer journey and affects the value creation process where customers and insurance firms interact with each other through shared data [23], mean that insurance firms must explicitly include ethical design into their AI systems and implementation plans.

Digital Transformation of Insurance Markets

Digital transformation of insurance markets is part of the broader trend of business and societal changes occurring as a result of new applications of digital technologies, including cloud computing, Artificial Intelligence (AI), sensors, robotics, Internet-of-Things, smart cities, digital platforms and novel developments in finance such as cryptocurrency and blockchain-enabled e-commerce [24]. These disruptive changes, which are affecting all aspects of modern business organisations and society, and which exploit digital technology to create new forms of organisation and work patterns, have been described by numerous authors as a new industrial revolution, and termed 'Industry 4.0' [25]. Insurance services are an integral component of other sectors, e.g., automotive, production, smart cities, medical ecosystems, travel, and housing, and must therefore follow patterns of digital adoption from customers. In addition, it is highly likely that AI adoption in insurance markets will share common patterns with the general implementation of AI and related digital technologies with other market sectors [26].

A recent review of digital transformation concepts and practice proposes that digital transformation is a complex, iterative process where the novel use of digital technologies naturally leads to disruptive changes in firm strategies and customer expectations [27], where digital leaders use the technology to create new forms of business value. These general models provide a good overview, but they do not adequately cover the specific characteristics of insurance markets that make them distinctive from say manufacturing, biotechnology, or ecommerce firms. A specific business model approach for digital transformation in insurance is shown in Figure 3. This is based on the AI systems framework from Figure 1, and shows how the different elements of the AI systems definition relate to each other to create a cohesive business model designed around a set of inter-related business processes.

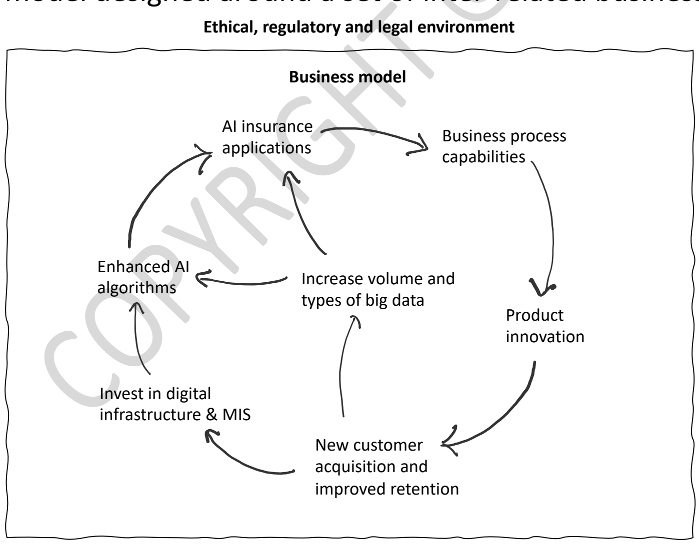

Figure 2. A Business Model Approach to Digital Transformation in Insurance

The logic of this business model is that AI algorithms are used to enable new insurance applications, which create new business process capabilities that lead to product innovation. Better products attract new customers and increase the volume of customer data available to the AI algorithms in areas such as pricing, risk, automated policy management, fraud detection and claims management. Increased revenues can then be invested to improve the digital infrastructure to support further innovation in AI technology and algorithms. New forms of business value are created by better products, and improved analytics from investments in digital infrastructure and MIS. A more detailed and expanded version of this model has been developed for behavioural insurance, and the circular nature of it, supported by data network effects, leads to what has been termed the AI data flywheel effect [14].

Discussion of Challenges

Prima facie, an AI systems perspective is the natural approach to defining and modelling the role of AI and big data technologies in insurance markets because it incorporates the digital and business contexts and relates the use of AI to important regulatory and ethical concerns. There is huge potential for AI to disrupt insurance markets, but it is also necessary to consider the more mundane applications of AI such as simple automation of existing business processes and models. The scale of the AI implementation challenge/project is therefore defined to a large extent by the difference between the legacy MIS and the new digital infrastructure, and the difference between the legacy business model and the AI-enabled target business model.

This result has very different implications for incumbent insurance firms that are defending their market positions versus new entrants who are attacking the market. Incumbent firms must balance the need to manage existing business models, whilst at the same time developing new strategies that exploit AI technology, either building on their existing systems and processes, or as new standalone business entities, whereas new entrants must calculate and determine how to enter the market and gain access to sufficient data to train and calibrate their AI models. Incumbent firms therefore have a significant data advantage, where data scale is an important barrier to entry. Attacker firms have the advantage that they are not constrained in any way with legacy system maintenance costs or to consider the constraining effects of an existing business model – they have a clean sheet of paper to develop whatever business model they consider to be the most effective and disruptive in a particular market.

The ethical dimensions of AI are arguably more acute in insurance than in many other markets because of the nature of the personal data that is required to offer insurance, especially personal data in consumer markets, combined with the fact that insurance is a necessity for modern societies to protect individuals from exposure to risks that can only be shouldered through the collective sharing of risk through insurance policy premiums.

