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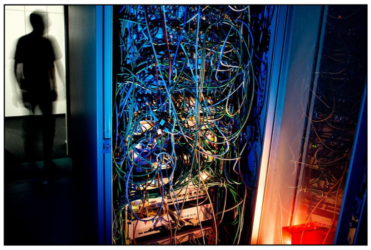

Artificial Intelligence and Innovation Management

Welcome to the December issue of the Technology Innovation Management Review. We invite your comments on the articles in this issue as well as suggestions for future article topics and issue themes.

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Overview

The Technology Innovation Management Review (TIM Review) provides insights about the issues and emerging trends relevant to launching and growing technology businesses. The TIM Review focuses on the theories, strategies, and tools that help small and large technology companies succeed.

Our readers are looking for practical ideas they can apply within their own organizations. The TIM Review brings together diverse viewpoints — from academics, entrepreneurs, companies of all sizes, the public sector, the community sector, and others — to bridge the gap between theory and practice. In particular, we focus on the topics of technology and global entrepreneurship in small and large companies.

We welcome input from readers into upcoming themes. Please visit timreview.ca to suggest themes and nominate authors and guest editors.

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Contribute to the TIM Review in the following ways:
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About TIM

The TIM Review has international contributors and readers, and it is published in association with the Technology Innovation Management program (TIM; timprogram.ca), an international graduate program at Carleton University in Ottawa, Canada.

Editorial: Artificial Intelligence and Innovation Management

Stoyan Tanev, Chief Editor and Gregory Sandstrom, Managing Editor

Welcome to the December issue of the *Technology Innovation Management Review*. This is the second edition, after the one published in October 2019, which includes articles that were initially presented at a conference of the *International Society for Professional Innovation Management* (ISPIM), which took place June 16-19, 2019, in Florence, Italy. The ISPIM conference in Florence was dedicated to Leonardo da Vinci: "Celebrating Innovation: 500 Years since Da Vinci". The focus of the present edition is on the relationship between Artificial Intelligence (AI) and Innovation Management (IM). The edition was inspired by Helena Blackbright and Stoyan Tanev, who managed the activities of the ISPIM special interest group (SIG) on AI & IM at the Florence conference, and chaired the conference session for scholars and practitioners presenting articles focusing on the same theme. It is published with the support and cooperation of the ISPIM Board.

The conference provided a forum for the presentation of articles focused on diverse themes. The articles included in this special issue were presented at the conference session focusing on AI & IM. The authors were invited to submit revised versions of their articles to be considered for publication following a rigorous double-blind peer review process. The relevance and timeliness of the topic are undisputable. In many cases, the adoption of AI by companies changes the ways they do business, the ways they innovate, and the ways they create value. This fact implies a responsibility for innovation scholars and professional innovation managers to examine these changes and generate insights that could help in dealing with the challenges of emerging new practices.

The first article by **Erich Prem**, "Artificial Intelligence for Innovation in Austria," provides empirical evidence for specific innovation management needs faced by companies using AI. The long-term objective of the study is to help in designing a national AI strategy, along with specific support measures for AI-based innovation. The data collected from expert interviews regarding AI-based innovation identifies key challenges for innovation management. Some of these challenges are specific to AI-based solutions. The interviews suggest that significant emphasis needs to be put on human factors, including training and communication involving AI techniques. The author points out that successful AI innovation management needs to address the availability of high volumes of good-quality data, especially in SMEs. The study aims to inform the development of an Austrian national AI strategy, but the data would be also useful for innovation managers seeking to understand both the opportunities and challenges of companies aiming to deploy innovative AI solutions. The results suggest potential new focus topics of further research such as, for example, AI-related business model development, proper management of expectations in AI-related innovation processes, and further insights into the constraints emerging from the historic aspects of data, along with required metadata expertise.

The next paper is by **Sergey Yablonsky**: "Multidimensional Data-Driven Artificial Intelligence Innovation." Yablonsky points out that it is a critical time for the adoption of AI, since the field has already become viable for commercial markets. The research study emphasizes opportunities for cross-fertilization between AI, big data, and advanced analytics with other related disciplines. The article suggests a multidimensional big data-driven AI innovation taxonomy framework that focuses on data-driven human-machine relationships and applying AI at different levels of data-driven automation maturity. It discusses emerging issues that are becoming important and will require action in the nearest future. The evaluation logic results in the development of a tool that managers, company owners, and investors can use in managing their AI enterprise innovation process. It will allow them to interact with all relevant stakeholders to discuss new ideas, receive feedback, and try new solutions; it will help in evaluating the effectiveness of AI innovation and decision-making regarding the design of big data-driven AI products and services.

The third article by **Wolfgang Groher, Friedrich-Wilhelm Rademacher & André Csillaghy**, "Leveraging AI-based Decision Support for Opportunity Analysis," proposes a front-end innovation risk management model. The research is methodologically grounded in design science and applies a novel AI-based approach, which draws on natural language processing and information retrieval. It provides decision support that includes market-, technology-, and firm-related criteria. The model allows for the replacement of some intuitive decision-making with more fact-based considerations. The early testing results of the conceptual model have

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demonstrated increased quality and speed of decision-making. Applied in business environments, the approach can contribute to remediate fuzziness in early front-end activities, thus helping managers to enhance the viability of their innovation outcomes.

Navneet Bhalla's article "The 3S Process: A Framework for Teaching AI Strategy in Business" presents a new framework called the 3S Process. It is a method for academic educators and leaders involving how to adopt AI as part of their organizational change strategies. The 3S Process consists of three stages (Story, Strategy, and Solution), which are described in detail in the article. The Story stage was inspired by the Harvard Case Method to provide context for a problem. The strategy stage uses the Design Thinking approach to produce candidate solutions. The solution stage is where learners advocate for their conceptual AI solution in the context of a case study. The author emphasizes that the complexity of AI systems requires students to consider feedback loops and the potential for unintended biases to enter a deployed solution. The suggested 3S Process suggests further empirical studies, including assessment and evaluation in classroom settings.

The article by **Laura Kemppainen, Minna Pikkarainen, Pia Hurmelinna-Laukkanen & Jarmo Reponen**, "Connected Health Innovation: Data Access Challenges in the Interface of AI Companies and Hospitals," explores data access innovation challenges and potential solutions in the realm of connected health environments. The study builds on insights from data management and innovation network orchestration studies and adopts a new approach to some issues that have emerged in these research streams. The empirical context refers to the development of an AI-driven surgery journey solution in collaboration with hospitals and companies. The authors point out that data access challenges and solutions can be categorised according to specific emergence levels: individual, organisational, or institutional. According to them, organisational level solutions seem to hold wide-ranging potential for addressing many of the current data access challenges. The greatest challenges among healthcare providers and health technology companies relate to the multiple uncertainties and various interpretations concerning regulation, data strategy, and guidelines. The authors indicate that creating guidelines for data use and access in a hospital can be a first step to building further connected health innovations in collaboration with AI companies. Companies, on the other hand, need to engage in gaining in-depth knowledge and understanding of the processes and standards in the healthcare sector.

The TIM Review currently has a **Call for Papers** on the website for a May special edition on "The sharing economy as a path to government innovation." For future issues, we invite general submissions of articles on technology entrepreneurship, innovation management, and other topics relevant to launching and scaling technology companies, and solving practical problems in emerging domains. Please contact us with potential article ideas and submissions, or proposals for future special issues.

Stoyan Tanev
Chief Editor and
Gregory Sandstrom
Managing Editor
December 2019

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Keywords: Artificial intelligence, AI, innovation, Austria, SME, AI innovation management, Big Data, Advanced Analytics, enterprise platform, AI value chain, AI maturity, front-end of innovation, environmental scanning, information processing, opportunity, innovation search field, information retrieval, decision-making, latent semantic indexing, design science, design thinking, 3S Process, business education, Harvard Case Method, data access, orchestration, governance, information mobility, connected health, data management, patient- centered.

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> *"We've never seen a technology move as fast as AI has to impact society and technology. This is by far the fastest moving technology that we've ever tracked in terms of its impact and we're just getting started."*
>
> Paul Daugherty
> Chief Technology and Innovation Officer, Accenture

It has been claimed that Artificial Intelligence (AI) carries enormous potential for service and product innovation. Policy makers world-wide nowadays aim to foster environments conducive for AI-based innovation. This paper addresses the current lack of empirical data for evidence-based innovation policies and the management of AI-based innovation. It focuses on "AI and innovation management" in addressing the question whether innovation that is based on new AI technology requires a management approach different from other forms of IT innovation. We present results from a study of Austrian companies on the degree of use and implementation of AI, and on challenges related to AI-based innovation management. This study used a keyword-list approach to define "Artificial Intelligence" and to find AI-based innovation projects in research databases. These projects facilitated the identification of experts from organisations developing AI-based innovation. In total, eleven experts were interviewed about their AI-based innovation activities. The results show that AI is a very fast emerging technology that is being applied in many sectors. A broad range of innovative solutions are being developed and some have already reached the market. Specific AI business models are, however, less clear and still developing. Companies are facing multiple challenges from regulation to human resources and data collection. Managing AI-based innovation will be particularly difficult for smaller enterprises, where problems are often more pronounced than in larger industries. Explicit challenges for managing AI-based innovations include the necessary attention to managing expectations and ensuring historic metadata expertise essential for many AI-based solutions. Policies to support AI-based innovation therefore should focus on human aspects. This includes increasing the availability of AI experts, but also concerns the development of new job profiles, such as experts in AI training. AI innovators also require clear AI regulation and research investments in key challenges, such as explainable AI.

Introduction

It has been claimed that Artificial Intelligence (AI) carries enormous potential for service and product innovation. In this paper, the term *AI-based innovation* refers to new and improved products and services that are based on the use of AI-technologies, rather than to the use of AI as a tool for innovation management. Examples of AI-based innovation include new monitoring tools that use the automatic identification of objects in a video stream from learned data, new services based on speech recognition, or new optimization techniques for improved logistics based on automated knowledge acquisition using historic data. These innovations use AI technologies (definition to follow below) in one of its many forms, such as deep learning from sequences of data, knowledge-based decision making, or complex pattern recognition. With a history of more than half a century, AI technologies can no longer be called "new". However, recent advances in data processing tools, falling prices for computation and data storage, and a pervasive sensorization and digitization of our environment, have led to a new surge in AI-enabled products and services.

There are numerous opportunities for new and improved services and products arising from AI technology, many of which are based on the fact that the technology often relies on learning from data. Such an approach is very different from traditional IT system design, and can result in systems that deliver entirely new functionality or improved quality features (for

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example, recognition rates of pattern recognition systems). However, AI systems may often be more difficult to explain than conventional software systems, as they employ statistical techniques that are not easily explainable using everyday (that is, non-mathematical) language. Also, such systems often require large amounts of data, either for training or for large knowledge bases, which also may impair easy and straightforward explanation of its actions. Since historic data, learning, and evaluation are of central importance in the design and construction of AI-based systems, their development can be very different from conventional systems. Similarly, questions of user interaction and user acceptance can be very different from traditionally developed IT systems, for example, as regards explainability or ethics. Finally, learning systems involve important issues of data acquisition, quality of data, and responsible use of personal data. All of these characteristics pose the question of whether or not managing AI-based innovation implies challenges that are specific to the development of AI-based solutions.

There is little published empirical work on AI innovation management challenges to date. This contrasts with many studies, including those published by large multinational consulting firms, proclaiming enormous potential for AI technologies. Although the visionary dimension of these studies is often inspiring, they often use broad and general projections about AI technology and its potential benefits. In order to avoid both the fear and hype surrounding AI, real-world data about the status quo of AI-based innovation is necessary for evidence-based innovation policy making. Such factual evidence is even more important for specific approaches to AI-based innovation management, in order to provide an early understanding of actual real-world coming challenges, and to develop management and policy answers to those challenges. Consequently, the aim of this study is to present empirical data from Austrian companies on specific challenges of AI-based innovation.

The main aim of this paper is to provide empirical evidence for specific innovation management needs of companies using AI, based on a broadly defined group of economic entities. This breadth was chosen with the purpose of supporting evidence-based policy making for AI-based innovation. The long-term perspective of this study aims to help design a national AI strategy, along with specific support measures for AI-based innovation. The paper concludes with recommendations for AI-based innovation management to meet the needs of policy makers interested in supporting AI-based innovation.

Existing work and context
Smart technologies are considered as major drivers of innovation (Lee & Trimi, 2018; Makridakis, 2017) and knowledge for innovation (Fischer & Fröhlich, 2001). A broad range of policy papers (Agraval et al., 2019; Dutton, 2018) and marketing studies from consulting companies have argued for the innovation potential and economic benefits of AI (PAICE, 2018; Li et al., 2017). However, little empirical data on specific practical challenges of AI-based innovation exists.

The study in this paper was part of a larger exercise to estimate the economic footprint of Austrian AI companies, and current international strategies to support an AI environment conducive for innovation. The study design therefore included a larger-scale estimation of AI technology application in various sectors of the Austrian economy. For this, data from multiple innovation and research project databases was analysed. The resulting information was placed in the context of economic statistical data, in order for the Austrian government to understand the size of the overall importance of AI technologies already deployed. Expert interviews were part of the exercise. Here, we report only on these interviews in the context of innovation policy and innovation management. From a more general point of view, this study provides an example of technology-related innovation management challenges, that is, specific challenges for innovation management that are contingent upon a technology, cf. (Prem, 2015).

Defining Artificial Intelligence
The current lack of empirical data is aggravated by the lack of a commonly accepted definition of AI. Many including the European Commission (EC, 2018) define AI based on the objective of creating human-like behaviour in machines for perception, reasoning, and action. Another possibility is to define AI entirely based on their ability to learn, that is as learning systems. Although this includes a vast amount of applications and sectors, it excludes more (symbolic) rule-based systems, for example, in so-called diagnosis system applications or in other systems that require predictable and understandable behaviour. A definition solely focused on learning would exclude many traditional AI systems in natural language translation. Expert systems, or case-based reasoning systems and other types of rule-based reasoning systems would also be excluded.

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An appropriate definition of AI can also be based on the various academic subfields of AI as a field in computer science and engineering. These subfields include: reasoning (logic), learning (neural networks), machine perception (understanding of speech, text, images, & videos), and autonomous behaviour (driving, robotics). Note that this is a mixture of technology-related aspects (learning) with more application-oriented ones (machine perception).

For analysis in this paper, we use the latter characterization based on various academic and engineering AI subfields. Such a definition is well aligned both with the organization of AI research, and also with classification schemes of funding agencies. Industrial robotics was excluded for this reason as it is more a field of automation and production engineering, while autonomous robotics (such as autonomous vehicles from lawn mowers to self-driving cars, etc.) was included as a field of AI. In addition, focusing only on machine learning, as seems to be a current emerging trend, would exclude the field of rule-based AI that has a decades-long tradition, and is comparatively strong in many countries including Austria.

Methodology

Focus and selection

The focus of our study is on Austrian companies using AI technologies for innovative services and products (AI-based innovation). We report on results from 11 interviews with experts, both producers and users of AI technologies as innovative products and services. The selection of potential AI-innovators was based on a keyword list (in English and German) to identify AI technologies belonging to academic AI subfields. The list includes topics in machine learning, knowledge representation and reasoning, autonomous robots (including autonomous driving), machine learning, pattern recognition, and natural language processing. For example, it includes “neural network”, “deep

Table 1. Excerpt from the keyword list used for identifying relevant entities (11 of 36)

English	*German*
Artificial Intelligence	Künstliche Intelligenz
Machine Learning	Maschinelles Lernen
(Artificial) neural network, neural net	(Künstliches) neurales Netz, neuronales Netz
Expert system	Expertensystem
Knowledge representation	Wissensrepräsentation
Natural language processing	Sprachverarbeitung, natürlichsprachige Systeme
Computer vision, Image understanding	Computervision, Bildverstehen
Autonomous robots, autonomous system	Autonome Roboter, autonome Systeme
Problem solving	Problemlösen
(Automatic) Reasoning	Automatisches Schlussfolgern
Knowledge engineering	Wissenstechnik, Wissensverarbeitung

Source: Author’s translations

learning", and "connectionism" to discover innovation and research projects in machine learning. The list is based on IT expert knowledge and existing classification schemes such as the ACM classification often used by innovation agencies. Potential companies were identified using innovation agency databases, industry data, and job search data related to artificial intelligence.

Interviews
Our interviews were with employees of private research institutes creating AI applications. In most cases, the persons interviewed were CEOs, CTOs, or department heads of these companies. The set includes both small-and-medium sized enterprises, as well as large industry players. All companies in our set deploy or develop AI solutions with the aim of creating innovative services or products. The interviews were performed following a structured interview process about company characteristics, activity sectors, core competencies, innovative AI applications, motivations for using AI, technologies used, the role of start-ups, business models, main customers, barriers, and obstacles.

Results

The study resulted in a rather coherent picture of the current state-of-deployment involving AI technologies. This means that there was broad agreement between the experts on aspects such as general opportunities for innovation involving AI, the current state of its deployment, and on many of the challenges and problems which companies that aim to innovate by using AI are facing today.