The nature of the digital transformation process is dynamic, and involves complex inter-relationships between technology entities, people, business processes, products, software, economic partners in the insurance value chain and regulators. The Critical Success Factors (CSFs) to make this possible must therefore have sufficient variety and requisite complexity to deal with digital transformation where AI is pervasive in advanced insurance business models. A proposed CSF model is described in the next section.

Proposed CSFs Model for AI Implementation

The proposed model identifies a set of CSFs, which are grouped into a 2x2 typology, which distinguishes between business and digital factors, and between strategic and tactical elements. Business factors are organisational, strategic, and behavioural factors that influence the AI implementation process, which are clearly distinct from digital factors that are directly concerned with the digital infrastructure, hardware, software, and data, i.e., the digital building blocks of AI systems. Strategic factors are concerned with the overall direction and strategic objectives of the project, and the tactical factors are related much more to activities that turn the project into reality and instantiate it in practice. The model is shown in Figure 3.

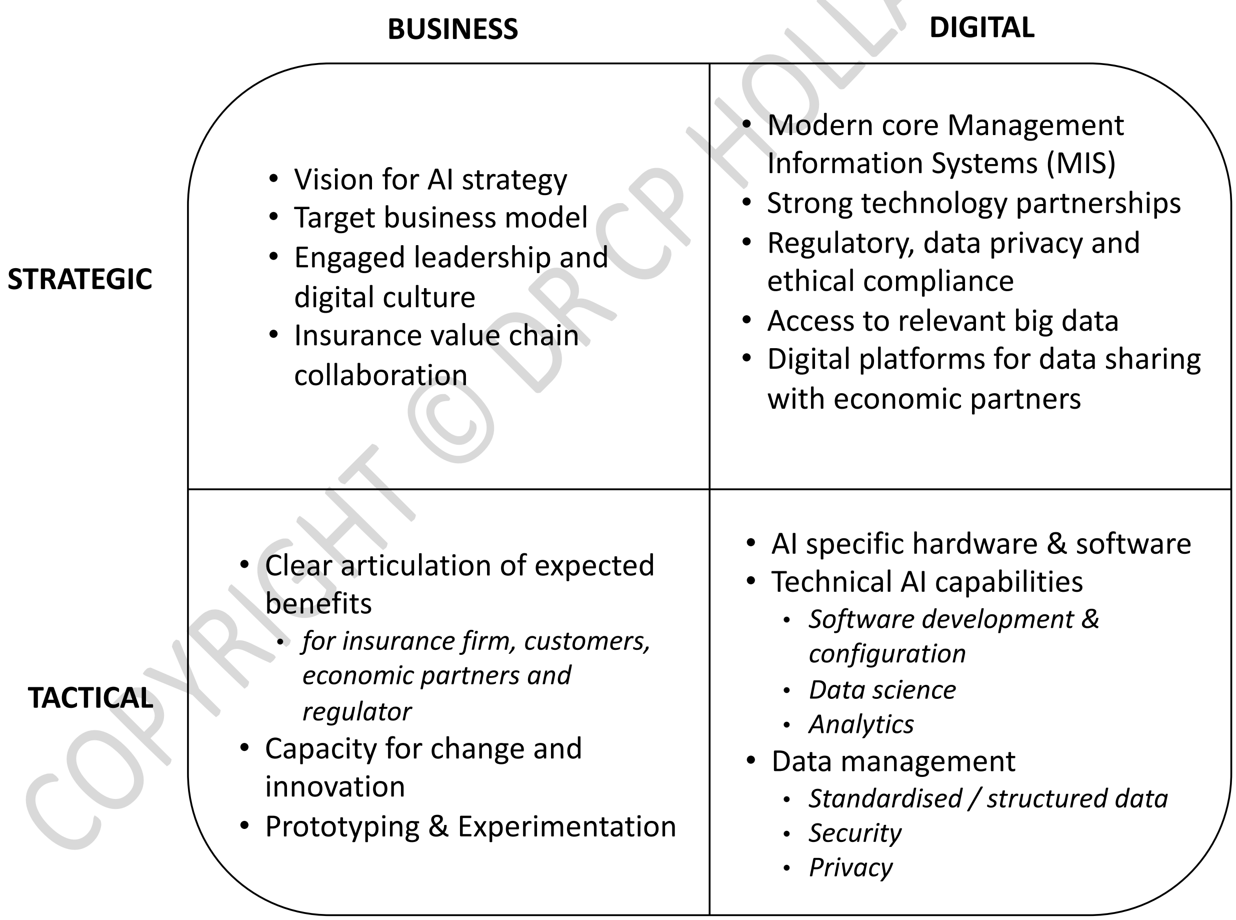

Figure 3. A Critical Success Factors Model of AI Implementation in Insurance Markets

The logic of the model is that CSFs can be grouped broadly into business and digital factors, and then sub-divided into strategic and tactical factors. Business factors are strategic, organisational and leadership elements of AI systems, e.g., the vision for AI, definition of benefits and capacity for change in the organisation. Digital factors are concerned technology-focused issues, including legacy MIS, technology partnerships, algorithmic design to ensure ethical and regulatory compliance, and AI-specific hardware and software such as telematics and sensors, and AI cloud computing platforms. Each of the factors is described below.