Sectors and application areas
The selected company experts covered a range of sectors, with added focus on automotive and other machining industries, that are traditionally strong areas of the Austrian economy with many innovative SMEs and also large industry. They included people at

Table 2. AI application areas and examples of AI-based innovations

Area	*Example*
Language, speech and dialogue systems	Chatbots, travel agent, HR-assistant, semantic search, support systems, search
Text analysis, knowledge management and knowledge extraction	Trend and threat analysis in texts, information extraction, sentiment analysis
Industrial automation and plant operation	Industry 4.0, optimization, predictive maintenance, simulation, video-based error detection, automation of complex manual procedures, sensor fusion
Video and image classification	Processing of sound, image, video and text; security applications
Autonomous operations	Autonomous vehicles, autonomous operation of plants
Information technology applications	Software defined networks, software maintenance, security, anonymisation
Finance	Finance and risk management

Source: Expert interviews (right column) and author's classification (left).

dedicated AI companies that address broad economic sectors including the service sector. The experts were asked about their core competencies to better distinguish consultants and AI application developers from other enterprises that internally develop their own AI-based solutions. The interviews listed the following areas:

• Analytics, Text Mining, Information Capture
• Enterprise Content Management
• Privacy protection
• Transport and mobility
• Automotive
• General AI
• Sign language
• Natural language understanding

Although experts from only 11 companies were interviewed in detail, the number of developed AI applications discussed in these interviews was more than 35. They include a broad range of AI application areas, from online sentiment analysis to trend and incident analysis in documents, autonomous driving, intelligent searches to identify experts, predictive maintenance for industrial applications, rolling stock optimization in the transport domain, software defined network management, intelligent travel agency, sign language translation, financial risk management, and AI assistants for human resource management. The applications can be roughly classified in the following area categories with examples (see Table 2):

The main motivations for using or developing AI for innovative products and services include automation, process optimization (adaptation, acceleration), improved efficiency (with respect to costs or personnel), increased flexibility, complexity management, and knowledge management. AI technologies used include machine learning, data analysis and prediction techniques, natural language processing, image analysis, deductive systems, and knowledge graphs.

Technologies
Table 3 provides an overview of the concrete AI technologies that experts mentioned in their interviews, along with the corresponding AI field.

The role of start-ups and new AI business models
An opinion prevails among those interviewed that start-ups have a vital role to play in both the application and deployment of AI innovations. They are considered the main leaders and competence carriers in AI technology and are praised for their flexibility compared to large industry actors. Specialized start-ups are also believed to

Table 3. Technology field and concrete technologies mentioned by the experts

Technology field	*Used technologies*
Machine learning	Neural networks, convolutional neural nets, deep learning evidence-based methods
Data analysis and prediction	Predictive analytics, prescriptive analytics
Natural language processing	Language generation, language understanding (text, speech), text mining, semantic search, content analysis
Image and video processing	Image recognition, pattern recognition, video analysis
Knowledge processing	Deductive systems, knowledge graphs, knowledge representation systems

Source: Expert interviews (right column) and author's classification (left) invest more in the development of novel AI methods compared with the large software industry. Also, the interviewees consider their solutions to be more straightforward for deployment in comparison with the more complex environments of comprehensive framework providers. On the downside, AI start-ups can be difficult to identify and learn from as they are small and often still developing their value propositions for various sectors.

Regarding AI solution business models, the respondents suggest that these are not fully clear and still being investigated, as the focus is often on quality improvements rather than new business models. It is expected that price planning and dynamic pricing may become a more important aspect of AI applications. AI-as-a-service has already emerged as a specific case and there is a trend towards licensing per service, per application case, or based on usage volume. In addition, there is a trend to shift the development of solutions to the customer given the emergence of more mature training tools for data-driven AI solutions.

AI-applications and AI-development are central to many consulting activities in the domain. Indeed, it is sometimes difficult to clearly delineate consulting companies from AI application developers. There are even indications that a new profession of “AI trainer” is emerging: experts in the computer application domain with competencies in data analytics, where the former is often considered more important than the latter.

Many interviewed experts were convinced that sooner or later no company (at least in a technical domain) will be able to achieve success without a certain degree of automation and, hence, autonomy. This will make AI a general computing method with a strong focus on data-driven approaches to system creation, and also automation.

Challenges and barriers

From an innovation management perspective, the lack of IT and AI experts was the biggest challenge in our interviews. This concerns general IT-experts, but also IT-staff with dedicated AI expertise: AI generalists, AI specialists in neural networks, AI software engineers, and data scientists. The interviewed experts also pointed out that currently even graduates from technical universities, including computer science graduates, may not have acquired sufficient AI expertise during their curriculum. Another main barrier is the cost of creating the required know-how for innovations; AI techniques often require many trial-and-error cycles during the development process. This implies long development times and an inherent difficulty in predicting development time. In addition, it was pointed out that robotic technologies are often costly because of hardware requirements and human effort needed for building or developing robotic systems.

The respondents also identified a current lack of knowledge about AI in the sense that there is insufficient general awareness and knowledge in their own company, including among C-level executives. This often results in people having unrealistic expectations about AI. Managing AI-based innovation is thus a huge challenge for experts when there is not even an agreed definition of AI. Today’s lack of AI knowledge also reduces the credibility of AI solutions. There are many claims from marketing professionals that cannot be confirmed in practice, which unfortunately also results in a lack of acceptance of failures during the innovation process. This comes on top of the recognized challenge that many solutions based on machine learning cannot easily give explanations for their own behaviour. The lack of clear regulation and legislation is a related problem, for example, involving responsibility in the health sector, with control applications or in other engineering fields.

Small and medium-sized enterprises (SMEs) trying to apply AI are often hesitant because of these uncertainties. In addition, they are challenged by the fact that they may be lacking data in terms of volume or quality. Innovation managers often have difficulties estimating the realizability of AI-based innovation projects, in particular when using statistical techniques such as neural networks.

Table 4 provides an overview and classification of the barriers and challenges mentioned in the interviews.

Discussion

Many Austrian companies have by now come to recognize AI as an important technical enabler of innovation. Although there has been research in AI technology for more than 50 years, there is nevertheless still a sense of novelty today that seems to be driving experimentation. Many aspects of this technology are still emerging, and companies are trying to understand the technology’s possibilities, what their own capabilities are, and where the benefits really lie for innovation.

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Table 4. Barriers and challenges and some examples (interviews)

Barriers and challenges	*Examples*
Lack of qualified staff	IT-experts (general), IT-staff with AI expertise, data scientists, specialists and generalists, software developers, AI experts
Costs	Know-how creation, development costs, long development times (trial and error for innovative solutions), hardware costs for robotics
Lack of knowledge	Insufficient information about AI (general), unrealistic expectations, insufficient competence in AI (with not even the definition being clear)
Credibility of AI solutions	Unrealistic claims regarding AI and disappointment
Technical aspects	Lack of explainability for learning systems, lack of data - a strong limitation for AI, especially for SMEs
Regulation	Current legal regulation, e.g. in the health sector; unclear responsibilities for overall system behaviour
Hesitation	Executives hesitate, especially in SMEs; but so do customers
Hype	Risk that the current hype about AI hampers its development, because it blurs the vision of real opportunities and creates wrong expectations

Source: Expert interviews (right column) and author's classification (left).

Innovation characteristics of AI

Although AI has been studied for more than half a century, it still rapidly developing. There is broad agreement that it is not even fully clear which methods, approaches, or techniques should be included in its definition. The concept of "AI" often describes features of a desired application; this means that the term is defined as making computers do what so far only humans can do. This meaning comes with how the term originated around the 1960s in the US. It should be obvious now that this characterization of AI is really an oxymoron, as it implies that it is a definitional moving target: it emphasizes technological abilities that are somehow not yet demonstrable by computers. This also seems to mean that whenever a technology that originated as a result of AI research matures, it then becomes part of the standard repertoire of computer science and is no longer considered as being "proper AI." Examples of this include search methods studied for chess computers and early feature detection for image recognition. These techniques eventually became part of the canon of computer science curricula, rather than being framed as due to AI research. Such revisionary history is one of the reasons for the difficulties in clearly defining the term.

The general aim of AI is to make computers smarter for the aid of human perception, decision-making, and action. In this sense, AI systems do not necessarily always have to outperform humans. In many new application areas, AI systems are developed with the aim of achieving automated perception, decision-making, and action with less-than-human degrees of precision. In many useful application scenarios, the AI system can add round-the-clock performance, or simply a way to deal with very large amounts of data. Examples are image recognition and classification applications that may not be always 100% correct, but which nevertheless help to pre-sort cases for human inspection. Other applications of AI may actually target improved quality, for example, in AI-based medical image classification or high-precision robotics applications. These examples point to general value propositions of AI technologies regarding potential innovation, including attempts at AI-based innovation ranging from performance and quality gains, to radically new features that would not be achievable without AI technology, for example, in cases of learning from historic data where no explicit parallel human knowledge is available.

The motivations listed in the interviews about why to use AI are broad and often overlap. Automation and process improvements are a big driver. Another area is management of complexity including knowledge management. Other obvious motivations are increased efficiency regarding technical parameters, personnel resources, and costs.

Besides these qualitative innovation targets, the use of AI promises to deliver technical solutions in areas that could not previously be solved by computer applications. For example, AI learning systems trained on large amounts of data can be used for automated video classification. This will enable previously unavailable solutions in security applications that help to improve quality and reduce costs. Again, this underlines that AI-based innovation is both incremental, and also often an enabling technology where no automated system with satisfactory performance was previously available.

In summary, there are a broad range of innovation promises for AI; from mere improvements to enabling completely novel product and service offerings. And indeed, the innovation examples provided in the interviews clearly range from incremental innovation (for example, quality production improvements using AI for error detection) to “new to the world” innovation (automation of sign language translation). The emphasis in the interview examples was generally on incremental improvements, with some examples given of process automation that could not have been done without the application of AI.

AI in engineering

There are good reasons why many companies in Austria innovating with AI operate in the engineering domain. AI learning systems in many cases require large amounts of training data. Such data is usually difficult to create, unless it is already provided by a company’s technical systems, such as digital production systems, plant control systems, or other technical systems that continuously monitor, and often control operation. Engineering environments (in electronics, automotive production, or machining) therefore appear as prime candidates to roll out novel AI services, simply due to the availability they have of sufficient amounts of data. It became clear in our interviews that indeed the very existence of data is a major driver of experimentation with AI-based innovations. This “data-push” combines with a “technology-push” from current AI development tools, which are now widely available, often at rather low costs, or even for free online.

In addition, engineering companies are more likely to have the required skillsets in-house with regard to computer engineers and data scientists, for example, compared to the service sector. People with these skillsets experiment with novel technologies and typically have a mindset adjusted to technological competitiveness.

Experimentation, resources and capabilities

The focus on experimentation in the interviews had both a technological and a company dimension. The relative novelty of AI for most companies means that they are in ongoing exploration of their AI innovation resources and capabilities (Tidd & Bessant, 2014). This includes functional capabilities in particular, such as experienced personnel, but also resources, specifically data. Other potentially limiting technical aspects include computational requirements for AI training or AI application.

There is a second dimension inherent in the technological characteristics of AI, at least for learning systems and data-driven systems. At the current state-of-the-art, developing AI systems is a process of trial-and-error. While there are of course often situations in which novel technical solutions require an iterative approach, the situation is exacerbated in the case of AI because of the inherently statistical nature of many AI solutions. For such statistical (learning) systems it is often not fully clear if a solution is possible at all. In addition, the process of tuning a learning system requires several stages of training and test cycles. The lack of technical predictability becomes an important challenge for innovation management if there are inflated expectations about AI's technological possibilities. Many company experts warned about the danger of disappointment that may arise from very high expectations, followed by only mediocre or modest performance from an AI solution. The resulting disillusionment could eventually mean that companies refrain or delay too long from exploring potentially promising solutions.

It is particularly interesting for AI innovation management that companies may not fully understand their data resources to the extent necessary for AI solutions. Small companies may lack the kind of long and consistent data sets that are typically required for deep learning solutions. More critically, the interviews suggested that this is a specific problem for smaller companies and that it is very hard for most of them to know precisely what information is in their data, for what time periods that data is reliable, etc. A new kind of "metadata expertise" could therefore become essential for assessing the technical viability of an AI solution, and for designing an AI system and an efficient development process.

From the perspective of innovation management, data is an interesting case as it represents both a technical and a historic dimension. The usability and value of any given data set will depend on the technical characteristics of the precise AI technology, for example, deep learning, case-based reasoning, or a symbolic expert system. In addition, data carries an element of history that is typically not well described in explicit metadata information. Rather, this data history requires competent interpretation by human domain experts in order to understand any potential limitations or opportunities. In the interviews, this aspect of domain knowledge in combination with a proper appreciation and understanding of the available data was mentioned as a current shortcoming. Here, some of the experts we spoke with suggested the potential future job profile of an 'AI training' expert. These AI training experts are knowledgeable in how to develop data-based AI systems and they also understand important limitations of AI systems. However, they are not necessarily experts in the application domain.

In summary, there are at least three specific aspects of AI innovations that require consideration for innovation management at the level of business innovation: technologies, resources, and capabilities.

- Technologies: data sets and knowledge in combination with data expertise
- Resources: AI tools in combination with AI tool / AI training expertise
- Capabilities: domain experts providing the required domain knowledge

This suggests that the successful development of AI-based innovations at an early (pre-market) stage may already require three different types of experts: AI experts, domain experts, and metadata experts. The current lack of experts in science and engineering in many OECD countries also underlines the importance of proper policies for human resources in these areas.

Value creation

On the demand side, customers consider obvious criteria such as the cost and value proposition of an innovative solution. Less obvious AI-related aspects are trust and understandability, as well as the ability to explain and predict system behaviour. These aspects are closely linked. In engineering domains, it is particularly important that solutions (for example, involving control, but also maintenance, automation, etc.) are reliable. In many cases where AI solutions promise improvements over traditional approaches this comes at the price of reduced clarity and predictability. This is not necessarily only true for statistical learning systems, however. Even large-scale rule-based systems may easily become practically untraceable and extremely difficult to predict. The related and specific challenges for AI-based innovation have already become an important subject in research policy, and also in AI research itself. Interestingly, the focus in public discussion is often on explainability, which is a rather different concept. In any case, the typical iterative development and necessity to assess quality through testing is a challenge for AI-based innovation in engineering as many potential customers express concerns about the reliability of innovative AI solutions even where they may outperform existing systems.

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For the case of Austria there is a further key aspect to consider. As mentioned before, the strong machining, electronics, and automotive industries can build applications based on historic data. However, they may also have very tight requirements or expectations regarding predictability, reliability, and explainability of systems. For the AI innovation manager, this may imply a preference for solutions that exhibit these characteristics. And in areas that are less regulated or where there is no hard requirement for full predictability and explainability, it means a focus on testing, evaluation, and demonstration to gain the necessary trust.

Following our interviews, the question about AI-specific business models remains an interesting open issue. Many of the respondents did not see such a model emerging just yet. The mention of change in the business model, such as shifting from products to services, is more in line with typical business model innovation following digitization (Prem, 2015b). The more interesting case is AI-as-a-service, where it may be necessary to distinguish online creation of AI systems (for example, training neural network models), from online use of already trained AI systems. Issues such as data ownership, dynamic service pricing, and intellectual property rights of AI models could become AI-specific innovation challenges and methods.

Conclusion

The data collected from expert interviews regarding AI-based innovation identifies key challenges for innovation management. Some of these challenges are specific to AI-based solutions. In the context of recently published AI strategies, the interviews suggest that significant emphasis needs to be put on human factors, including training and communication involving AI techniques. Successful AI innovation management also needs to address the availability of high volumes of good-quality data, especially in SMEs. Of particular importance is human expertise in the AI and application domain, as well as for historic and semantic aspects in the case of statistical techniques that rely on past data.

The study aimed to inform the development of an Austrian national AI strategy. The data may also be useful for innovation managers seeking to understand both the opportunities and challenges of companies aiming to deploy innovative AI solutions. For researchers, the data suggests potential new focus topics of further research, for example, AI-related business model development, proper management of expectations in AI-related innovation processes, and further insights into the constraints emerging from the historic aspects of data, along with required metadata expertise.

For policy makers interested in supporting AI-based innovation, the results suggest focussing on human resources such as AI experts, as well as developing further emerging new job profiles such as “AI-trainers” who are proficient in training AI systems without necessarily developing novel AI techniques. In addition, research policies should support investment in technologies for explainable and trustworthy AI. Regulatory aspects concern the freedom to work with new business models and the development of a clear and reliable regulatory framework for AI-based innovation.

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Multidimensional Data-Driven Artificial Intelligence Innovation

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> *Information is the oil of the 21st century, and analytics is the combustion engine.*
>
> Peter Sondergaard
> Gartner Research

This is a critical time for the development and adoption of Artificial Intelligence (AI). The field has existed since the 1950s and is only now emerging as viable for commercial markets. Many enterprises are placing bets on AI that will determine their future. Today AI innovation becomes useful when it enriches decision-making that is enhanced by applying Big Data (BD) and Advanced Analytics (AA), with some element of human interaction using digital platforms. This research investigates an opportunity for cross-fertilization between AI, BD, and AA with related disciplines. The paper aims to investigate the potential relationship of AI, BD, and AA with digital business platforms. In doing so, it develops a multidimensional BD-driven AI innovation taxonomy framework with an AA/BD/AA innovation value chain, related levels of BD, and analytics maturity improvement. This framework can be used with a focus on data-driven human-machine relationships, and applying AI at different levels of data driven automation maturity.

1. Introduction

Digital transformation of enterprises across industries enabled by new digital technologies is an emerging phenomenon. Firms are challenged to succeed in embracing transformation through digital technology to enable competitive advantages or they will face collapse at the hands of their competitors that do (Fitzgerald et al., 2014). For enterprises to digitalize their products, services, or business model, they need to find a role for digital innovation (Bughin & Zeebroeck, 2017; Manyika et al., 2016). The transition to digital business thus requires enterprises to make a leap toward a new view of data and analytics.

The future of digital business faces enterprises with abundant possibilities to create value for their company through data and analytics. Enterprises need to look at data as the raw material for decision-making, and consider that data comes from both within and outside the enterprise. The growing digitization of the economy is exposing the limitations of traditional assets, as the boundaries between the technologies and the business blur, and new data asset classes emerge.

Big Data (high-volume, -variety and -velocity information) continues to increase rapidly in all three dimensions, and is a major factor in many industries (Manyika, et. al., 2011). The volume of data is speedily growing. Manyika et al. (2011) define Big Data (BD) as datasets, the size of which is beyond the ability of typical database software tools to capture, store, manage, and analyze.BD is thereby interpreted as “information assets characterized by such a high volume, velocity and variety [as] to require specific technology and analytical methods for its transformation into value” (De Mauro et al., 2016: 103). BD now requires new forms of data processing to facilitate enhanced decision-making, insight discovery, and process optimization (Cavanillas et al., 2016). BD has become useful nowadays when it enriches decision-making that is enhanced by applying analytical techniques and some elements of AI. This research investigates an opportunity for cross-fertilization between BD and the field of AI with related business disciplines, based on the merging of data and information in contrast with knowledge and intelligence. It continues previous work done on big data and advanced analytics platforms (Yablonsky, 2018 a,b,c).

Along with the increasing importance of digitalization, digital innovation has become an important research agenda due to the rising need for new digital solutions. Digital innovation is defined by Nambisan et al. (2017), as the creation of market offerings, business processes, or models that result from the use of digital technology.

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Their definition includes a range of innovation outcomes, such as new products, platforms, and services, as well as new customer experiences and other value pathways (Khin & Ho, 2018).

In our study, Artificial Intelligence (AI) is a digital innovation that offers solutions to transform enterprise products, service and business using AI, Big Data (BD), and related Advanced Analytics (AA). Indeed, AI is at the heart of digital disruption. AI disruption aims to drive better customer engagement and lead to accelerated rates of innovation, higher competitiveness, higher margins, and more productive employees (Jyoti et al., 2019). AI innovation is powered by BD and AA. BD involves collecting from of a wide variety of inputs, including publicly available data, information, or knowledge, human intelligence, and active gathering, then processing the resulting inputs to better understand and predict competitor strategies and actions (Erickson & Rothberg, 2015; Marr, 2015). In a number of ways, AA and AI actually anticipate interest in BD more than other BD disciplines do. Data and analytics need to be thought in terms of processing enterprise digital business platforms, thus taking on a more active and dynamic role in powering the activities of the entire organization (Yablonsky, 2018b).

Despite the growing research interest in AI innovation, most of the studies on AI innovation look at innovation from a technical, architectural, or information system perspective (Lyytinen et al., 2016), rather than from a managerial perspective. Hence, this study takes a different approach to AI innovation by choosing the BD and AA context. This is done to see how strategy, products, and solutions are transforming into innovative data-driven AI business strategy, products or solutions, that subsequently impact traditional business strategies, products, and services, and can even lead to the creation of new businesses.

This paper aims to investigate the potential relationship and value of BD, AA, and AI within a multidimensional framework that combines AI maturity and AI/BD/AA value chains. In doing so, it develops a data-driven AI innovation taxonomy framework with related levels of AI/BD/AA maturity improvement across innovation value chains.

The paper is structured as follows. Section 2 discusses the main definitions and conceptual backgrounds of AI, BD, and AA based on literature review. Section 3 describes the methodology. Section 4 discusses the place of AA in platforms. Section 5 illustrates the AI/BD/AA value chain. Section 6 presents a multidimensional data-driven AI innovation framework that combines AI/BD/AA value chains, and data-driven AI innovation. Section 7 explains the study's results, provides discussion and addresses implications.

2. Research Methodology

In our research we aimed for a multidimensional, multilayered framework development in order to facilitate understanding, analysis, and structure of AI, BD, and AA for enterprises. This approach proved particularly beneficial for the field due to the current lack of systematic empirical analysis in AI management research. Despite its increased importance, little research has been done to systematically examine why and how AI engages in BD and AA, or how BD and AA technologies impact AI. The current conceptual study seeks to develop an AI/BD/AA relation framework through the lenses of a growing AI research agenda in the age of BD and AA. It aims to categorize the main BD/AA dimensions of AI and create a strategic multidimensional data-driven AI framework that is adopted to identify the AI/BD/AA relationship and apply a strategic AI-driven enterprise transformation framework. The paper aims to address this critical gap by focusing on trying to answer why and how BD and AA engage AI.

The framework development was guided by the approach of Nickerson et al. (2012), which facilitates an iterative combination of conceptual-to-empirical and empirical-to-conceptual approaches. Leaning on Moyer (2016), an industry vision of digital transformation consists of four parts: concepts, capabilities, assets, and research. Using this framework, we collected qualitative data through literature review and semi-structured expert interviews. Subsequently, we collected qualitative data through the interviews for identifying sub-dimensions and instantiations of each framework. Our interview partners were members of technologies groups, founders, and CTOs of the Russian National Technology Initiative (NTI - http://www.nti2035.ru/; https://asi.ru/eng/nti/). We conducted one interview per NTI market, with an average duration of 50 minutes. All of the interviews were recorded, transcribed, and analyzed thematically.

The analysis showed that rather than searching for a single acceptable definition, a better approach would be to develop a classification system or taxonomy (Nickerson et al., 2012). This is because having a clear and precise description and structuring of information in the advanced analytics domain are prerequisites for conducting common research. Taxonomies and other types of controlled vocabularies are the preferred means of achieving a common understanding by specifying the terms of the domain, disambiguating them from each other, identifying synonyms, and structuring the domain via terminological relationships.

We use definitions from different information resources from 2010 to 2019 to conceptually ground the categories in advanced analytics taxonomy,. The pilot version of the advanced taxonomy is shown in the figures and tables below (mainly in the hierarchy of the 2 first layers of taxonomy concepts). Taxonomy includes a set of basic concepts, a set of relations holding between those concepts, and a set of instances, including both international and local AI and AA firms and service providers. The total number of all taxonomy features (>100) is too complex to be represented here in its entirety, but a sample part of the taxonomy is provided in order to demonstrate both the process of classification and the intermediate result. We suggest that although classification systems have traditionally been used in business and management disciplines, the more advanced quantitative methodologies now available have not yet been widely used.

3. Current Understanding

Digital business involves creating new business designs that blur the boundaries between the digital world and the physical one, due to the convergence of people, businesses, and smart things/machines/services. It promises an unprecedented convergence of a) people, b) businesses, and c) smart things/machines/services that change existing business models and create new revenue opportunities (Cavanillas et al., 2016; Yablonsky, 2018b). This is a critical time for digital business transformation in the history of AI development and adoption. The field is more than 70 years old, yet is only now emerging as viable for commercial markets. Artificial intelligence technologies nowadays impact most application categories and many business challenges. Vesset et al. (2018) state that many enterprises are placing bets on AI that will determine their future. Those sitting on the side-lines are risking being left behind.

Yet many organizations lack the AI literacy needed to make critical investment decisions. In recent years, one of the shortcomings in the AI commercial sphere has been the misrepresentation of the possible automation scope. Too often, we hear claims of AI systems automating end-to-end processes and predictions of what may result in massive labour losses. These proclamations and promises of AI's ability to solve all societal ills, from diseases to crime, and from hunger to war, do a disservice both to enterprises and individuals trying to plan for the appropriate level of investment in AI, as well as vendors developing marketing AI solutions (Gentsch, 2018). To help with planning and investment decisions related to AI-based enterprise automation, Vesset et al. (2018) developed a five-level framework that can be put to pragmatic use identifying industry and functional use cases, where current AI can automate specific tasks, activities, and processes.

Over the last decade, business has become more and more focused on data. This trend is a consequence of the success of many organizations that have used collected data to drive their business. Digital transformation is influencing big data creation (BDVA, 2017). The data landscape is rapidly changing and with it, organizations need to evolve the ways they manage and govern data. Most organizations today are faced with an increasing volume of data that is gathered through a wide scope of processes and range of formats. The increase in volume and variety adds complexity to data management. At the same time, data consumers now demand quick and easy access to data. They want to be able to understand data and use it to address critical business questions in a timely manner.

Today organizations must be flexible enough to work in a growing environment. To do so, organizations need to clarify basic questions about ownership, collaboration, accountability, and decision-making. Contemporary business decision-making that directs the share of different resources for exploration, discovery, building, or testing of ideas is based upon data, that when structured and processed creates information and knowledge. Nevertheless, the gathering of more and more data from multiple sources, coined as "big data" (BD) has led to challenges involving how best to integrate and meaningfully manage data to support improved decision-making for greater impact. The data lakes and databases that continuously store large amounts of data will eventually become larger and larger over time. Thus, applying BD analysis approaches will be inevitable (Cavanillas et al., 2016; Sivarajah et al., 2017; Günther et al., 2017). BD analysis is the collection of data and technology that accesses, integrates, and reports all available data by filtering, correlating, and reporting insights not attainable with past data technologies, while supporting more robust decision-making. Data-driven AI decision-making adds value to BD and is crucial for successful AI enterprise innovations.

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AI and advanced analytics

Artificial Intelligence (AI) started as a field at a conference at Dartmouth College in 1956 when John McCarthy coined the term "artificial intelligence." It was defined to be the field of computer science aimed at developing computer programs or applications that would have capabilities comparable in some way to human cognitive abilities (for example, speech recognition, visual pattern or image identification, language translation, natural language processing [NLP], or making inferences in decision-making) (Kumar, 2017). Today AI is an umbrella term for multiple technologies, including machine learning, deep learning, computer vision, machine reasoning, and natural language processing (NLP). There is still no single definition of AI that is universally accepted by researchers and practitioners (Kumar, 2017).

Gartner contends that AI applies advanced analytics (AA) and logic-based techniques, including machine learning, to interpret events, support and automate decisions, and take actions. However, research on AI focuses primarily on four key components of human intelligence: *learning, reasoning, problem solving*, and *perception*. The European Commission suggests AI refers to machines or agents that are capable of observing their environment, learning, and based on the knowledge and experience gained, taking intelligent action or proposing decisions (EU, 2018). AI systems are likely to play a key role in search processes on the Internet, shopping online, seeking a medical diagnosis, and many more. These AI systems seek the best plan of action to accomplish their assigned goals using assistive, augmented, and autonomous capabilities (see Figure 1).

What exactly is "analytics"? Davenport and Harris (2007) define analytics as "the ability to collect, analyze, and act on data". Gartner notes that analytics has emerged as a general term for a variety of different business intelligence (BI) and application-related initiatives. For some, it signifies the process of analyzing information from a particular domain, such as website analytics. For others, it means applying the breadth of BI capabilities to a specific content area, for example, sales, service, supply chain, and so on. Increasingly, the term "analytics" is used to describe statistical and mathematical data analysis that clusters, segments, scores, and predicts what scenarios are most likely to happen. Whatever the use cases, "analytics" has moved deeper into business dialect. Analytics has gained increasing interest from business and IT professionals looking to exploit huge mounds of internally generated and externally available data.

The field of analytics is broken down into five categories: *descriptive, diagnostic, predictive, prescriptive,* and *augmented analytics* (Hurwitz et al., 2015; Siegel, 2013; Quintero et al., 2015; Yablonsky, 2018b). Figure 2 illustrates how these five categories help to define advanced analytics.

4. Research Design

The complexity of the AI field often lends itself to classification schemas, or taxonomies, which provide ways to understand similarities and differences among objects of study. Developing a taxonomy, however, is a complex process that is often done in an ad hoc way. Nickerson et al. (2012) proposed a method that combines both empirical-to-deductive and deductive-

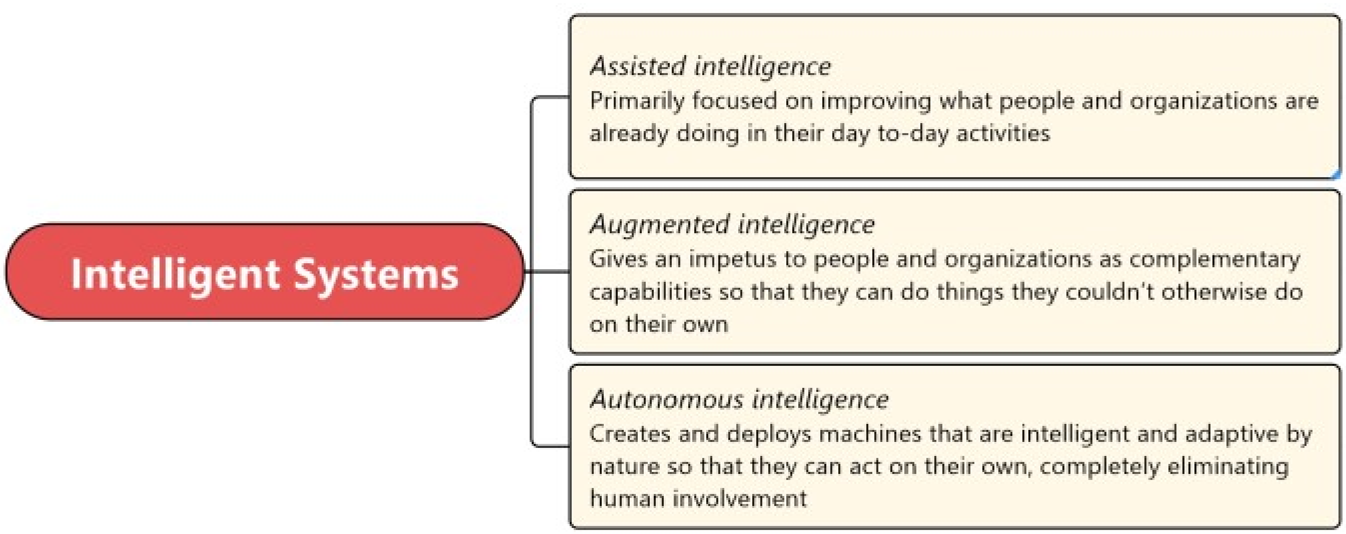

Figure 1. AI systems

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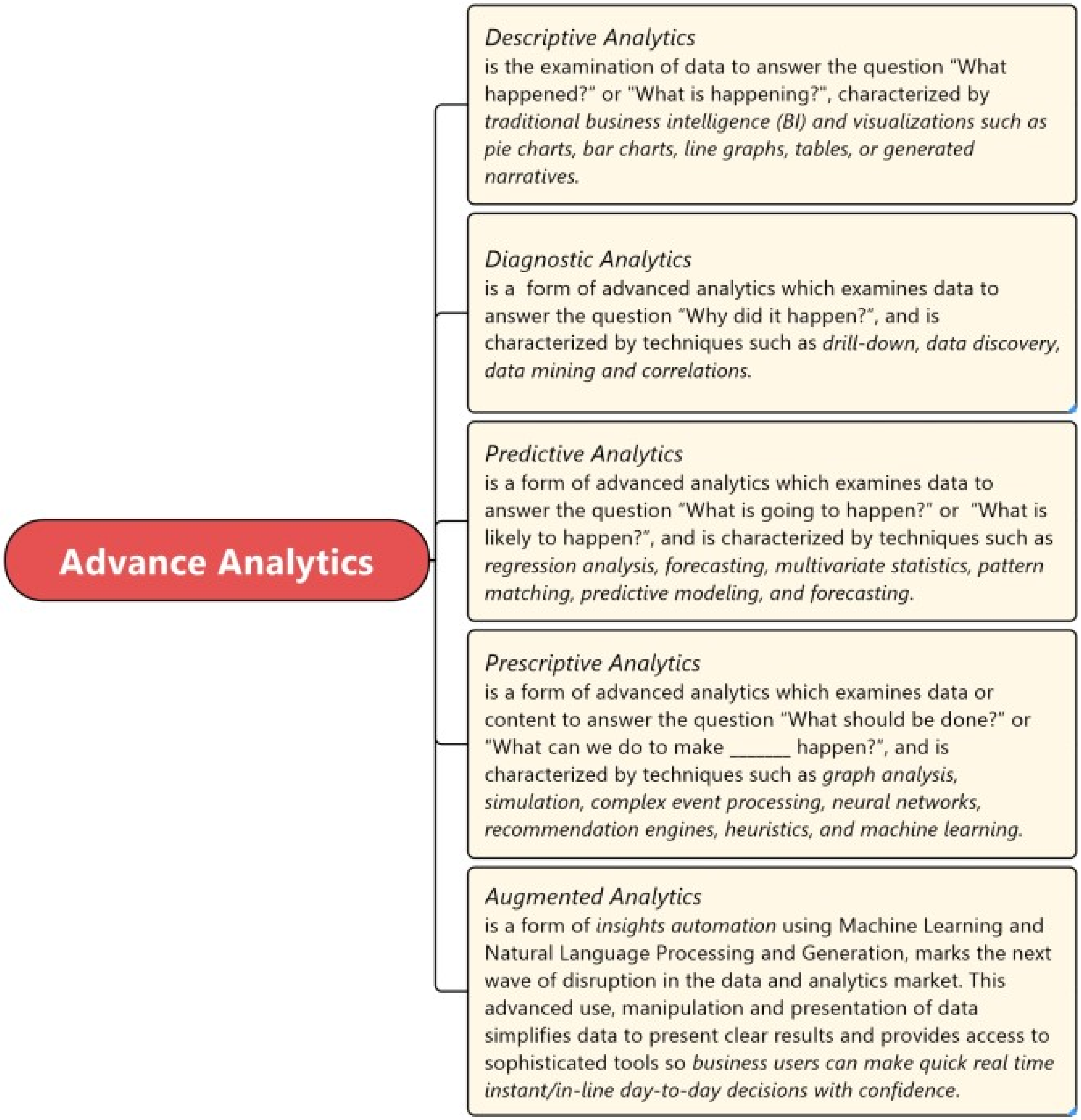

Figure 2. Advanced Analytics

to-empirical approaches. The method presented here facilitates the iterative combination of conceptual-to-empirical and empirical-to-conceptual approaches.

At this point, our research process consists of four distinct steps. We initiated our process through a conceptual-to-empirical approach by defining the primary 5 dimensions of an established data-driven AI/BD/AA operations conceptualization. We then evaluated this method by using it to develop a taxonomy of data-driven AI platform innovation. The resulting taxonomy contains seven dimensions with twenty characteristics.

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AI platform strategy becomes extremely complex as firms consider the dynamic interactions in a multilayered business ecosystem (Teece, 2012). The concept of data-driven AI platform innovation can be widely defined as architecting new platform strategies and business models, making and promoting new platform products and services, developing new platform processes to facilitate platform activities, interacting with platform actors, and designing new platform structures for industry institutions (Yablonsky, 2018ab).