Business-Strategic

Vision for AI strategy
The strategic vision for AI is crucial because it defines the organisational scale and scope of AI systems, which vary considerably in terms of their application to organisational problems. It also sets out a vision that can be communicated to managers, so that everyone in the organisation is clear about the nature of the likely investments and changes to the business model.

AI systems cannot be described as a standard technology such as office productivity software, enterprise systems, and e-commerce software packages, where the business processes are effectively standardised through common software packages, and where the principal challenges of implementation are alignment of the organisation with the software through a combination of organisational change and software configuration. AI systems are at a much earlier stage of development in terms of the technology product lifecycle and are characterised by bespoke implementations. There is therefore much more variety of AI projects, compared with, say, ERP and e-commerce systems. For example, AI projects range from a relatively small project that automates a set of routine tasks such as document management using Robotic Process Automation (RPA), through to something much more ambitious such as the launch of a brand-new insurance service based on behavioural insurance, where AI is pervasive in almost every aspect of the new business model. The commitment for the strategic vision is an indication of the top management support for AI projects, which is crucial to ensure appropriate organisational and technology resources, to facilitate alignment with the target business model, and to encourage cross-functional integration within the organisation and where relevant, along the insurance value chain with economic partners.

Target business model
Consultants and managers often assume that AI technology will involve the digital transformation of the insurance business model. Whilst this is true in a small number of cases, e.g., Ping An, Lemonade, and HUK-COBURG, there are many examples of AI use cases where the effects on the business model is highly focused on an individual problem such as dealing with online customer queries, or augments the existing approach through the use of AI to analyse and interpret new forms of big data such as GPS location, IoT data and shared data with economic partners.

As part of the TECHNGI research project, four generic target business models were identified, based on the extent of business model change and the level of data innovation: incremental; reengineering; add-on strategy; and transformational.

An example of incremental change, with little or no change to the business model and making use of existing data sets, is to apply AI to a very narrow problem, such as Robotic Process Automation (RPA).

Reengineering is where the insurance firm uses Business Process Reengineering (BPR) techniques to change its business processes, again using similar data to historical business. For example, to simplify an insurance product and target a very focused segment of the market.

An add-on strategy is to use new forms of data such as IoT or GPS data, and use it to make a significant improvement to an existing business model, e.g., to improve risk analysis or enhance customer service using ChatBots or voice recognition. This typically involves sophisticated use of AI technology and big data, but the underlying business model remains broadly the same.

A transformational approach is a radically new business model, that exploits new forms of big data and AI applications, in an integrated and coherent strategy, to create a brand-new business model, which is typically an example of digital-first, i.e., it does not attempt to retain any aspects of legacy systems but builds every aspect of the firm from scratch. Lemonade is a superb example of a new entrant that is characteristic of this business model.

Engaged leadership and digital culture
Engaged leadership incorporates top management support and knowledge of the capabilities and mechanics of AI systems. Senior leaders set the agenda for AI projects, and it is necessary that they are fully engaged in the strategy process, especially to set the overall AI vision and target business model. An engaged leadership is also important in providing an umbrella of support and to ensure resources to support the remaining CSFs. Digital culture is needed to embrace AI technology because it provides the environment in which new ideas and AI systems can be explored, trialled, and evaluated. The rapid evolution of AI technologies requires a willingness on the part of senior managers to embrace new developments and concepts in AI, and to move quickly as the technology improves and adapt organisational processes and strategies to take advantage of AI capabilities. Experimentation and failure are a natural stage of this innovation process and must be handled as effectively as AI project successes.

Insurance value chain collaboration
The discussion so far has been limited to the firm as the unit of analysis. The insurance value chain and collaboration between stakeholders such as customers, insurance firms, re-insurance, capital markets and data holders, creates huge potential for improving the flow of data along the value chain, and to exploit new AI applications where the critical mass of big data may only be possible by sharing data between multiple firms. Two prominent examples are fraud detection based on collaborative data sharing between consumer insurance carriers, and in the transformation of Lloyd’s of London, which involves complex collaboration between large

business organisation customers, specialist underwriters, the digital infrastructure of the London Market, and the capital markets.

Business-Tactical

Clear articulation of expected benefits

The definition and evaluation of the business benefits of information systems in general and for AI systems in particular, is a hard problem because it is often difficult to disentangle and separate out the specific effects of digital investments from related changes to business processes and models. The beneficiaries also extend beyond the insurance firm to include customers, economic partners, and regulatory bodies. The approach taken here is to look at benefits using the analytical lens of business value creation, which fits naturally with business model theory.

Capacity for change and innovation

AI system implementation requires changes to data acquisition, data analytics, big data management, the development of ethical AI policies, business process change and potentially disruptive and transformative changes to the overall business model. For these changes to take place, the firm must have the capacity for change, i.e., it must be able to allocate enough technology and organisational capacity, to manage the transformation from the existing set of traditional Management Information Systems (MIS) to an AI-enabled system. Those firms with complex legacy systems that demand a huge amount of investment simply to stand still and overcome the entropy and inertia of complex, bespoke systems, are in a difficult position because they are naturally focused on keeping the existing business model and systems operational, rather than thinking imaginatively about new innovations that may be possible. This is one of the reasons that digital leaders that have already invested in updating core digital systems are in an advantageous position to exploit AI technology, because they are much more likely to have robust data management systems and modern business processes, where AI can be more easily integrated than into complex legacy systems.

Prototyping & Experimentation

The AI system landscape is quite varied, with some relatively mature AI applications that tend to focus on simpler, and very narrow tasks, and cutting-edge technology in areas such as Natural Language Processing (NLP) and voice recognition that are much more ambitious in their scale and scope. Relatively mature and established AI systems, e.g., simple ChatBots, a/b testing, customer propensity models, automated policy management, fraud detection, automated claims management and pricing, now cover all aspects of the customer lifecycle from new customer acquisition, through to customer renewal [23]. In cutting-edge AI systems, there are ongoing developments in the underlying algorithms, new and emerging sources of big data, and novel application areas. Cutting-edge AI is a complex area and one where insurance firms must balance the timing of adoption with the associated implementation risks and expected benefits.

Regardless of whether the AI technology is relatively well established or at the digital vanguard, insurance firms must have the ability to prototype and experiment with new AI applications, often in partnership with technology partners, or through in-house development, to quickly assess and evaluate the potential value of AI applications in their own organisational context. All

AI technology needs to be configured to work in a unique business context and integrated with existing systems to share data and link to the workflow through shared business processes. It is therefore a prerequisite of successful AI implementation for insurance firms to have a willingness to experiment with AI technology, initially through prototypes before more extensive trials.

Digital-Strategic

Modern core Management Information Systems (MIS)
A lot of attention in AI and insurance is naturally focused on the new AI technologies and high-profile InsurTech new entrants that are seeking to disrupt insurance markets. For example, technology-focused articles explore AI and related digital innovations, e.g., IoT, machine learning, and blockchain, and new InsurTech firms such as Lemonade are analysed and presented as exemplars of new business models that are based on novel data and AI-technologies, and which offer superior performance to incumbent firms in key areas such as cost structure, customer experience, risk management and mitigation, and pricing. However, there is a risk that incumbent firms and legacy systems are neglected as the novelty of new AI naturally attracts the attention of researchers and managers. N.B. The term legacy system here is used to describe existing systems, which could impede change because of their poor performance and high maintenance costs, and could also enable change by being modern and up to date, and therefore provide a building block that facilitates the development of new technology such as AI systems.

Legacy systems are crucial for the operation of existing business models because they represent the core systems and processes that define the information blueprint for an insurance firm in areas such as policy management, underwriting; and product design and marketing [28]. According to recent research by IBM, most investments are concerned with improving existing business models, which involves adaptions and extensions to legacy systems. The key point here is the strategic role of data in historical insurance business models, which remains the case in AI-enabled business models. The IBM research identifies the potential of unlocking the value of data held in legacy systems, and its importance in developing new AI applications [29].

An important corollary of the importance of data is that incumbent insurance firms must have strong and high-performing legacy systems before they can successfully deploy new AI applications, otherwise, they lack the essential building blocks of large-scale systems that provide access to data, enable data management systems for developing and training new AI applications, and more generally, have the digital capabilities for integrating AI into existing systems and processes. This concept of Information Systems evolution and stages of growth, where progress requires mastery and completion of earlier stages of evolution, is a well-established theoretical concept with extensive empirical evidence to support its utility [30]. Poor quality legacy systems, characterised by unreliability and high maintenance costs, may therefore impede an insurance firm from progressing to adopt AI systems. Conversely, up to date and high-quality core MIS systems are an enabler for new AI systems, because they provide valuable historical data, and enable new AI systems to be quickly scaled once they have been successfully trialled.

Strong technology partnerships with key vendors

Insurance firms generally partner with InsurTech to gain access to AI technology, because AI is changing quickly, and most insurance firms do not have the scale to warrant in-house development of core AI technology [31]. The question is not whether to outsource AI systems, but rather how best to 'in-source' AI systems. There is also the competitive pressure to adopt AI technologies quickly, across a broad front of AI application areas in the customer lifecycle [32]. Incumbent firms are therefore much more likely to use their in-house AI expertise to manage the integration of external technology, and to focus their resources on AI trials and experiments, and the rapid growth of the most promising AI applications, which typically go hand in hand with the creation of new business models, or adaptations to existing business models. There is a consensus that AI applications are needed to maintain competitiveness with other insurance carriers, and to respond to new entrants.