Drawing on existing knowledge in the field of platform research (Evans & Gawer, 2016) we argue that a meta-structuring perspective which aims to serve a data-driven AI landscape, represents an important missing contribution. The objective of this research was to create such a meta-structuring perspective. We applied a taxonomy-enabled methodology to create the consistent structure for an AI platform innovation framework.

In our research we sought a data-driven AI value chain and data-driven AI strategic innovation framework. Namely we were focused on a strategic conceptual multidimensional taxonomy-like maturity framework for AI decision making, with related levels of AI maturity improvement across AI/BD/AA innovation value chains. his approach proves particularly beneficial for the field due to the current lack of systematic empirical analyses coming from within management research.

The concept of “Industry AI platform innovation” entails changes to infrastructure, standards, and rules that enable transactions between multiple firms in industry (Leiblein, 2015). The vision of industry AI platform innovation shows what platform business could look like if enterprises used AI/BD/AA technology innovations to their full potential. Having an industry vision framework gives firms a structure to refine and fill out their thinking about digital business. When their ideas have matured, they can use the framework to explain the concept to the rest of their organization, as well as to their partners.

This paper addresses the following questions:

– What necessary data-driven AI innovation components/concepts are required to support the capabilities of information-based enterprises?
– What are possible data-driven AI value chains?
– Is there a necessary data-driven AI innovation framework?
– How can data be co-organized and managed in a strategic conceptual multidimensional framework for AI decision making, with related levels of AI maturity improvement across AI/BD/AA innovation value chains?

5. Platforms, AI and Analytics

A digital business requires much more than technology (for example, leadership, talent, skills, and new platform business models).

According to one definition (Burton & Basiliere, 2016), a digital platform is a business-driven framework that allows a community of partners, providers, and customers to share and enhance digital processes and capabilities, or to extend them for mutual benefit.

To design a digital business platform, organizations must lead their business to take a business driven, outside-in approach (Evans, Gawer, 2016; Yablonsky, 2018b). Digital business platforms empower flexible and dynamic digital business transactions. Digital platform disruption is a process of impacting multi-sided markets through digital capabilities, channels, and assets. Digital business innovation creates disruptive platform network effects or externalities. To manage digital platform business models and multi-layered platform business ecosystems, companies are building a digital business platform stack to share critical assets. The variance in a company’s digital business performance is a function of differences in their platform’s resources and capabilities in comparison with competing companies.

Contrast with clear inside and outside traditional business, a platform provides a digital business with a foundation where resources can come together in various combinations to create value. Some resources may be inside, permanently owned by the company, some may be shared, and others can come from an outside ecosystem. The combined value comes largely from the dynamic connection of resources and actors, and the potential network effects between them. Platform design facilitates matches among providers and consumers (“users”) or, in other words, the creation or exchange of goods, services, and social currency, so that all participants can capture value. Platforms offer unique opportunities to engage members of a business ecosystem in transactions to exchange value (Blosch & Burton, 2016).

Business platforms are supported by technology platforms in the following seven overlapping areas (Yablonsky, 2018ab):

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1. *Information Systems Platform* (ISP): Supports the front and back office and operations, such as ERP and other core systems.
2. *Customer Experience Platform* (CEP): Contains the main customer-facing components, such as customer and citizen portals, omni-channel commerce, and customer apps.
3. *Data and Analytics Platform* (DAP): Includes information management and analytical capabilities. Data management programs and analytical applications fuel data-driven decision making, while algorithms automate discovery and action.
4. *IoT Platform* (IOTP): Connects physical assets and things (devices) for monitoring, optimization, control, analytics, and monetization. Capabilities include connectivity, analytics, and integration to core and IOT systems. With the emergence of the IoT, these “things” develop through several stages, eventually gaining autonomous purchasing capabilities, and being recognized as “smart things” with their own rights and responsibilities.
5. *Ecosystems Platform* (EP): Supports the creation of, and connection to, external ecosystems, marketplaces, and communities. API management, control, and security are its main elements.
6. *Trust Platform* (TP): A blockchain technology used to foster trust.
7. *Integration Platform* (IP): Supports the integration of all the above platforms in a way that allows maximum flexibility to support business transformation demands.

Technological platform overlap is shown in Figure 3.

Each area of the platform can deliver insight that is descriptive, diagnostic, predictive, and/or prescriptive. Data, analytics, and algorithms are essential to the digital business platform, and should be integrated by integration platform services to permit other platforms to use external and internal data and analytics to execute its functions. To democratize data processing

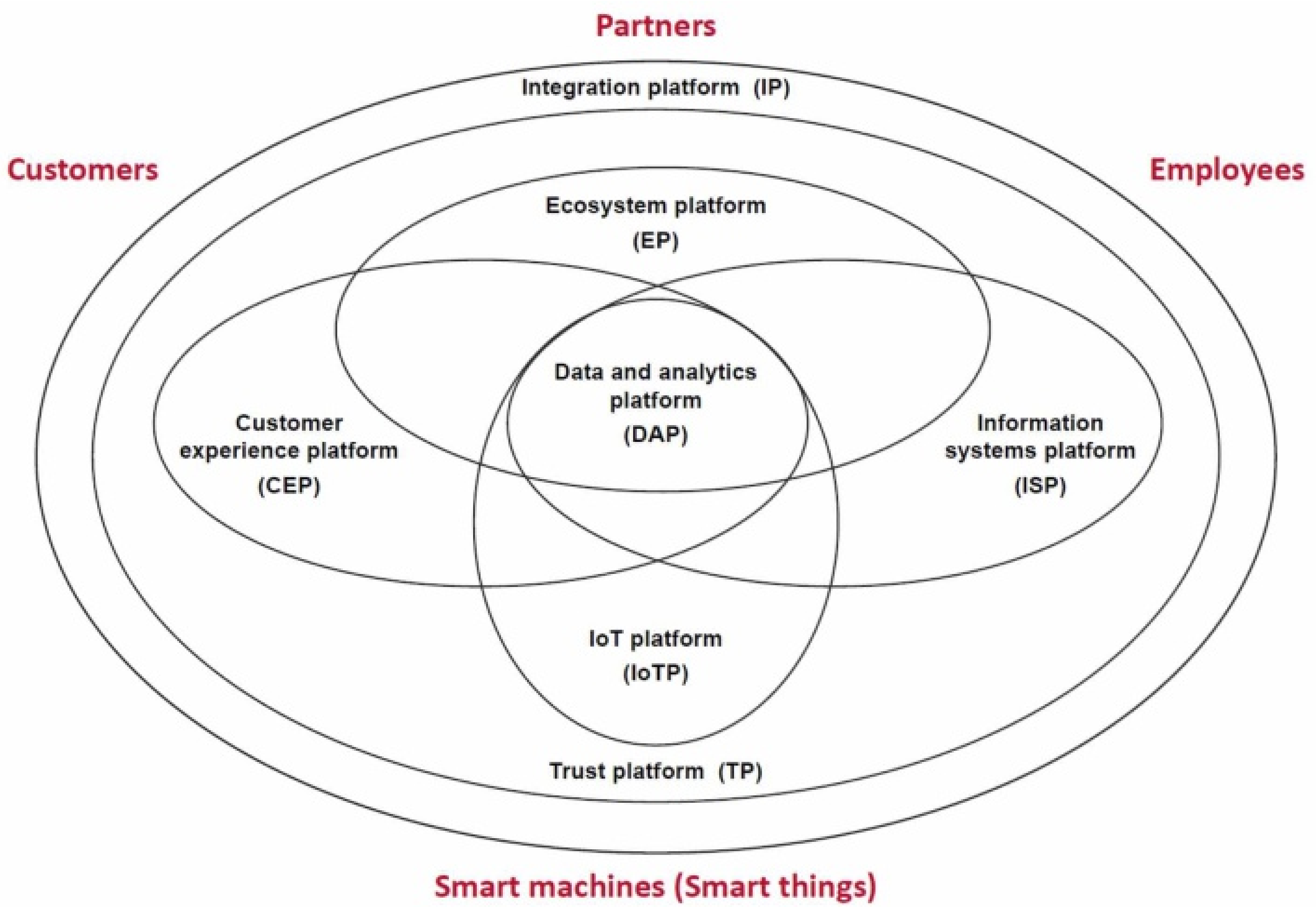

Figure 3. Technological platforms overlapping (Yablonsky, 2018a)

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Platform type	AA processing type	BD resources
D&A (Intelligence) Platform	Decision Models Algorithm and AI Engines	All
IoT Platform (Things)	IoT Analytics	Connected Things (Enterprise) Connected Things (Partner) Connected Things (Customer) Endpoint Computing
Customer Engagement Platform (Customers)	Customer Analytics	Multichannel Commerce Social Networks Customer Portal Customer Apps Customer Facing and Public APIs
Ecosystem Platform (Partners)	Partner and Supplier Analytics	Partner Facing Public APIs API Marketplaces Enterprise Run Ecosystems Industry & Partner-Run Ecosystems
Information Systems Platform (Employees & Suppliers)	Business and Operational Analytics	Core IT Systems Back-Office Systems Supplier Portal Supplier Apps

Table 1. AA/BD in enterprise platform

and visualization, this platform should include self-service features to enable onboarding of increasingly wider enterprise constituencies.

Data and analytics infuse business platforms in all of the above mentioned seven overlapping areas (Table 1).

6. AI/BD/AA Value Chain

New concepts for AI/BD collection, processing, storing, analyzing, handling, visualization, and, most importantly, usage, are emerging with data-driven AI-enabled strategies and business models currently being created around them. Identifying sustainable business models and ecosystems in and across sectors and platforms is an important pressing challenge. In particular, many SMEs that are now involved in highly specific or niche roles will need support to help them align and adapt to new value chain opportunities in the future.

The real value of AI/BD/AA could be determined through the life cycle of AI/BD/AA. We plotted the value of AI/BD/AA over its life cycle as a framework to consider how an organization might determine the value of enterprise data (Liebowitz, 2013). Curry (2016) defines "data value chain" as follows (p.31): "A value chain is made up of a series of subsystems each with inputs, transformation processes, and outputs … As an analytical tool, the value chain can be applied to information flows to understand the value creation of data technology. In a Data Value Chain, information flow is described as a series of steps needed to generate value and useful insights from data." The European Commission sees the data value chain as the "centre of the future knowledge economy, bringing the opportunities of the digital developments to the more traditional sectors (e.g. transport, financial services, health, manufacturing, retail)." (DG Connect 2013)

The focus here is mostly on the BD micro-level value chain (Cavanillas et al., 2016) as defined by Curry

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(2016). BD micro level value chains are used to model the high-level activities that comprise an enterprise.

The proposed AI/BD/AA micro-level value chain identifies the following key high-level AI/BD/AA activities/dimensions:

– *AI Awareness/Big Data Acquisition* is the process of gathering, filtering, and cleaning data before it is put in a data warehouse, data lake, or any other storage solution on which data analysis can be carried out, meaning the availability of BD and access to BD sources. There are a variety of BD types and sources. Value is created by acquiring and combining data from

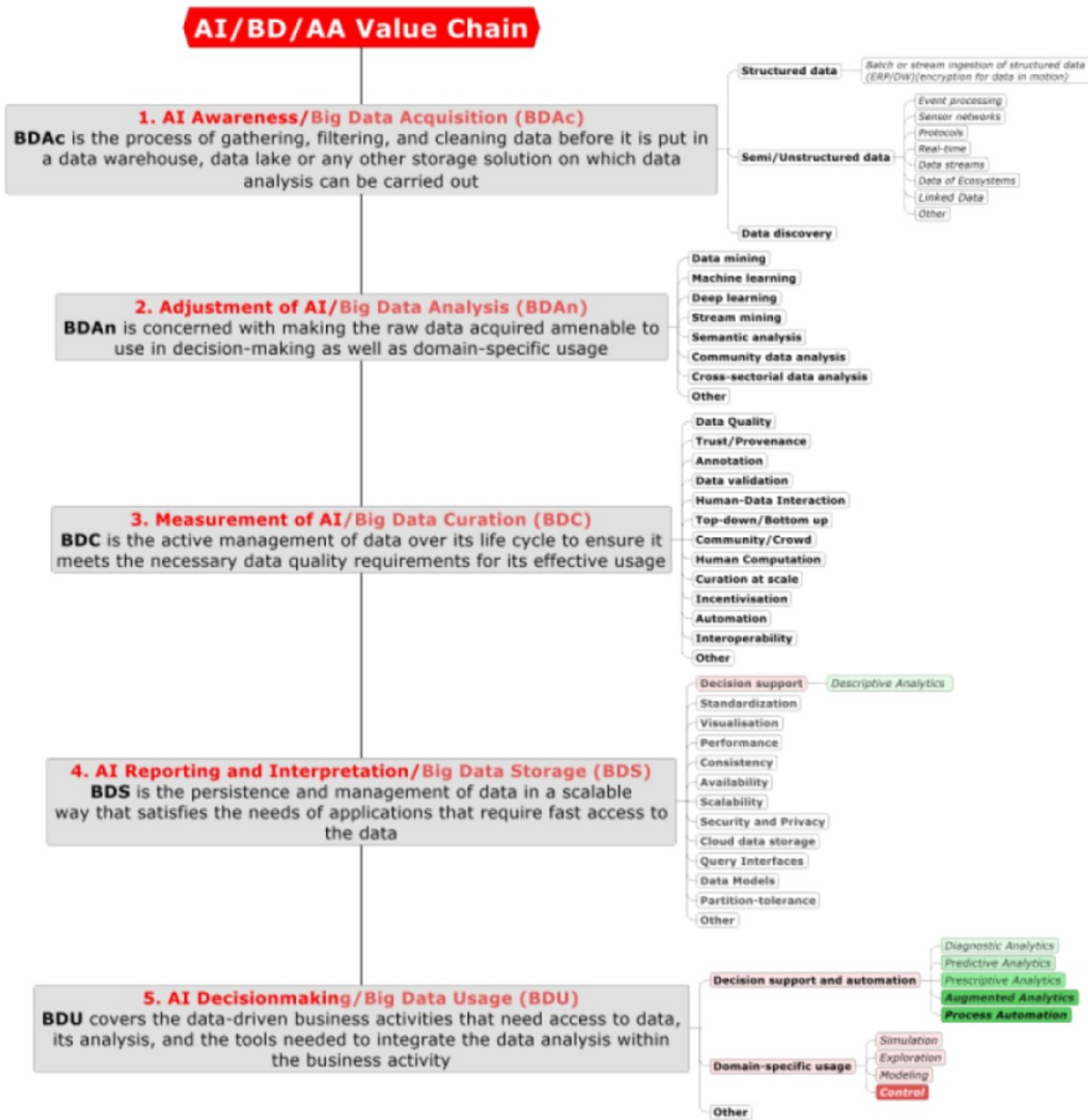

Figure 4. The AI/BD/AA micro-level value chain

different sources. BD pre-processing, validating, and augmenting, as well as ensuring data integrity and accuracy add enterprise value.

– *Measurement of AI/Big Data Curation* is the active management of data over its life cycle to ensure it meets the necessary data quality requirements for its effective usage. It is based on the active management and measurement of AI/BD assets over a life cycle to ensure it meets the necessary BD quality requirements for effective usage.
– *AI Reporting and Interpretation/Big Data Storage* is the persistence and management of data in a scalable way that satisfies the needs of applications that require fast access to data.
– *AI Decision making/Big Data Usage* covers data-driven business activities that need access to data, its analysis, and the tools needed to integrate data analysis within the targeted business activity. It covers the main AI/BD assets used in business decision-making that can improve competitiveness through reduction of costs, increased added value, or any other parameter that can be measured against existing performance criteria.

The AI/BD/AA micro-level value chain, as illustrated in Figure 4, is used to model high-level activities that comprise an enterprise.

Table 2. General multidimensional data-driven AI innovation framework (Adopted from Vesset et al., 2018 and Yablonsky, 2018b)

Stage of AI/BD/AA maturity	Who produces insights?	Who decides and how?	Who acts based on decision?	AA/BD level
1. Human Led	Human analyzers and produces insights using limited technology.	Human decides based on experience and rules.	Human acts or executives.	Partly* 1, 2
2. Human Led, Machine Supported	Human analyzers and produces insights using a portfolio of tools.	Human analyzers based on optimized machine prescriptions.	Human acts or executives.	Partly* 1,2,3,4
3. Machine Led, Human Supported	Machine analyzers and produces insights with human review.	Human decides based on optimized machine prescriptions.	Human acts or executives with machine oversight.	1,2,3**, partly* 4,5
4. Machine Led, Human Governed	Machine analyzers and produces insights without human review.	Machine decides within a framework of human governance.	Machine acts or executes with human oversight.	1,2,3,4**, partly* 5
5. Machine (Machine Led & Machine Governed)	Machine analyzers and produces insights.	Machine decides.	Machine acts or executes.	1,2,3,4,5**

Comments: * - levels of the AI/BD/AA value chain.
** - the specific completeness of the AI/AA/BD implementations are determined by the size of the organization, domain-specific usage and industry.

7. Data-driven AI Innovation Framework

Organizations now employ AI in data-rich aspects of their operations. To help paddle through the exaggerations associated with AI, BD, and AA innovations, we have developed a multidimensional framework. It allows the evaluation of AI innovation's dynamic nature by placing focus on data-driven human-machine relationships, and the application of AI at various levels of data driven automation maturity scope: from tasks and activities to AA processes and platforms, as shown in Table 2.

According to Vesset et al. (2018) we describe the general organizational characteristics at five levels of AI maturity, from a completely ad hoc approach with limited awareness to one in which an AI innovation strategy is integrated into the organization's culture at every level. The identifiable relation with BD/AA maturity is intended to help organizations evaluate current business transformation initiatives and thus identify the steps they need to take BD/AA to the next advanced stage of maturity.

To appreciate the likely growth of AI-based automation, it's important to evaluate the interaction of humans and machines across these five levels, and to understand who analyzes the data, who decides based on the results of the analysis, and who acts based on the decision.

Key stakeholders of AI-based transformation initiatives include executives, IT leadership, line-of-business managers, employees, partners, and suppliers.