Access to relevant big data

There are two categories of big data that are relevant in the insurance industry [33][34]. These are traditional insurance data sources and new digital sources of data, typically from new forms of technology and applications. The Geneva Association research identified the typical data sources for each category [34] , which was used as the basis for further development by EIOPA in its thematic review of big data in European insurance [33].

Traditional data sources are medical, demographic, exposure, simple behavioural data types, loss data, population data, natural hazard statistics and 'other', which includes customer financial data and data from economic partners in the insurance value chain. Traditional in this context means those data that have always been available to insurance firms. The data can typically be collected through simple forms, whether electronic or not, and the data on a per customer basis could therefore be described as 'small' data, though in aggregate, with millions of customers, is extremely valuable. This type of data is also static from year to year and only changes when a major event or significant change occurs such as a new medical condition, an accident, a new policy, or changes to behaviour such as stopping smoking.

New forms of big data include Internet of Things (IoT) data from car telematics or watches, clickstream data, customer interaction information from voice or online communication between insurance firms and customers, detailed spending patterns from online bank data, and image information from customers. This data is characterised as 'big data' because it has volume and variety, and is inherently dynamic and therefore has velocity [35]. For example, consider GPS data used in behavioural insurance [36]. This changes on a second-by-second basis, and provides rich, dynamic insights into customer driving behaviour [37]. Contrast this with the historically crude estimate of a driver's skill from estimated annual mileage and a simple no claims calculation to estimate historical risk.

AI systems require access to relevant big data, whether this is from existing core MIS, which may contain valuable and insightful information and insights into claims and loss correlations with customer segments, or from dynamic GPS, IoT and behavioural health statistics. Insurance carriers therefore have an inherent advantage in mature markets though new entrants can take advantage of market discontinuities caused by new kinds of digital technology. In behavioural health and driving insurance, historical data has limited value compared to the dynamic feed of real-time information about customers.

Ethical and regulatory guidelines

AI systems are assumed to be endowed with some type of intelligence and decision-making, and where these decisions affect people's lives there are important ethical issues that need to be considered [38]. The topic has therefore attracted attention from consultancy firms [39], professional bodies [40], academics [41], government bodies [42] and industry regulators [12]. The nature of automated decision-making in insurance supported by AI technologies makes it a sensitive topic regarding ethical and data privacy issues such as transparency, algorithmic bias, GDPR, fairness of algorithms, use of private data, and exclusion from insurance markets because of high-risk evaluations [22].

The European Insurance & Occupational Pensions Authority (EIOPA) has proposed a set of guidelines expressed in the form of six key principles to regulate the use of AI in the insurance industry: proportionality; fairness and non-discrimination; transparency and explainability; human oversight; data governance of record keeping; robustness and performance.

The argument for including ethics and regulatory compliance as a CSF is that insurance firms should ensure that their AI systems comply with industry standards and regulatory guidelines because otherwise their decision-making is open to attack by competitors, customers and regulators. In this manner, it is a pre-requisite and minimum condition to satisfy. In addition, it can be used to enhance the reputation of an insurance firm, and to contribute to the value and perception of its brand, i.e., to be seen as a firm that designs trustworthy and ethical AI systems.

Digital platforms for data sharing with economic partners

Data sharing along the insurance value chain [43] is essential to coordinate business processes between economic partners. It is the equivalent of data and systems-sharing in manufacturing supply chains and there are equivalent arrangements in bank supply chains, e.g., Just-In-Time (JIT) cash payments and correspondent banking relationships [44]. Although the term insurance value chain is often used, the pattern of inter-relationships between the set of economic partners in insurance markets is more accurately described as a market network because it contains horizontal relationships as well as vertical relationships. The complex web of relationships between customers, primary insurers, reinsurers, third-party claims managers and loss adjustors, capital markets, insurance brokers, Managing General Agents (MGA), reinsurance brokers, claims data aggregators, commercial risk modelers and external scientific research in specialist areas such as climate risk, is more accurately a web or network of relationships [45].

The complexity of data sharing in insurance markets is generated from the range of relationships that are possible, a diversity of data types and a high variety of business processes that determine the actual purpose and outcome of the data sharing [45].

Digital-Tactical

AI specific hardware & software
AI algorithms have a capability to adapt in the light of new data – this evolutionary pattern, sometimes referred to as a learning capability, where the software can be 'trained' is what distinguishes AI systems from earlier generations of Information Systems, where the underlying algorithms such as Materials Requirements Planning (MRP) in a production environment, were static. Of course, Information Systems that use static algorithms can adapt and evolve over time, but this is through a process of software updates and maintenance, which are instigated by programmers and systems developers, who actively design and shape the Information System in response to new requirements and changes to the business environment.

An AI systems development team has a dedicated software environment that is focused on AI-specific algorithms. AI algorithms rely on very large data sets and often have high computational requirements, which means that there is a requirement for specialised memory and processors that are designed specifically for AI applications. AI-specific processors, memory, storage, and networking are likely to form a crucial technical component in advanced AI systems because they will enable more ambitious analyses of big data and overcome some of the technical limitations associated with compute-bound problems [46]. Companies must therefore develop capabilities to manage this new type of IT infrastructure, which will underpin all AI systems development and applications.