8. Conclusion

Organizations worldwide must evaluate their vision and transform their people, processes, technology, and data readiness in order to unleash the power of AI and thrive in the digital era (Jyoti et al., 2019). To help with strategic innovation planning and investment decisions related to AI-based automation, we have developed a multidimensional data-driven AI innovation framework. This allows for evaluating the human-machine relationship supported by BD/AA platforms and their application at different levels of automation scope across any industry and functional use case.

The paper adds the following results to the current knowledge based about AI innovation.

1. An AI/BD/AA micro-level value chain was created (Figure 4).

2. A multidimensional BD-driven AI enterprise maturity framework was created through adoption from an earlier AI automation framework (Vesset et al., 2018) and AI/BD/AA (decision-making) value framework. It was shown that a multidimensional data-driven AI enterprise innovation framework has five levels of maturity:

– Human Led/Initial Analytics;
– Human Led, Machine Supported/Advanced Analytics I;
– Machine Led, Human Supported/Advanced Analytics II;
– Machine Led, Human Governed/Advanced Analytics III;
– Machine Controlled/Advanced Analytics IV.

3. Levels of AA maturity correspond to the following levels of the AI/BD/AA value chain:

– Initial Analytics: partly* 1, 2;
– Advanced Analytics I: partly* 1,2,3,4;
– Advanced Analytics II: 1,2,3**, partly* 4,5;
– Advanced Analytics III: 1,2,3,4**, partly* 5;
– Advanced Analytics IV: 1,2,3,4,5**.

4. For each maturity level, BD-driven AI innovation value chains as end-to-end processes related to BD-driven AI enterprises, ecosystems, and components were created and tested.

We believe our framework can be put to pragmatic use to identify industry and functional use cases where current AI can automate specific tasks, activities, or processes. It can also be used to better communicate to clients the value of AI capabilities through the lens of changing human-machine interactions and in the context of legal, ethical, and societal norms.

While business, IT, and analytics leaders need to recognize how AI is different from previous cycles of IT-based innovation, today's leaders need to embrace AI and become involved in contributing to the discussion of AI ethics. Not only because a few can co-opt AI for nefarious purposes, but also because in the absence of human-driven ethical norms, commercial self-interest and technological evolution that incorporates emotional AI will likely lead to negative unintended consequences for commercial organizations and society at large. With the broad participation of a diverse, global population in the conversation about the future of AI, we are more likely to advance through levels of AI-based automation while accumulating benefits for the largest possible population of humans.

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A clear and precise description and structuring of information in the BD-driven AI enterprise maturity framework are prerequisites for a common understanding of BD-driven AI innovation. We have provided for the first time a BD-driven AI innovation taxonomy framework with related BD-driven AI/AA innovation value chains. The new dimensions of BD-driven AI innovation maturity and value chain frameworks allow for repeating the analysis with different types of business components (technology, leadership, talent and skills, ecosystem, and new data-driven business models). The emergence of a new wave of data from sources, such as the Internet of Things (IoT), Sensor Networks, Open Data on the Web, data from mobile applications, and social network data, together with the natural growth of datasets inside organizations, creates new ways to reuse and extract value from BD assets through BD-driven AI innovation.

This paper looked at emerging issues that are becoming important and will require action in the nearest future. The evaluation logic presents a tool that managers, company owners, and investors can use for identifying and managing a multidimensional BD-driven AI enterprise innovation framework. This will allow them to interact with different groups of contributors in order to receive new ideas, feedback, and solutions, and later evaluate the effectiveness of AI innovation, and decision-making regarding the value offering design of BD-driven AI products and services. Since the BD-driven AI innovation taxonomy framework has been additionally designed for evaluating the innovation potential of BD-driven AI business platforms, it should prove to be particularly convenient for analyzing several types of data-driven AI business models. In our current digital age, when intangible assets are becoming more crucial for a firm's performance, new BD-driven AI value dimensions can support business leaders and their management teams to provide more effective measurement and management of their intellectual and informational capital assets.

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Leveraging AI-based Decision Support for Opportunity Analysis

Wolfgang Groher, Friedrich-Wilhelm Rademacher & André Csillaghy

"What all of us have to do is to make sure we are using AI in a way that is for the benefit of humanity, not to the detriment of humanity."

Tim Cook
CEO, Apple Inc.

The dynamics and speed of change in corporate environments have increased. At the front-end of innovation, firms are challenged to evaluate growing amounts of information within shorter time frames in order to stay competitive. Either they spend significant time on structured data analysis, at the risk of delayed market launch, or they follow their intuition, at the risk of not meeting market trends. Both scenarios constitute a significant risk for a firm's continued existence. Motivated by this, a conceptual model is presented in this paper that aims at remediating these risks. Grounded on design science methodology, it concentrates on previous assessments of innovation search fields. These innovation search fields assist in environmental scanning and lay the foundation for deciding which opportunities to pursue. The model applies a novel AI-based approach, which draws on natural language processing and information retrieval. To provide decision support, the approach includes market-, technology-, and firm-related criteria. This allows us to replace intuitive decision-making by fact-based considerations. In addition, an often-iterative approach for environmental scanning is replaced by a more straightforward process. Early testing of the conceptual model has shown results of increased quality and speed of decision-making. Further testing and feedback is still required to enhance and calibrate the AI-functionality. Applied in business environments, the approach can contribute to remediate fuzziness in early front-end activities, thus helping direct innovation managers to "do the right things".

Introduction

The dynamics and speed of change in corporate environments have increased. Firms today find themselves confronted with volatility, uncertainty, complexity, and ambiguity, classified under the title *VUCA*. This development has added to the difficulty of making right decisions. Firms are now challenged to evaluate growing amounts of information within a shorter period of time in order to stay competitive. Applied to innovation, decisions on which opportunities a firm wants to pursue must be taken fast (Gassmann & Schweitzer, 2014).

In this context, the early front-end activities of an innovation process draw our attention. Identifying opportunities and risks at an early stage, along with classifying, evaluating and interpreting them to make timely and well-founded decisions, are considered as key tasks of strategic innovation management (Gerpott, 2013). Thus, the innovation process does not start with gathering and developing ideas, but rather with defining search fields for localizing where to innovate. A strategic innovation search field (ISF) is described by trends affecting the firm, by technologies, or by customer needs, and serves as a starting point for idea generation (Durst & Durst, 2016). Based on this understanding, assessing ISFs is a combined task of opportunity identification and opportunity analysis during early stages of the innovation process, as defined by Koen et al. (2002). It concentrates on assessing whether or not the pursuit of an opportunity makes sense by consulting technological and market-related criteria, along with the business perspective (Cooper, 1996). Without defining ISFs, ideas are often not in line with market needs or actual requirements. In consequence, plenty of ideas are existent, but very few or none advance into realization (Durst & Durst, 2016). This points out the high relevance of assessing ISFs. However, in business practice this relevance is not yet reflected, and the reasons behind it need to be analyzed.

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Established process models for innovation management, such as the frequently cited stage-gate model of Cooper, commonly start off with idea generation. Upstream scanning of a firm's environment is partly recognized or presumed as part of a strategic definition. The amount of data to be consolidated, processed, analyzed, and interpreted rises with increased dynamics and complexity of a firm's environment. Considering the exponential growth rate of data, this calls for tailored IT-support. According to Spath et al. (2010), information provision is the key determinant in the innovation process. In business practices, Internet-based search engines are broadly used in this context, but receive critical feedback. This is due to the significant time-effort involved, low quality of search results, insufficient support in limiting the search, as well as poor presentation of results. Owing to these obstacles, firms spend up to 10 hours or more per week simply retrieving information. These findings illustrate that there is currently no adequate IT-support for these activities. The strength of IT lies in supporting well-structured processes. Little-structured, knowledge-intensive processes, in contrast, call for tailored AI-support.

In this context we refer to AI as "tools and technologies than can be combined in diverse ways to *sense, cognize* and *perform* with the ability to learn from experience and adapt over time" (Akerkar 2019: 3). Within the broad field of AI, the ability to *cognize* natural language is especially relevant for assessing ISFs. Natural language processing has also contributed to developing the area of information retrieval, which is fueled by the currently exponential growth rate of text data on the World Wide Web. Content and link analysis of web pages, text mining, extraction of specified information from documents, automatic classification, and personalized agents hunting for information of interest to a specific individual are some of the active areas associated with information retrieval today (Akerkar, 2019). With the available information far exceeding the limits of human imagination, the named areas are of high relevance for assessing ISFs.

The situation described above leads to our central research questions:

- *How can innovation search fields be evaluated in a way that stimulates the quality and efficiency of the innovation process?*
- *How can selected AI-functionality be applied to identify the innovation search field with the best fit to a particular firm?*

In this context, quality refers to selecting the innovation search field with the best fit to the company´s innovation strategy, while efficiency considers the time-effort spent for evaluating a search field.

The purpose of this paper is to develop a conceptual model to assess ISFs, grounded on the methodology of design science research (Hevner et al., 2004).

Current Understanding

Our research looks at the innovation process from an information management and processing perspective. This is in line with Brentani and Reid (2012), who state that the process for developing new market offerings in firms, at its core, is an information processing activity.

Through information processing activities, information about markets, technologies, and competitors is translated into designing new market offerings. Cooper (1996) refers specifically to information acquisition, and proficiency in handling it during the early innovation process as key to new product success. Brentani and Reid (2012) highlight the importance of quality and speed of information flow, each having an important, but different impact on a firm's performance. According to them, quality of information impacts the specific focus of the innovation process. This ensures the creation of superior products for the marketplace, leads to product or service advantage, and has a positive impact on the firm's overall financial performance. At the same time, speedy information flow can result in significant first mover advantage. This has been shown to positively affect the ability of a firm to achieve competitive edge. Thus, quality of information flow leads to product advantage, while speed is important for achieving competitive advantage.

Considering this, it is surprising that so far little research has been dedicated to this topic. This is reflected in the currently available methods and IT-tools for opportunity analysis and evaluation in the early phase of innovation, which we have analyzed. Findings from this literature can be summarized as follows:

Regarding methods, three types can be distinguished. The first type covers methods for customer research and the involvement of customers, especially lead users. The

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second type refers to the topic of idea management, and the third one to process methods, such as design thinking. All of these methods presume that the appropriate ISF has already been defined. They each facilitate a different approach to generating, enhancing, and revising ideas with the aim of identifying the right one for follow up.

IT-tools for the innovation process, referred to with the term *computer aided innovation* (CAI), can be assigned to four categories, reflecting the potential benefits (Hüsig & Kohn, 2009):

- Efficiency enhancing
- Effectiveness enhancing
- Competence enhancing
- Creativity enhancing

Functions which automate the generation of reports, documentation, or analysis increase the efficiency of the user and are assigned to the category of "efficiency enhancing". Tools with the potential to enhance decision making by improving quality, accuracy, and timeliness of the information provided describe the category "effectiveness enhancing". This category also includes visualizing information. So far, ISF analysis and evaluation is not assisted by these first two categories.

The category "competence enhancing" addresses the fact that the implemented knowledge of many CAI-supported methods enables less proficient users to apply more sophisticated methodology with less effort. Examples of this are the integration of customers into the early innovation phase, or co-operative innovation processes between several involved parties. Such tools presume that the ISF has already been determined and that required information is readily available. In that respect, this category comes close to the first category, "efficiency enhancing". The last category, "creativity enhancing", comprises all IT-supported creativity methods. Again, this assumes that the appropriate ISF has been identified in advance.

The review of existing IT-tools makes apparent that the assessment of ISFs is so far not adequately supported. Summarizing the findings by analyzing existing process models, methods, and IT tools for opportunity analysis and evaluation, leads to the conclusion that current research on innovation processes mainly focuses on defining *how to win*, whereas understanding *where to play* remains a critical weakness.

Theoretical Framework and Approach

Compared to the later stages, the front-end of innovation is characterized by a high degree of uncertainty concerning market and technology development. This is associated with the following key questions:

- Which social, political, and economic trends are relevant for the core business, or can be leveraged to develop new market offerings?

- Which technologies, or novel combinations of technologies, can stimulate customers and increase market demand?

Our approach is grounded on the view of Brentani and Reid (2012) that considers the innovation process as an information processing activity. Our model draws on research by Koen et al. (2001), which shows that strategy alignment is crucial for innovation success. According to this, we include the novelty of an ISF itself into our model. This enables us to assess its level of development and thereby match it with the timing strategy of a firm for market launch. Finally, we refer to the innovation architecture of Augsten et al. (2017), who view innovation search fields from a market and technology perspective, describing their mutual dependencies. Connected to this, we include existing competences within the firm into our model.

Consolidating these different research streams, we have developed a novel model, denoted *Front-End Engine* (FEE), which assists in evaluating ISFs (Figure 1). The applied approach is guided by the design science methodology (Hevner et al., 2004), which is recognized in information systems research. Hevner et al. note that, "In the design-science paradigm, knowledge and understanding of a problem domain and its solution are achieved in the building and application of the designed artifact" (2004: 75). The artifact resulting from our work represents a conceptual model for assessing ISFs, which is discussed in the following section.

Conceptual Model Design

Model structure
The backbone of our model is built on selected AI-technology, which is capable of performing the functionality of "cognizing" for natural language (as per definition of AI above on pg. 30). To be precise, we apply

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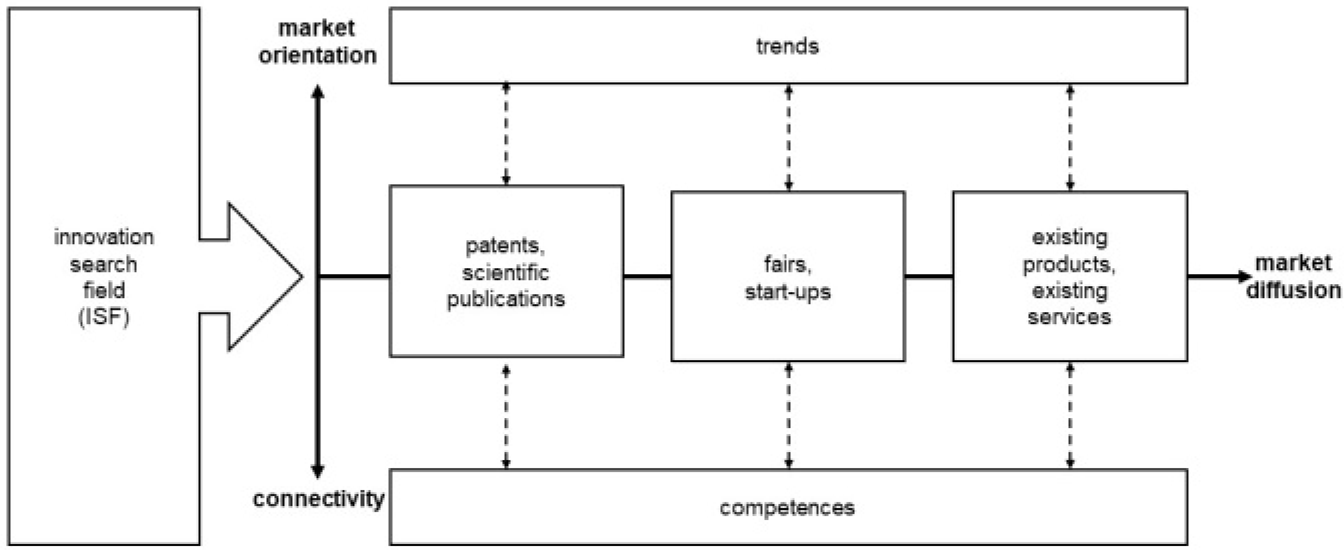

Figure 1. Structure of the Front-End Engine (FEE) model

information retrieval algorithms that capture semantic similarity between documents. After consulting the research of Thorleuchter and van den Poel (2013), we chose latent semantic indexing to proof the feasibility of the approach, based on knowledge that performance can be improved by using later approaches. Inside the model, documents are assigned to categories. Applying mutual reference of selected document categories, three different dimensions were analyzed.

The first dimension considers the time aspect by indicating **market maturity** of an ISF. The categories of patents, scientific publications, fairs, start-ups, and existing products and services each serve as a reference against which the ISF is compared. In the case that matches with patents or scientific publications dominate, an ISF is referred to as *pre-market*. At a later state, when relevance at industry and trade fairs or start-ups are detected, the ISF is rated as market entry. Finally, in the case of matches with existing products or services, it is characterized as *market domain*.

The second dimension captures the fit of an ISF with competencies and technologies that are available within the firm. We refer to this relation as **connectivity**. To allow for this, the model requires that competencies and technological assets of the firm are identified and described before evaluation starts.

Finally, the third dimension, **market orientation**, captures the conformity of an ISF with trends. Both connectivity and *market orientation* presume that market maturity has been determined, as they build upon their results. Those documents in each of the categories of patents, scientific publications, fairs, start-ups, and existing products and services, which show the best match with an ISF, form the basis for the subsequent comparison against competencies, as well as against trends.

Evaluation process

The FEE-objective is to substantially reduce the manual effort for evaluating an opportunity. Simultaneously high relevance and completeness of consulted documents need to be ensured.

As input for the evaluation process may serve multiple ISFs, which are generally the outcome of a moderated workshop. An ISF is typically described in one sentence and then enriched with associated functions and attributes. As a first step, the data base for each category is created. This is performed by means of vertical crawling using predefined entry points from the World Wide Web, as well as from firm-internal data sources. Each data source is assigned to one of the categories: patents, scientific journals, fairs, startups, existing products and services, or trends. In the following step, a semantic comparison of an ISF against the documents within each of the categories is performed. Subsequently, documents are ranked and shortlisted inside each category, according to the degree of matching. These shortlists are used to measure the characteristics for each of the three dimensions of the model. During the final step, results are consolidated

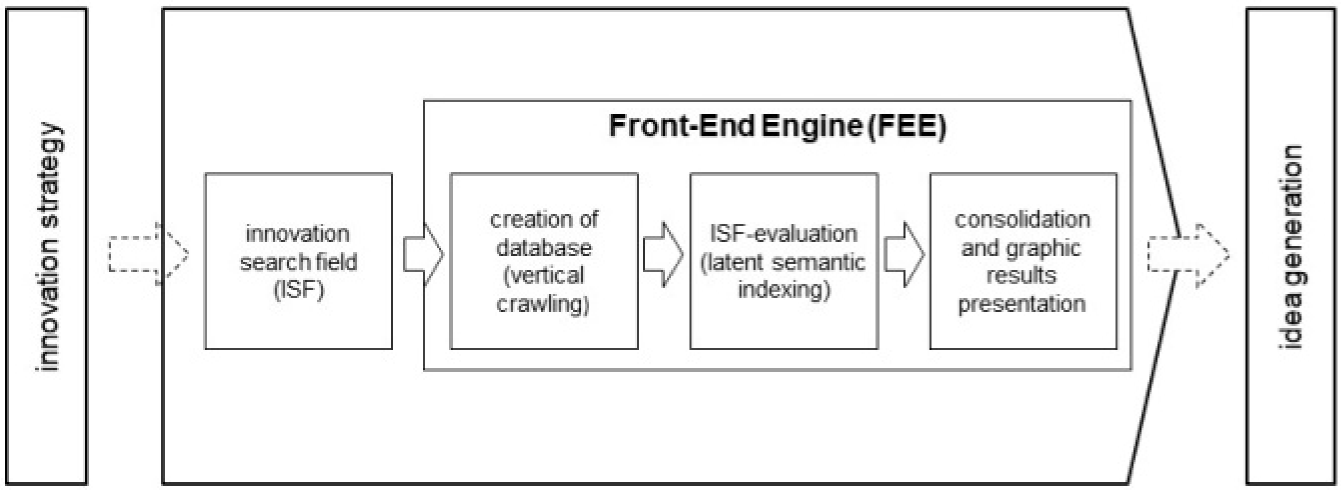

Figure 2. Process of ISF-evaluation

into a graphic results presentation. The corresponding process is shown in Figure 2.

Market maturity is captured on a nominal scale, differentiating the values *pre-market, market entry,* and *market domain*. Each value is associated with a characteristic search result profile, derived across all associated categories, except for trends, which are required in a later step. Market orientation and firm compatibility are both calculated as percentage values.

The chosen indicators enable a 3-dimensional interpretation of each ISF regarding conformance with timing strategy, firm-specific competences, and market orientation.

The novel aspect of this approach is that an often-iterative strategy for ISF-evaluation, if at all existent, is replaced by a more straightforward process. This is enabled by combining vertical crawling with semantic-based information retrieval. Specifically, latent semantic indexing (LSI) converts documents into a vector space, allowing for subsequent machine processing. By applying dimensionality reduction, the main topics covered in the documents can be grouped and extracted. The similarity between an ISF and identified topics can be determined based on distance measurement in the vector space. Search results are then grouped and listed in descending order. Finally, results are consolidated into a graphical results presentation. On that basis, multiple ISFs can be compared with a firm's particular innovation strategy to select the most appropriate one.

Findings and results

The FEE-approach was first elaborated in a research project (in the period from Nov. 2017 to Dec. 2018), sponsored by Innosuisse, the Swiss innovation agency. Project-internal tests and human-machine comparisons with industry users were successfully completed in Aug and Sep 2018. In a user lab setting, the FEE competed with two industry experts during the process step "creation of database" (Figure 2). The competition's scope was limited to the category of patents. The associated task was to identify documents online and select those with relevance for a chosen ISF. In this setting, and for two chosen ISFs, the test showed that the FEE can significantly reduce the required manual time effort. To reliably specify the FEE improvements, further testing needs to be conducted.

Furthermore, tests so far have revealed, that the original results list in each category, automatically created by the FEE, may need to be adjusted. This is because users may have various different perspectives in looking at an ISF. An industrial ISF can serve as an example to illustrate this. One user may restrict patent results exclusively to industrial applications, whereas another user might be interested in medical applications as well. Therefore, the FEE architecture adapts to this variance. It now allows leveraging the expert knowledge of the user, by offering the possibility of navigating within the results lists, and selecting a specific focus area. Based on the feedback of test users, this adjustment contributed to improving the quality of search results in a way that aligned to individual needs. Referring to the definition of AI in the introductory chapter, this added functionality provides the FEE with the ability to learn more specifically from user feedback, and thereby adapt to individual needs.

Another finding is that for technical documents, such as patents, the quality of search result tends to be higher than for colloquial texts, such as trends. The reason for this is that texts on technical patent topics consist of a higher chance of frequent co-occurring technical terms. As a result, a specific technical term occurs more frequently together with a paired term than expected (Thorleuchter & van den Poel, 2013). Both characteristics, the occurrence of characteristic terms and the frequent co-occurrences, enable researchers to identify more descriptive topics than can be realized by using only colloquial texts.

Limitations
Based on findings of our research so far, the developed conceptual model has proven to be capable of supporting the assessment of ISFs. Following a design science paradigm, the FEE currently requires further testing of all process steps in order to refine the conceptual model. Especially use cases from a broad range of industries should be conducted and reflected upon to enhance and calibrate the applied algorithms.

Practical relevance
The described results qualify the conceptual model as being applicable for practical use cases in the near future. Small firms especially can benefit, as little prior knowledge on how to assess ISFs is required, and the previous manual efforts required for environmental scanning are significantly reduced. As the FEE can adapt to user feedback, it has a positive impact on quality and speed of decision-making in the early front-end. The full benefit of the FEE can be reached in assessing and comparing multiple ISFs for a firm. In this scenario, intuitive decision-making can be replaced, or at least informed and supplemented by fact-based considerations. Hence, the described approach contributes to remediate fuzziness in firms' early front-end activities with a novel AI-based decision support, which serves to direct innovation managers to *do the right things*.

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Leveraging AI-based Decision Support for Opportunity Analysis

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Spath, Dieter, Heubach, Daniel, Ardillo, Antonio 2010. Unterstützung des Innovationsmanagements durch IT-Systeme. Bedarf und Anwendungen in der Praxis. In Josephine Hofmann (Ed.): IT-basiertes Innovationsmanagement. Open Evaluation, Crowdsourcing in Dienstleistungsunternehmen, Kundeninteraktion im Maschinen- und Anlagenbau, Plattformen für innerbetriebliches Innovationsmanagement, Kollaboratives Trendscouting, Innovationsnetzwerke in der Textilindustrie. Heidelberg: dpunkt-Verl. (HMD, 273): 6–20.

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The 3S Process: A Framework for Teaching AI Strategy in Business Education

Navneet Bhalla

> *"I have been impressed with the urgency of doing. Knowing is not enough; we must apply. Being willing is not enough; we must do."*
>
> Leonardo da Vinci

A gap has emerged in teaching artificial intelligence (AI) in business education, where a style of curriculum based on strategy is missing. This article presents a new framework, the 3S Process, as a method for teaching leaders how to strategically adopt AI within their organizations. At a high-level, the 3S Process consists of three stages (Story, Strategy, and Solution), which are described in detail in the article. Stage 1: Story in the process is inspired by the Harvard Case Method to provide context for a problem. Stage 2: Strategy uses Design Thinking to produce candidate solutions. The substage of Empathy in Design Thinking plays a crucial role to reduce bias in designing AI. Virtualization technology is a tool for students to experience hands-on learning in prototype development. Stage 3: Solution is where students advocate for their conceptual AI solution in the context of the case study. AI is a type of complex system; therefore, students should consider feedback loops and the potential for unintended biases to enter a deployed solution. The presentation of the 3S Process in this article is conceptual. Further empirical studies, including evaluations of the 3S Process in classroom settings, will be considered in the future.

Introduction

There is a growing interest in teaching artificial intelligence (AI) and machine learning (ML) in business schools around the world (S.-W., 2018). However, an acclaimed approach to teaching AI (Figure 1) in the context of business, especially in terms of entrepreneurship, remains elusive.

Based on the author's experience working with numerous corporations of varying size, current Master of Business Administration (MBA) programs that include AI can be grouped according to three styles of curricula:

1. General Technology (providing a broad overview of AI techniques),

2. Specialized Technology (in-depth instructing of AI algorithms, data science, and optimization), and,

3. Decision Making (using AI/ML to inform the decision-making process).

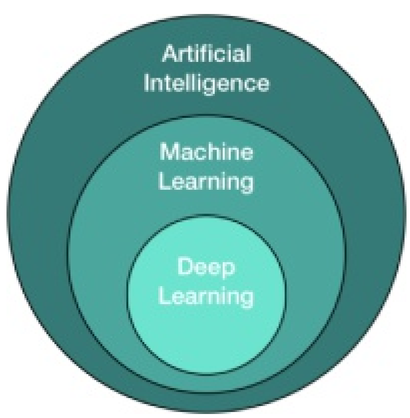

Figure 1. AI Venn Diagram.

A fourth style based on strategy is missing from approaches to business education. How should leaders be educated in strategically adopting AI/ML in their organizations, and within their products and services (Stachowicz-Stanusch & Wolfgang, 2019)? Watkins writes, "A business strategy is a set of guiding principles that, when communicated and adopted in the organization, generates a desired pattern of decision making" (2007). To glean the most from AI, it should be adopted strategically in organizations to solve business problems (and not just be another piece of technology), in order to garner exponential benefits overtime. The goal of this article is to provide a significant step towards addressing these problems by providing a new framework for a strategy-based approach, referred to as the *3S Process* (Bhalla, 2019).

At a high-level, the 3S Process consists of *story, strategy,* and *solution* (Figure 2). The 3S Process is inspired by the Harvard Case Method (Rebeiz, 2011) and the approach of Design Thinking (Brown, 2009). The case method provides the context for an example problem, and Design Thinking provides a strategic process for developing a considered solution. Design Thinking has been shown as an effective tool in business education, and in particular, in entrepreneurship education (Brown & Katz, 2011).

Methodology

One of the aims of this work is to understand how to develop AI/ML in order to innovate products and services, and ultimately grow organizations. The 3S Process is the result of codifying the author's experience in teaching technical, graduate-level courses in AI and ML (in computer science departments at universities), and the author's experience in consulting with business and technical leaders (C-suite executives) in small to medium enterprises (SMEs). It was observed that although many organizations *wanted to adopt AI*, it was not clear to them *how to adopt AI*. This observation fits with a survey of thousands of executives about how their companies use AI, and the data shows that only 8% of firms engage in core practices to support widespread adoption of AI (Fountaine et al., 2019). The author's objective was to devise a step-by-step process, which was based on commonly known educational techniques and strategic practices, to enable delivery of an approachable framework.

Framework: The 3S Process

Stage 1: Story is based on the Harvard Case Method. Broadly, there are four types of case situations (Ellet, 2007):

• Problems,
• Decisions,
• Evaluations, and,
• Rules.

For the purposes of the 3S Process, only case types of problems are considered (since other case types are not applicable). The intention of using a case method is to set the context of the problem to be solved. Harvard Business School (HBS) is in the midst of creating their own set of AI cases (Kenny, 2018). It will be interesting to see how HBS frames their AI cases (as well as other business schools that use case methods), and if/how the AI cases extend beyond typical problems.

Figure 2. 3S Process

Stage 2: Strategy is inspired by the approach of Design Thinking. Design Thinking was originally conceptualized for the design of physical products (Brown, 2008). Over time, Design Thinking has been applied not just to the field of industrial design, but to several others also, including the design of businesses themselves (Martin, 2009). Since its inception, there have been many variations and extensions to Design Thinking, each suited to a specific type of problem (Tschimmel, 2012). In this work, the original description of Design Thinking is used, which has five phases:

• Empathy,
• Define,
• Ideate,
• Prototype, and,
• Test.

Stage 3: Solution is the result of the Design Thinking approach within the context of a specific story. It is important to note that arriving at a solution is in actuality building an AI system (Meadows, 2008), which is integrated into another product or service. The performance, or even the behaviour itself, of the system may change with use, for example, the collection and variation of data over time.

To navigate through the framework, the 3S Process is subdivided into nine substages (Figure 3). The graph, with substages as nodes and with transitions from one substage to another as directed edges, represents common paths through the 3S Process. The connectivity (traversals through the graph) should be adapted to the problem to be solved. Table 1 provides a high-level description for each of the nine substages.

Stage 1: Story – Scenario
A case study, provided by educators to students, establishes the context of the problem space. Equally as important, the case study is the basis for discussion between students and educators.

Stage 1: Story – Research
Conduct research to better understand the problem space. What are the important details regarding the problem? What aspects of the problem space can be ignored? Narrow the scope of the problem, focus.

Stage 2: Strategy – Empathy
Understand the potential biases, for example, training data, particular algorithms, and potential users. Examine the problem from multiple opposing viewpoints (Martin, 2009). What are the privacy and security concerns?

Stage 2: Strategy – Define
What exactly is the problem to be solved? Define a set of quantitative/qualitative metrics to measure the success of a solution for solving the problem.

Stage 2: Strategy – Ideate
Brainstorm several candidate solutions. What are the

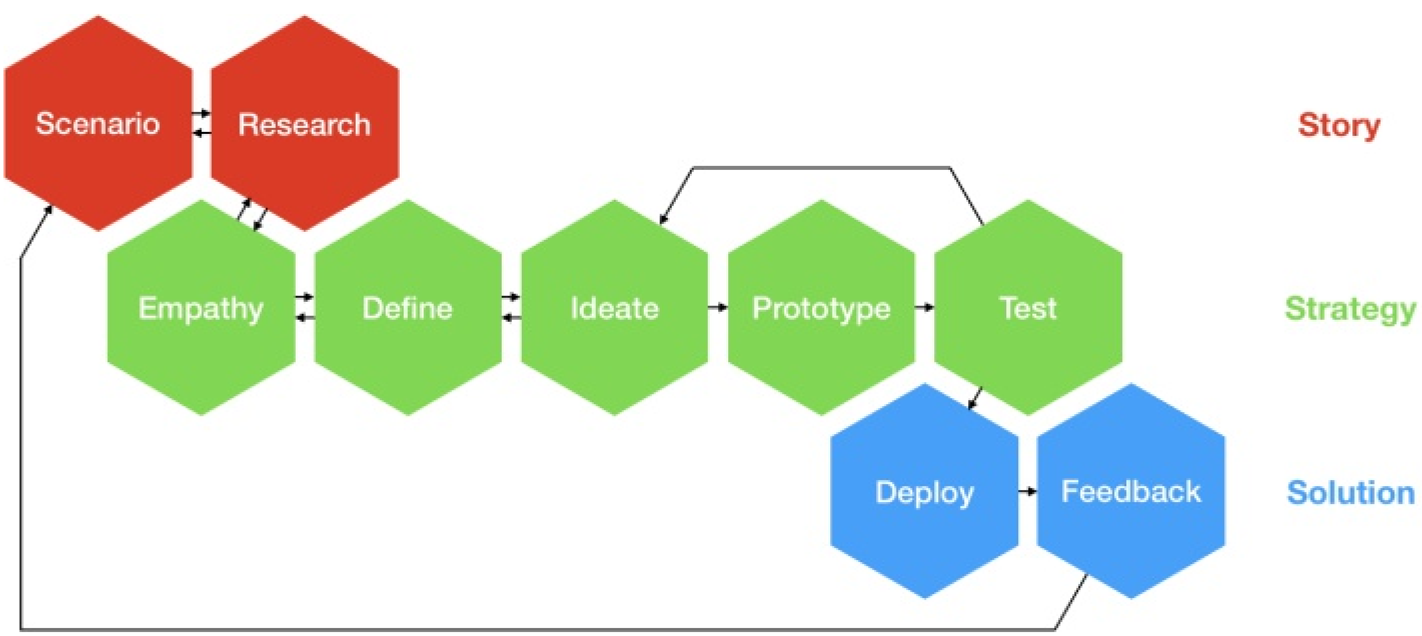

Figure 3. Graph of the nine substages of the 3S Process.

Table 1. Description of the nine substages of the 3S Process

Stage	*Substage*	*Description*
Story	Scenario	Understand the context of the general problem space.
	Research	Uncover the details and nuances of the problem space.
Strategy	Empathy	Anticipate and properly address biases.
	Define	Articulate the specific problem to be solved.
	Ideate	Brainstorm approaches to solve the problem.
	Prototype	Design candidate solutions.
	Test	Run trials and measure the results.
Solution	Deploy	Release the selected solution.
	Feedback	Process the information returning to the system.

available resources (for example, data and infrastructure)? If a full, candidate solution cannot be implemented as a prototype in a classroom setting, can a subset of the problem be addressed?

Stage 2: Strategy – Prototype
Ideally, a prototype should be designed quickly and implemented efficiently. Fast prototyping leads to the possibility for a greater number of iterations of the Ideate-Prototype-Test cycle.

Stage 2: Strategy – Test
Perform quantitative and qualitative measurements to evaluate the level of success of the candidate solution. If possible, compare the candidate solution to other solutions that were tested previously, and compare to other solutions in the market (or discussed in the case study).

Stage 3: Solution – Deploy
In the context of the case study, make persuasive arguments for the reasoning behind the selected solution. How would the adoption of the selected solution be marketed externally of the organization, or sold internally within the organization? How would the performance of the selected AI system be monitored over time?

Stage 3: Solution – Feedback
How will the transition from training data to continuous data be managed? What derived data can be realized?

Important Features of the Framework

There are three important features of this framework. First, the step of *Empathy* in Design Thinking is used to help address ethical issues when developing and deploying an AI solution. Second, a software stack using virtualization technology is discussed for how AI prototypes can be developed in practice. Third, complex systems are examined, since even a simple set of rules and algorithms can lead to unpredictable results. Complexity is an important, but often ignored aspect of AI, which is ultimately the pursuit of designing a complex system that displays agency.

Empathy
One of the greatest aspects to Design Thinking is in the phase *Empathy*. The ability for a designer to empathize with the end customer (and other stakeholders in the design-production-consumption process) for a product in the context of its environment leads to more human-centric and sustainable solutions. In the 3S Process, the designer is to be empathetic to reduce bias in the end solutions, be it for human-to-machine or machine-to-machine interfaces.