Technical AI capabilities
Three key technical capabilities are outlined, which are required to implement AI systems in insurance: AI software development & configuration; data science; and analytics.

Software development and configuration is an integral component to all software projects. For in-house development of AI systems, there is a software development process, and for standard packages, most of the effort from internal staff is in the configuration process of the software package. The nature of AI systems in insurance is that it they are at a relatively early stage of development, and although standard processes have been recognised and documented [28] the market for standard software packages for a general insurance companies is at an early stage in the product development lifecycle and most software vendors focus on a specific set of processes rather than attempt to build an enterprise-wide insurance system. This is also true for AI software solutions, which focus on specific aspects of the customer journey such as customer acquisition, claims management and new product design [32]. Insurance firms must therefore have capabilities to acquire and / or work in partnership with Insurtech companies to select, configure and implement standard AI software, or develop the algorithms and related IT infrastructure themselves.
Data science is highlighted because of the vital role of big data sets in all kinds of AI systems, both in the training and development of new AI algorithms, and then in the ongoing development, evolution, and calibration of live AI systems. Data science skills are therefore required in terms of specification of the problem and requirements engineering, identifying potential sources of

new forms of big data [33] and organising access to relevant data, and then ensuring the accuracy and suitability of data in AI systems. The generation of business value is intrinsically linked to data, and this is termed analytics.

Analytics is defined as the interpretation of data, and in an AI context, uses AI algorithms to analyse large data sets to produce results in application areas such as risk analysis, forecasting and prediction, automation of routine administration tasks, and automation of complex processes such as claims management. The interpretation of results derived from AI systems may be fully automated, i.e., decisions are made by the AI system, or could require involvement from humans, e.g., a change in driving behaviour based on an improved understanding of risk from AI-generated advice from a behavioural insurance product.

Data Management

Data management has emerged as a separate and distinct discipline in organisations because of the importance of data in all aspects of a firm's operations, regulatory and ethical compliance, and for competitive advantage [47]. The pervasive nature of data in a modern organisation has led to new requirements for data security, resilience, and data privacy for customers, employees, and economic partners [48]. AI systems accentuate the importance of data management because of their total reliance on big data throughout their IT lifecycle. A traditional view of business data was focused on highly structured, transactional data such as sales, market forecasts, production planning and accounting data. AI systems expand the scope of business data to include all possible forms of data that could be relevant to improving a firm's intelligence about its competitors, markets, customers and operations, and includes social media data, unstructured customer interaction data from ChatBot and email channels, IoT data and clickstream data from web servers. This increased scope and level of detail in new forms of data that are used in AI systems has several important implications: data management should be recognised as a discipline in itself; it requires dedicated organisational resources and attention; data management should be set up as a cross-functional resource with a mix of technical and business skills to ensure its successful role as an integrating function between specialised technical-focused department such as AI technology and MIS, and business-focused functions such as marketing, product development and sales.

Conclusions

AI systems need to be placed within a business context that includes organisational, strategic and regulatory influences and objectives – see Figure 1. This is important to identify and manage the broad range of business and digital Critical Success Factors (CSFs) involved in AI system implementation projects.

An organisation must manage both business and digital CSFs to achieve a successful AI system implementation. An organisation that is strong in business CSFs and weak in digital factors is likely to create an appropriate AI strategy in concept but fail to build a digital AI system. Conversely, an organisation that is strong in digital CSFs and weak in business factors could build the wrong solution or fail to create any meaningful business innovation, e.g., by simply replicating legacy business processes and models. Weaknesses in business CSFs could also lead to lack of resources and commitment, which would result in stalled projects, or a failure to achieve meaningful benefits for all the stakeholders.

The CSFs model is a useful framework to facilitate successful AI system implementation by helping managers focus on clear, specific factors that must be addressed to increase the likelihood of AI project success. By identifying specific business and digital factors, it can be used to create an AI agenda to integrate business and digital facets of a business, and to serve as an ongoing assessment of progress by measuring an organisation’s performance against each CSF. This is useful to identify strengths and weaknesses in an organisation’s AI project, and provides an opportunity to remedy areas of weakness before they negatively impinge on an AI project.

The distinction between strategic and tactical factors is of secondary importance compared to the business / digital grouping but is nonetheless important in terms of allocating responsibility and project resources to an AI project. The strategic / tactical split also makes it clear that AI project success requires commitment from senior management to ensure that a high-level vision and strong IS infrastructure is in place, as well as managers who are responsible for day to day operations, capacity planning, prototyping, software development and data management processes.

References

[1] J. F. Rockart, “Chief executives define their own data needs.,” *Harv Bus Rev*, vol. 57, no. 2, pp. 81–93, 1979.