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For example, Microsoft Inc. released Tay, a chat-bot, in March 2016 (Johnston, 2017). Tay used Twitter as the interface to converse with humans. By people posting offensive Tweets to Tay, the chat-bot quickly learned and then started to post its own inflammatory Tweets. Tay was taken down after only 16 hours of public operation. By employing the stage of Empathy to this research project, the developers could have anticipated the possibility of such an outcome and could have added measures to their AI chat-bot to mitigate bias.

Virtualization

While *Stage 1: Story,* with the case method at its core, is purely an intellectual exercise, *Stage 2: Strategy* offers the opportunity for learning through practical examples and exercises with software. It would be difficult, if not impossible due to time constraints, for students (for example, in an MBA course on AI) to implement a full-fledged AI system in the context of solving a case study problem. Instead, the emphasis should be on implementing a solution that addresses a subproblem, as a way to gain experience in AI through hands-on learning.

Virtualization software, for example, Docker (Boettiger, 2015), can be used as part of the *Ideate-Prototype-Test* substages of the 3S Process. Docker performs operating-system-level virtualization and runs software packages referred to as containers. Containers are isolated from each other and bundle their own application, tools, libraries, and configuration files. Containers can communicate with each other using specific channels and message passing. Docker works with operating systems that run on desktop personal computers and servers. Therefore, the focus here can be thought of as AI running in the cloud and not at the edge (that is, embedded AI).

The idea here is that educators develop software that is built on top of virtualization technology (Figure 4), thus allowing students to focus on the code, algorithms, and concepts needed to build prototypes to address specific subproblems. Depending on the technical know-how of the students, they could work at a high-level (that is, determining effects based on adjusting parameters), at a low-level (write the code for specific algorithms), or somewhere in between these two positions.

There are five advantages to using virtualization software from an educational perspective.

1. **Cross-platform**. This allows the software to be available to a wider audience, and independent of the host operating systems (macOS, Windows, and many distributions of the Linux operating system).
2. **Software bundles**. The particular software needed can be used and pre-configured (for example, pre-populating a database).
3. **Customizable**. Specific applications can be written that run on top of Docker (for example, Python programs, which can use the vast number of AI/ML packages that are readily available).

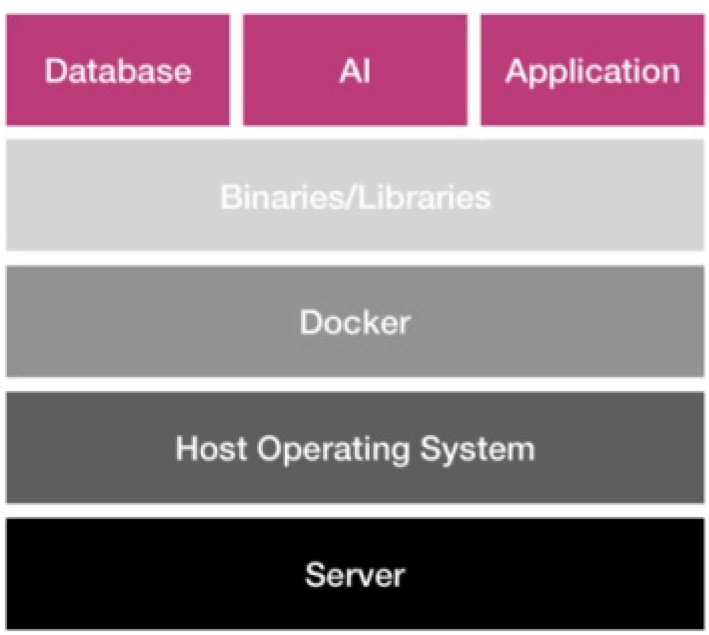

Figure 4. Docker stack.

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4. **Modular**. Each software bundle running on top of Docker can be developed and updated independently, meaning that educators can take a step-by-step approach to creating curriculum.
5. **Cloud-ready**. Containers can be integrated into web services for production (that is, use the code that was developed for a prototype as part of the code base for the solution).

Furthermore, developing web services offer the opportunity to integrate with other cloud services (for example, Amazon Web Services, Microsoft Azure, Google Cloud, IBM Watson), through application programming interfaces (APIs), resulting in faster prototyping, access to pre-trained AI models, and continuously receiving new capabilities. Interoperability between web services based on virtual containers is one of the best methods to realize powerful, complex AI systems today.

Complexity
Stage 1: Story is based on the Harvard Case Method to provide context to a problem space, and *Stage 2: Strategy* uses Design Thinking and virtualization to develop practical prototypes to address subproblems. *Stage 3: Solution* completes the 3S Process. Since it is not reasonable for students to implement a production-ready AI system in a classroom setting, the best practice would be for students to develop persuasive arguments for their particular, conceptual solutions, and try to anticipate unintended consequences. Unexpected behaviour can occur in AI due to it being a type of complex system.

Mitchell defined a “complex system” this way: “A system in which large networks of components with no central control and simple rules of operation give rise to complex collective behaviour, sophisticated information processing, and adaptation via learning or evolution.” (2009)

Information returning to an AI system can be considered as either as a positive feedback loop (amplification) or a negative feedback loop (dampening). It is critical to understand the information returning to the system, the correct method to process the information, and the best practice to store the information. For example, unexpected feedback changed the behaviour of the chat-bot Tay, as discussed previously.

Conclusion

To summarize, this article presents a new framework, the 3S Process, for teaching AI in the context of business education. *Stage 1: Story* uses the Harvard case method to set the context of the problem space. Students are expected to engage in discussion to further understand the problem at hand, to uncover details and narrow the scope of the problem space. *Stage 2: Strategy* is based on the approach of Design Thinking to develop a prototype, which for practical purposes in a classroom setting addresses a subproblem unveiled in the case study. Particular emphasis is placed on the substage of *Empathy* to reduce potential biases in the final AI system. Furthermore, virtualization software can be used to create practical candidate solutions, and thus provide a hands-on learning opportunity for the *Ideate-Prototype-Test* substage cycle. *Stage 3: Solution* is where students advocate for their conceptual AI solution in the context of the case study and describe their Design Thinking thought process to reach their AI solution. Students should remember that AI is a type of complex system and postulate potential feedback loops, while taking into account the potential for unintended biases to enter the system.

When educators use the 3S Process the expectation should not be that business students develop a deep, technical understanding of AI. Instead, the hope is that the 3S Process provides students with critical thinking and hands-on experience with AI, so that they can make more informed strategic decisions about AI as leaders in their future organization and as part of teams. Business education using the 3S Process can equip leaders with common language and understating regarding AI, thereby improving communication between management and technical experts.

It should be noted that the 3S Process can be adapted from use in education to be applied to entrepreneurship. Instead of using a case study, *Stage 1: Story* is based on the business problem to be solved and context is provided by market realities. Instead of addressing a subproblem, *Stage 2: Strategy* directly addresses the business problem. As with the education case, leaders should be aware of bias in the business case as well. The use of virtualization software at this stage has a real benefit, as it can be transferred with ease to production, *Stage 3: Solution*, particularly for cloud services. Leaders will have to sell their solutions

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internally within their organization and measure external market response. Complexity will still play a factor and require leaders to continually monitor the performance of their AI system.

Finally, the 3S Process is a complex network itself. The author's intent is that leaders can leverage the 3S Process, and that the resulting collective behaviour will lead to the emergence of creative thinking around integrating AI in business.

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Keywords: 3S Process, Artificial Intelligence, Business Education, Design Thinking, Harvard Case Method

Connected Health Innovation: Data Access Challenges in the Interface of AI Companies and Hospitals

Laura Kemppainen, Minna Pikkarainen, Pia Hurmelinna-Laukkanen & Jarmo Reponen

> *"The applications [and technology] are ready, the main reason for data access problems … [are] … the questions about who owns the data, where it can be stored, [and] how to keep it safe."*
>
> Innovation manager, AI company

The purpose of this paper is to explore the challenges and potential solutions regarding data access for innovation in the realm of connected health. Theoretically, our study combines insights from data management and innovation network orchestration studies, taking thereby a new approach into issues that have emerged in these research streams. Empirically, we study these issues in the context of a development endeavor involving an AI-driven surgery journey solution in collaboration with hospitals and companies. Our study indicates that the challenges and solutions in data access can be categorised according to the level where they emerge: individual, organisational, and institutional. Depending on the level, the challenges require solutions to be searched from different categories. While solutions are generally still scarce, organizational level solutions seem to hold wide-ranging potential in addressing many challenges. By discussing these dynamics, this paper provides new knowledge for academics and practitioners on the challenges and solutions for data access and management in networked contexts. The greatest challenges among healthcare providers and health technology companies lay on uncertainties and interpretations concerning regulation, data strategy, and guidelines. Creating guidelines for data use and access in a hospital can be a first step to creating connected health innovations in collaboration with AI companies. For their part, these companies need to put effort into gaining in-depth knowledge and understanding of the processes and standards in healthcare context. Our paper is one of the first to combine data management and innovation network orchestration literatures, and to provide empirical evidence on data access related issues in this setting.

Introduction

The contemporary environment for healthcare presents a constant need for innovations that use (heterogeneous) data (Gulbrandsen et al., 2016; Pikkarainen et al., 2018). In order to achieve social health improvements (Conway & VanLare, 2010) and cost-savings, (Meier, 2013), varying forms of data are increasingly needed in the creation and implementation of new Artificial Intelligence (AI)-based connected health innovations, for example, decision support solutions that create value for healthcare providers and patients (Down et al., 2018). The data can comprise anything from electronic health records to personal data that would have an impact on the healthcare quality, outcomes, or costs. (Meier, 2013).

The challenge is that although the technology for AI usage exists, data access is rarely straightforward, especially from the innovation management perspective. Since innovation in healthcare is often networked and collaborative in nature (Djellal & Gallouj, 2007; Gulbrandsen et al., 2016; Ramlogan et al., 2007), relevant data is stored in various places from internal hospital systems, to external network players' registers and databases. In addition, healthcare data management is governed by specific rules with regard to the access and use of data. Sensitive health and medical data about the patients is highly regulated. Due to tightening international and national data privacy regulations, innovation network players are often, quite understandably, hesitant to allow access to their data for any external partners. A dilemma thus emerges, where data access restrictions that are meant to safeguard patients, instead can end up limiting the possibilities of improving their healthcare environment.

Previous studies on collaborative innovation emphasize the importance of organizing data access and knowledge transfer in the collaboration process (Alhassan et al., 2018; Hurmelinna-Laukkanen & Nätti, 2018). Such need for data, information, and knowledge exchange is highly relevant in the context of AI and connected health. It has been acknowledged that emerging innovations in healthcare are and will be data-driven (Meier, 2013). This necessitates not only proper data access that allows identifying general patterns and understanding of varying cause-effect relationships based on information extracted from the aggregated data, but also very specific data access issues, such as accessing data in relation to services for specific actors, for example, access to one's own health information as a patient. In other words, data access is critically needed and highly important in the healthcare context in order to understand what kind of innovations are possible (as background information; as input in the innovation development), and to enable co-creation and use of smarter AI-based connected health innovations - the actual outputs - that are targeted either for patients, citizens, or medical experts.

The multi-layered nature of the need for data access (with which we refer to periodical vs. continuous, and general vs. specific needs) becomes highlighted even more when varying actors from the network come together with quite different motivations with respect to accessible data. Many innovation endeavors call for network orchestration where information and knowledge mobility are promoted with different means (Dhanaraj & Parkhe, 2006), and healthcare innovations are no exception. Generally, scholarly discussion has already addressed the question of information mobility and data sharing. Different means have been identified that allow data, information, and knowledge transfer for innovation in networked settings (Dhanaraj & Parkhe, 2006; Nambisan & Sawhney, 2011). However, there is a lack of research on how (or if) data access can be managed by means of innovation network orchestration when data access is inherently restricted, and when there are clearly articulated but diverse motivations and well-grounded reasons for such diversity. In addition, while the general challenge associated with data access is acknowledged, research insights are lacking about the precise nature and various dimensions of this challenge. Yet, this kind of information is urgently needed by both researchers and practitioners who are interested in contributing to the development of viable connected health innovations in order to overcome the related challenges.

In this study, we attempt to address this gap by identifying and discussing managerial data access challenges faced by AI-based connected health companies that are part of innovation networks operating in the healthcare sector. We also discuss potential solutions that could overcome these challenges, from the point of view of innovation network orchestrators. The research question is formulated as follows: Where do data access challenges in AI-based connected health stem from, and how can they be addressed by means of innovation network orchestration? We examine issues related to this question by integrating insights from a literature review and case study.

The paper is organized as follows. The next section briefly outlines the existing knowledge on connection points of network orchestration and data management (especially data access). This is followed by description of the empirical research design and evidence. Analysis of the data, and description of the findings then precede the concluding remarks, where new insights are reflected upon regarding existing theorization, and where managerial implications are introduced.

Network Orchestration and Data Management in Connected Health

This paper is based on the integration of theoretical frameworks on data management activities (Alhassan et al., 2018), and on information (knowledge) mobility as a central innovation network orchestration activity (Hurmelinna-Laukkanen & Nätti, 2018; Nambisan et al., 2017; Nambisan & Sawhney, 2011; Sabatier et al., 2010). Such integration enables a better understanding of innovation network orchestration challenges from the perspective of data access in the healthcare sector.

“Innovation network orchestration” refers to taking systematic, purposeful actions that focus on initiating and managing innovation processes with many stakeholders (Dhanaraj & Parkhe, 2006). This comprises various activities needed to facilitate innovation co-creation (Hurmelinna-Laukkanen & Nätti, 2018). These activities include promoting actor mobilization and network stability, ensuring knowledge mobility, and innovation appropriability, as well as setting an agenda for the network and coordinating follow-up activities (see Hurmelinna-Laukkanen & Nätti, 2018; Möller & Halinen, 2017). In this paper, the focus is placed on

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information mobility since it has been frequently identified as crucial in the context of connected health environments (Pikkarainen et al., 2017). Information mobility refers to making sure that relevant knowledge or data is available in the innovation network (Dhanaraj & Parkhe 2006, Hurmelinna-Laukkanen & Nätti, 2018).

Information transfer is also a central issue in data management. Based on a study that analysed 61 scientific publications on data governance, Ibrahim Alhassan, David Sammon, and Mary Daly (2018) suggest a data governance activity framework that includes eight categories: data policies, data standards, data roles and responsibilities, data technologies, data requirements, data processes and procedures, data strategy, and data guidelines. One can see that the transfer of information is just one aspect of data management (Cavoukian & Jonas, 2012; Corso & Paolucci, 2001), though a highly relevant one. According to Alhassan et al.'s (2018) framework, data access challenges and solutions can lie in any of the mentioned eight activities, or lack of them in any given situation.

These eight categories of activity, together with the information mobility dimension of innovation network orchestration, form key elements in the conceptual framework of this study, towards helping people understand data access problems and solutions in connected health environments. We suggest that the orchestration challenges and solutions are to be found at the intersection areas of these dimensions (See Figure 1).

Our central idea derived from the earlier theories is that outcomes of networked innovation endeavours depend critically on specific ways of dealing with data access challenges. Such challenges need to be identified and solved for all participating stakeholders (Corso & Paolucci, 2001; Möller & Halinen, 2017), which means that practical problems emerge from the collision between individual data management activities and collective knowledge, and information mobility (innovation network orchestration) activities. A systematic study of these collisions requires empirical studies focusing on detailed case studies.

Research Design and Context

Methodology

The present study adopts an auto-ethnographical approach (Rashid et al., 2015) to address the topic of interest. Ethnography is a research approach that focuses on a single case study and aims to develop deeper insights about the phenomenon under study (Myers, 1997). In auto-ethnographical work, micro- and macro-levels can be combined, as the researchers are immersed in the study topic. The context and the researchers' experiences therefore are in focus, to keep in mind the socio-cultural backdrops (Boyle & Parry, 2007; Chang, 2008).

Our study builds on data collection from a 12-month multi-disciplinary research project. In this project, a total of four hospitals in Finland and Singapore, and several companies came together to co-create an intelligent and patient-centric solution for adults who had to have surgery. In this project, the researchers acted as orchestrators and enablers for the data access needed in the process of researching, designing, and developing the solution. They therefore had firsthand experience with innovation network orchestration in a

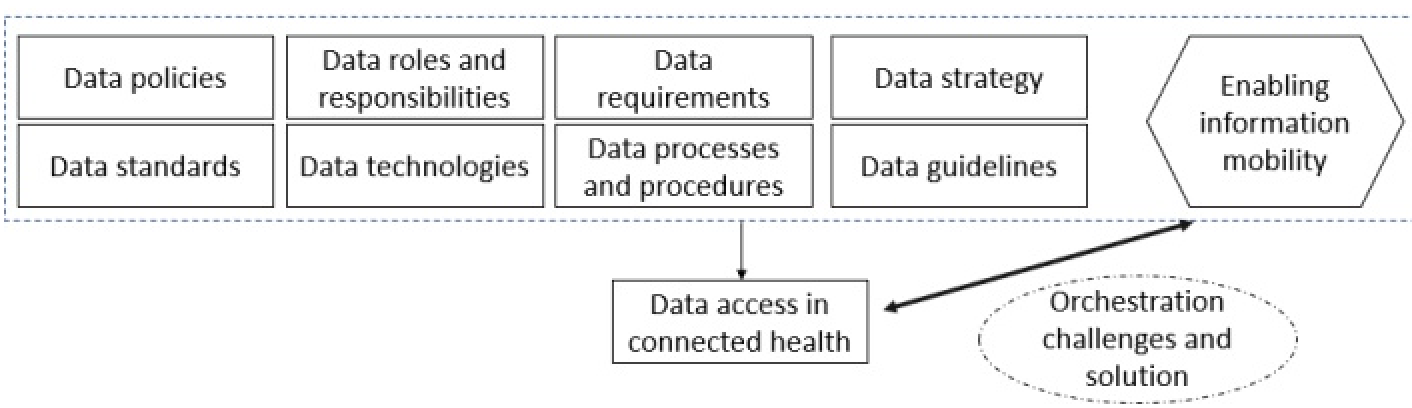

Figure 1. Conceptual framework on managerial orchestration challenges and solutions in data access for connected health.

complex real life setting.