[2] J. K. Pinto and D. P. Slevin, “CRITICAL FACTORS IN SUCCESSFUL PROJECT IMPLEMENTATION.,” *IEEE Trans Eng Manag*, vol. EM-34, no. 1, pp. 22–27, 1987, doi: 10.1109/TEM.1987.6498856.

[3] M. E. Shank, A. C. Boynton, and R. W. Zmud, “Critical Success Factor Analysis as a Methodology for MIS Planning,” *MIS Quarterly*, vol. 9, no. 2, p. 121, 1985, doi: 10.2307/249113.

[4] C. P. Holland and B. Light, “Critical success factors model for ERP implementation,” *IEEE Softw*, vol. 16, no. 3, pp. 30–36, 1999, doi: 10.1109/52.765784.

[5] D. Sculley *et al.*, “Hidden technical debt in machine learning systems,” in *Advances in Neural Information Processing Systems*, 2015, vol. 2015-Janua, pp. 2503–2511.

[6] M. Broadbent, P. Weill, and B. S. Neo, “Strategic context and patterns of IT infrastructure capability,” *Journal of Strategic Information Systems*, vol. 8, no. 2, pp. 157–187, Jun. 1999, doi: 10.1016/S0963-8687(99)00022-0.

[7] IEEE, "The IEEE Global Initiative on Ethics of Autonomous and Intelligent Systems. Ethically Aligned Design: A Vision for Prioritizing Human Well-being with Autonomous and Intelligent Systems, Version 2. IEEE, 2017," 2017.

[8] IMDRF, "IMDRF/SaMD WG/N10FINAL:2013 Final Document Title: Software as a Medical Device (SaMD): Key Definitions," 2013.

[9] S. Gerke, B. Babic, T. Evgeniou, and I. G. Cohen, "The need for a system view to regulate artificial intelligence/machine learning-based software as medical device," *NPJ Digit Med*, vol. 3, no. 1, pp. 1–4, Apr. 2020, doi: 10.1038/s41746-020-0262-2.

[10] I. Herbert, C. Holland, and K. Jain, "Next generation insurance operations: Talking tough about 'right'data," 2020.

[11] P. Junco, "To Add Value To Your Business, Don't Treat Data And AI As Islands," *Forbes*, Feb. 2021.

[12] EIOPA, "Artificial Intelligence Governance Principles: Towards Ethical and Trustworthy Artificial Intelligence in the European insurance Sector: A Report from EIOPA's Consultative Expert Group on Digital Ethics in Insurance," 2021.

[13] EIOPA, "Big data analytics in motor and health insurance," Frankfurt, 2019.

[14] C. Holland and A. Kavuri, "Artificial Intelligence and Digital Transformation of Insurance Markets," *Journal of Financial Transformation*, 2021.

[15] A. Azis, "The Power Of Purpose: How Lemonade Is Disrupting Insurance With Goodness (And A New Foundation)," *Forbes*, 2020.

[16] Economist, "How Ping An, an insurer, became a fintech super-app," *Economist*, 2020.

[17] J. Ngai, "Building a tech-enabled ecosystem: An interview with Ping An's Jessica Tan," *McKinsey Quarterly*, 2018.

[18] R. Balasubramanian, A. Libarikian, and D. McElhaney, "Insurance 2030 - The impact of AI on the future of insurance," *McKinsey & Company*, 2021.

[19] A. Andal-Ancion, P. A. Cartwright, and G. S. Yip, "The digital transformation of traditional businesses," *MIT Sloan Manag Rev*, vol. 44, no. 4, pp. 34–41, 2003.

[20] C. P. Holland, "Artificial Intelligence (AI) and Emerging Business Models in Insurance," *Insights: Willis Research Network*, 2019.

[21] C. P. Holland, "Influence of new business models and technology on technology strategy and partnerships," *The Routledge Companion to Managing Digital Outsourcing*, pp. 41–59, Jul. 2020, doi: 10.4324/9781351037785-3/INFLUENCE-NEW-BUSINESS-MODELS-TECHNOLOGY-TECHNOLOGY-STRATEGY-PARTNERSHIPS-CHRISTOPHER-HOLLAND.

[22] B. Keller, "Promoting Responsible Artificial Intelligence in Insurance," 2020.

[23] C. P. Holland, "Artificial Intelligence (AI) and Digital Transformation in the Insurance Market: A Case Study Analysis of BGL Group," Jan. 2022. doi: 10.24251/hicss.2022.553.

[24] H. Lasi, P. Fettke, H. Kemper, … T. F.-B. & information, and undefined 2014, "Industry 4.0," *Springer*, vol. 6, no. 4, pp. 239–242, Aug. 2014, doi: 10.1007/s12599-014-0334-4.

[25] K. Schwab, *The fourth industrial revolution*. Penguin Random House, UK, 2017.

[26] B. Meindl, N. F. Ayala, J. Mendonça, and A. G. Frank, "The four smarts of Industry 4.0: Evolution of ten years of research and future perspectives," *Technol Forecast Soc Change*, vol. 168, p. 120784, Jul. 2021, doi: 10.1016/j.techfore.2021.120784.

[27] G. Vial, “Understanding digital transformation: A review and a research agenda,” *Journal of Strategic Information Systems*, vol. 28, no. 2. North-Holland, pp. 118–144, Jun. 01, 2019. doi: 10.1016/j.jsis.2019.01.003.

[28] IBM, “IBM Insurance Process and Service Models, General Information Manual,” 2016.

[29] IBM, “Three pillars of insurance transformation,” IBM Corporation, New Orchard Road, Armonk, NY 10504, 2020.

[30] R. D. Galliers and A. R. Sutherland, “Information systems management and strategy formulation: the ‘stages of growth’ model revisited,” *Information Systems Journal*, vol. 1, no. 2, pp. 89–114, Apr. 1991, doi: 10.1111/j.1365-2575.1991.tb00030.x.

[31] C. P. Holland, “Influence of new business models and technology on technology strategy and partnerships,” *The Routledge Companion to Managing Digital Outsourcing*, pp. 41–59, Jul. 2020, doi: 10.4324/9781351037785-3/INFLUENCE-NEW-BUSINESS-MODELS-TECHNOLOGY-TECHNOLOGY-STRATEGY-PARTNERSHIPS-CHRISTOPHER-HOLLAND.

[32] C. Holland, “Artificial Intelligence (AI) and Digital Transformation in the Insurance Market: A Case Study Analysis of BGL Group,” Jan. 2022. doi: 10.24251/hicss.2022.553.

[33] EIOPA, “Big data analytics in motor and health insurance,” Frankfurt, 2019.

[34] B. Keller, M. Eling, H. Schmeiser, M. Christen, and M. Loi, “Big Data and Insurance: Implications for Innovation, Competition and Privacy,” *The Geneva Association*, no. March, pp. 1–48, 2018.

[35] A. McAfee and E. Brynjolfsson, “Big data: The management revolution,” *Harv Bus Rev*, vol. 90, no. 10, p. 4, 2012.

[36] C. P. Holland and D. John, “HUK-COBURG: Innovation and Change in the Automotive Insurance Market using Artificial Intelligence (AI) and Telematics,” *SSRN Electronic Journal*, Mar. 2021, doi: 10.2139/SSRN.3803180.

[37] B. Sheehan, F. Murphy, C. Ryan, M. Mullins, and H. Y. Liu, “Semi-autonomous vehicle motor insurance: A Bayesian Network risk transfer approach,” *Transp Res Part C Emerg Technol*, vol. 82, pp. 124–137, 2017, doi: 10.1016/j.trc.2017.06.015.

[38] A. Jobin, M. Ienca, and E. Vayena, “Artificial Intelligence: the global landscape of ethics guidelines,” 2019.

[39] PriceWaterhouseCoopers, “A practical guide to Responsible Artificial Intelligence (AI),” *PriceWaterhouseCoopers*, pp. 1–20, 2019.

[40] IEEE, “IEEE Finance Playbook Version 1.0: Trusted Data and Artificial Intelligence Systems (AIS) for Financial Services,” 2021.

[41] T. Hagendorff, “The Ethics of AI Ethics: An Evaluation of Guidelines,” *Minds Mach (Dordr)*, vol. 30, pp. 99–120, 2020, doi: 10.1007/s11023-020-09517-8.

[42] AI High Level Expert Group, “Ethics Guidelines for Trustworthy AI: High-Level Expert Group on Artifical Intelligence,” Brussels, 2019.

[43] M. Eling and M. Lehmann, “The Impact of Digitalization on the Insurance Value Chain and the Insurability of Risks,” *Geneva Papers on Risk and Insurance: Issues and Practice*, vol. 43, no. 3, pp. 359–396, Jul. 2018, doi: 10.1057/s41288-017-0073-0.

[44] I. D. Blackman, C. P. Holland, and T. Westcott, “Motorola’s global financial supply chain strategy,” *Supply Chain Management*, vol. 18, no. 2, pp. 132–147, Mar. 2013, doi: 10.1108/13598541311318782.

[45] C. P. Holland, G. Zarkadakis, J. Hillier, P. D. Timms, and L. Stanbrough, "Data sharing models in the insurance industry - Willis Towers Watson," *Insights: Willis Research Network*, 2021.

[46] G. Batra, Z. Jacobson, S. Madhav, A. Queirolo, and N. Santhanam, "Artificial-intelligence hardware: New opportunities for semiconductor companies," 2018.

[47] M. E. Porter and J. E. Heppelmann, "How smart, connected products are transforming competition," *Harv Bus Rev*, vol. 92, no. 11, pp. 64–88, 2014.

[48] C. P. Holland, G. Zarkadakis, J. Hillier, P. D. Timms, and L. Stanbrough, "Data sharing models in the insurance industry," *Willis Towers Watson Research Insights*, 2021. https://www.wtwco.com/en-GB/Insights/2021/02/data-sharing-models-in-the-insurance-industry (accessed Aug. 26, 2022).