The research process of this study included the following steps:

- Initiating the development endeavor, including documentation
- Defining the research topic based on accumulating experiences
- Literature review involving managerial orchestration challenges and solutions in data access for connected health
- Conversational workshops and interviews were conducted in four hospitals in order to define needs and challenges related to surgery solutions development
- Field notes were taken in meetings where companies discussed data access issues with hospitals when co-creating their solution for surgery care
- Memos were created from all of the discussions
- Ethical permission writing was kept in a diary about data challenge issues that were discussed in the meetings between hospitals and companies.
- Data analysis by researchers led to drafting a narrative to capturing their experiences
- Further questioning and analysis that included external researchers to add general, cultural elements
- Documentation and categorization of the empirical findings using a thematic analysis

Reflection in light of existing theorizing

In the course of the project, various forms of research data were collected. While notes documenting the researchers' experiences as such were of central relevance, during observations, the research team also generated materials on conversational interviews and workshops for an in-depth discussion of the data access issues and to understand the nature of the related challenges (see the activities in Figure 1).

The conversational workshops and interviews were conducted in the hospitals involving healthcare providers and connected health companies. Data was collected through a field diary and memos taken during meetings with the hospital IT and law departments. In addition, field notes were taken during the workshops that involved representatives of innovation network orchestration, such as healthcare providers (doctors and nurses) and healthcare technology providers (see Table 1).

In addition to the core research group working hands on in development, two other researchers joined the team when analysing the collected empirical data and writing down the findings. These two researchers are co-authors in this paper and have a different rolecompared to the roles of researchers working in the research project. These two researchers stayed away from the actual project, embracing rather a role of asking questions and challenging the thinking of others from a new perspective (see Chang, 2008). The story below was written in collaboration with all the authors in this paper. Data analysis was done in an inductive thematic manner, with the purpose of categorizing themes and key data access challenges, along with solutions emerging from collected data.

Table 1. Innovation network orchestration activities and data collection details.

Innovation orchestration and data collection activity	Participants
Interviews, personal notes and interpretations	8 companies (10 people)
1st workshop with doctors, nurses and companies (University Hospital), personal notes and interpretations	1 hospital; 3 research organisations; 6 companies
2nd workshop with doctors, nurses and companies (with Singaporean Hospitals and researchers), personal notes and interpretations	2 hospitals; 2 research organisations; 7 companies; 2 national organisations
3rd workshop with integration provider company and AI company, personal notes and interpretations	2 companies (3 people); 4 researchers
Meeting memos from project sprint days, observation and project diary by the project facilitators (researchers)	All project stakeholders

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A connected health network

Altogether 12 researchers were involved in the research project, with two of them leading it. These two researchers were the main orchestrators of the project. The role of the orchestrators was to enable the dialogue between participants, connect the interests, and find and facilitate opportunities for collaboration among companies, and between companies and hospitals (see Dhanaraj & Parkhe, 2006; Möller & Halinen, 2017 for a description of orchestration tasks).

The project involved many stakeholders who were needed to develop and test a new solution in a live hospital environment. The network included four hospitals, three research organisations, two gaming start-ups in the health sector, a small video communication company, a large device provider, an integration provider, a patient engagement platform organization, and one AI company. When starting the work in our consortium, one company in the network had a monopoly in the Finnish market with strong relations to hospital systems and access to clinical data in Finland. Another company was continuously collecting patient data through a mobile solution. They held data from 1,400 patients from different hospitals. Yet another company was setting up video connections between patients and health professionals, but the company was hesitant to suggest any form of data collection or data usage to their hospital-customers because they felt that it would significantly decrease their possibilities to get access to the hospital market because of data privacy issues. The AI company had the capabilities to make data analysis and AI solutions, but no data to realize this potential.

In this network, the various participants had a common interest to create an AI-based connected health solution that supports patients and healthcare experts in activities related to the orthopedic surgery journey from home to hospital, and back to home. A key assumption of the project was the idea that getting access to data in the hospital systems requires tight collaboration. Data access was of interest to all stakeholders because it was the key resource that was necessary to build innovative solutions together.

During the project, we arranged continuous negotiations and discussions between the various stakeholders regarding data, access to data, data privacy, and project activities. Our field notes and interviews indicate that challenges became evident early in the project. The focus of the discussions shifted to understanding the types of challenges, so that orchestration activities could be directed to solving them.

Analysis and Findings

Challenges in data management

Our observations show that heterogeneous data was seen as a highly relevant resource in both the creation and actual application of innovative AI solutions. This was an issue brought up by multiple actors, from company representatives to the leading medical doctors at the hospitals. One company representative expressed this as follows:

> "when we have a lot of data…I think that's really valuable in studies and researches, developing new care protocols, treating methods. But if you just develop some algorithms that makes maybe some alarms or something like that, I think that those should be really part of the platforms and the kind of service providers like us. Or third-party can sell them." (Company CEO)

In many cases during our study, however, the managers of connected health companies faced major difficulties especially when negotiating about data accessibility with hospital management and the IT department. We saw several key reasons why data access is currently so painful, especially for the AI company in the project consortium. These observations created managerial implications and raised several issues to consider for connected health companies and hospitals.

First, data protection rules and regulations were changing in the European Union during our research project. The target of the new regulations was both to enable the secondary use of health data, and to create better data protection for individuals. For the former, "primary use" refers to using health data for the main purpose of treating a patient. Outside of this purpose, data sharing for research or development use is not legal, without specific permissions that cover particular situations. Regarding the secondary use of data, because practical guidelines for implementation and data use in digital innovations were still missing, the regulations seemed to have partly opposite consequences. Regarding better data protection, the EU general data protection directive added stricter organizational responsibilities in data processing, and sanctions in case of data breaches or unauthorized use.

Due to uncertainties, many players in the innovation network saw the changed laws and regulations rather as a problem than as an opportunity for future connected health innovations. Especially hospital personnel, for example, management and IT staff, were really frustrated about the continuous changes, and they felt it was difficult to proceed with companies before more information was available on interpreting and executing the new rules and regulations. Our experience was that this is an important message for hospital managers: one of the reasons for challenges in creating innovative solutions with external companies is in fact the lack of information and practical guidelines for implementing of the new rules. In some cases, it felt like the hospitals were lacking resources to get a better understanding about data usage potential. Companies saw that hospitals were hesitant to provide even anonymous data, or to allow those companies that held their data, to service it further.

> "I think the hospital is protecting their own data for many reasons. Yeah, safety but also there can be I think ethical reasons for too that, who they want to give the data. Even if it is anonymous data."
> (Manager, AI Company)

It is important to note that the secondary use of health information is not allowed even in anonymized form if the patient has not given his or her specific consent for anonymizing, or if permissions have not been granted from authorities. As the information cannot be modified from one use to another, and since R&D further requires their own permission processes, the situation is quite complex and sometimes organizations outside of core health care provision have a hard time comprehending the full picture. For example, in one case the hospital IT personnel needed to deny data usage and integrations from a company who, in principle, already had all the data that the AI company would have needed for their solution development. This was because of legal issues with regulations stating that a company technically storing and analysing data for a health care provider, does not have a legal basis for its further usage. The situation caused frustration among the parties, both in the company who had the data, and in the company who needed the data for solution development.

Related, but distinctive reasons for the hospital resistance, and issues for innovation managers in hospitals to consider, were the hospital personnels' uncertainty about the new practices and needs for securing private information. The hospitals also lack data governance processes.

> "I feel like the process is missing from the hospital side to give the AI company the access to data. So, kind of process is somehow too complicated or too much bureaucracy or, it's hard to get in."
> (Company Manager)

Regarding other uncertainties felt by the actors, hospital staff mentioned, for instance, the possibility that a small company goes bankrupt, and the patient data stays locked and inaccessible in some cloud server. Another example mentioned in discussion was the fear that the AI company would take the hospital data and start sending bills back to the hospital regarding its usage. For health technology companies, an important managerial implication of this study is that being transparent over how data will be used in an innovation, and where the data is stored can reduce the uncertainty and perhaps also the anxieties of some hospital personnel. This could be one way to more seamlessly co-create data-driven services within and between hospitals.

We tried to trace back to the reasons behind the worries beyond the obvious uncertainties interpreting the new legislation. One example was that one of the companies in our project consortium had previously had an attempt to get their solution to be adopted in the hospital, although not all protocols set up by the hospital's IT organization were followed. We got the impression that because of their previous experience, this hospital IT department had "set the company in their black list", which we believe had quite long-lived effects. The IT organization of the hospital continuously advertised this company as an example of how the hospital should not work with startups in their own innovation networks. In general, the earlier experiences that gave a negative imprint, together with a lack of adequate resources, as well as uncertainty about the regulations, emerged as core reasons why companies in our project found it hard to get access to anonymized or pseudonymized health-related data. At the same time, the data holders faced challenges of not violating any privacy regulations, along with the need to better understand the technological solutions' consequences regarding data use, especially long-term.

Adding to the challenges, it was not completely evident if the common resistance towards specific parts of the AI solution development was based on previous real experiences, or on beliefs and rumors. We learned, however, that at the same hospital, several parallel failed AI innovation cases had emerged. While these were not connected to our project or the particular innovation network, these parallel problems seemed to generate a negative reflection on the attitude of hospital personnel in our innovation network as well.

Emerging solutions
Our study has managerial implications for hospitals and health technology companies in showing that involved actors can identify several plausible ways to solve data access challenges. Our field notes considered that the orchestrators from each objective research team needed to take a coordinating role in order to help facilitate solutions for data access issues. In particular, numerous misunderstandings in the communication between companies and hospitals were considered as a hurdle for any progress with data access. Therefore, orchestrators needed to 'translate' the motivations and concerns between players in the innovation network. Relatedly, one solution identified to address the challenge was simply to continuously maintain an ongoing discussion between the companies and hospital employees in different departments, meaning the doctors, nurses, IT, and law department about data access issues.

This was not a straightforward process, however, as the discussions and subsequent calls for action required use of scarce resources. This was observed, for example, in the behavior of hospital IT departments and upper management who, in the end, did not want to discuss about the possibility of creating a data lake in the research project, that is, a secure place for data for the use of innovative services. This is because they were concerned that this possibility would take all their resources from other more crucial development actions. Our takeaway was that in the end individual perceptions and organizational resources were of essential importance.

Problems of withdrawal from the discussions escalated across the network. However, for the AI company, tight collaboration with healthcare providers, hospital IT departments, and the connected health companies was essential. Although the actors in the innovation network realized that orchestration activities would accommodate granting access to data by generating procedures of trust among healthcare providers and AI companies, in practice, this process became quite demanding and required personal connections in between participants. The AI company mentioned that they had managed to become a trusted partner for one hospital earlier, but that hospital was not involved in our innovation network. The earlier example pointed towards potential solutions (that is, creating individual level trusted relationships), yet in this case, the positive and negative experiences in different parts of the network, did not really align in a manner that would have promoted collaboration.

Nevertheless, the role of intermediaries became quite clear during the search for solutions. Company managers, in particular, highlighted it, together with developing clear responsibilities among actors in the innovation network.

> "Somebody who is… providing services to, let's say hospitals, needs to be somehow as an integrator or management of the overall solution, towards the hospital. Then different parties inside the overall solution will get their revenue based on some split that we as a group decide." (Company Manager)

Determining a leading organization was, however, very difficult for the companies involved. In particular, they often seemed to be extremely worried that the other players would become their competitors. The relatively small market was a special cause of concern. Again, a solution came with new tensions and challenges at the wider, contextual level.

Considering the solutions for data access as such, the missing processes and protocols in and between organizations were looked at under closer scrutiny. In the discussion with the hospital IT teams, it became evident that having a clear process and increased knowledge about the protocols for data sharing, and for granting data access for digital innovations would be a way to streamline the data access process and requirements for the AI companies. In practice, for example in Finland, there are many national level standards for the use of information and communication technology (see, for example, Reponen et al., 2017). However, the problem is that while the hospitals have many standards and protocols in use, their utilization requires special knowledge, which ordinary clinical units do not have. Thus, both in Finland and Singapore, it requires time for the involved innovation coordinators and medical doctors to clarify the protocols and standards to be followed in a particular situation in their own hospital.

In our innovation project, there would have been a possibility to use the project efforts to create a common framework design together with the companies and hospitals. In reality, however, the innovation project network had to adapt to the existing data management and equipment purchase policies in the local hospital environments. Consulting time for innovation network activities was limited mostly to clarifying the most urgent issues. This highlights the limited resources hospitals have for ad hoc innovation activities.

Finally, the study realized that more efforts are needed also at the governmental and national levels in order to enable AI innovation development. Comparisons are thus being made all the time to seek solutions:

> "I think the bureaucracy and world is kind of changing, but I think that Singapore is a good example of having this governmental sandbox for AI companies where there is already all the patient history data anonymously. So, AI companies have an easy place to go and just start to create new data models." (Manager, AI Company)

Categorizing data access challenges and solutions

Analyzing the available materials, specific categories of the challenges and solutions started to emerge. These may be grouped into three general categories: individual level (referring to representatives of different organizations), organizational level (referring to stakeholder organizations such as hospitals, companies, government agencies), and institutional level (that is, regional, national, and international frames for working beyond organizational boundaries, including legislation

Table 2. Managerial Orchestration Challenges and Solutions.

Area of data governance	Individual level	Organisational level	Institutional level (frames)
Data policies	C: There are many interpretations of the new laws and what they mean for data access and privacy	C: Hospital is protecting data for legal reasons S: Clearly define what data is needed and for what reason	C: New data privacy laws C: IT innovations are complex S: New regulation on data privacy and use
Data standards	N/A	C: There were many standards and protocols existing in the hospitals, but it takes time to clarify them	S: Standards defined/agreed to use at national level
Data roles and responsibilities	C: Interpersonal relationships and trust affect decision making and willingness to collaborate C: Misunderstandings affect decision making and willingness to collaborate	C: Lack of trust among the hospitals and service providers who ask for data access S: Define which parties need access to data S: Verify that data access requests comply with permissions and laws S: Partner with the right system providers	N/A
Data technologies	C: Limited knowledge with actual regard to tech properties	S: The integrations are in place and technology ready for data access	N/A

Table 2. Managerial Orchestration Challenges and Solutions (cont'd).

Data requirements	N/A	C: Companies have unrealistic expectations for data access C: Hard to decide where the data should exist S: Decide where data should be stored (e.g., Hospital Data Lakes) S: Using training data	N/A
Data processes and procedures	S: Discussing with hospital employees e.g. doctors, IT, and legal department	C: There are many guidelines in the hospital but they are often unknown C: Companies and hospitals collect data into different databases C: Bureaucracy in the hospitals C: Companies' limited understanding of hospital systems	S: There are national baseline interpretations of the regulations and permission processes
Data strategy	N/A	C: There is no data strategy in place at the hospital S: Have a discussion with the hospital district about data access	N/A
Data guidelines	C: Hospitals are afraid that something could go wrong if data access is granted	C: No clear guidelines how to use existing data in research and solution development S: Define what you need the data for S: Verify legal aspects	S: National level reports and framework created to support the use of data in new digital solutions

and policies) factors. These categories can be approached based on data management activities (see Alhassan et al., 2018). Summarizing the above discussion, and going into more fine-grained detail, we identify managerial orchestration challenges and solutions as mapped in Table 2 below.

The findings suggest, first, that challenges in data access may emerge at the individual level, meaning that the impressions and relationships between people at the hospitals and technology providers have an effect on how access to data is perceived. In particular, personal relationships between the hospitals and technology providers, for example, an AI company, become crucial for establishing and maintaining trust. For managers, it is good to understand that at the individual level, challenges and solutions may sometimes build on expectations and beliefs, rather than the actual state of things, and that many of these can be invisible. Therefore, although getting all the right parties at the same table is challenging (and may first introduce new problems), it is crucial for getting access to the data, and therefore to be reckoned with when it comes to orchestration.

In the examined project, the most (visible) orchestration challenges and solutions with regard data access seemed to occur at the organizational level. In particular, with respect to the (lack of) matching processes and protocols, uncertainties related to storing of the data, the extent to which, and what kind of, data should be available, and questions on securing privacy issues, were considered as central organization-level issues. While not surprising as such, these issues reside in the middle ground between individual and institutional levels, thus seem to provide the best possibilities for orchestration. As entry points, these organization-level issues are concrete enough (to define how representatives of a specific organization operate and interact with representatives of other organizations), and they are not taken too personally.

Finally, institutional level challenges and solutions are external to existing innovation network structures. What is noteworthy here is that institutional level issues are easily perceived as problematic rather than something that can be utilized as a stepping stone. However, upon closer look, in most areas of data governance, they are not strongly present at all, and they also can provide the needed frameworks for organizations and individuals to approach data access challenges and generate needed solutions. Markets and regulation could be explored for opportunities regarding differentiation, for example. Members of the various impacted networks could also try to influence these frames, if the possibilities for such action were recognized. Again, what was found is that network orchestration may provide the needed tools to realize such possibilities, especially if influential power can be aggregated efficiently and effectively.

Conclusions

As Thune and Mina (2016: 1546) note, hospitals are "central nodes in health-care networks because they perform multiple roles at key intersections of the system" (see also Ramlogan et al., 2007). This also means that they are organizations placed at the intersection of many varying, and even opposing expectations, which inherently affects innovation endeavors in this context (Djellal & Gallouj, 2005; 2007).

This study provided insight on the paradoxical features of data access and innovation network orchestration related to it. By identifying challenges and potential solutions at the intersection of innovation network orchestration and data management in the context of connected health, it adds to the existing knowledge that assumes data availability as a central part of network orchestration, and/or expects that securing information mobility is a matter of motivating the parties to share their data and knowledge (see, for example, Dhanaraj & Parkhe, 2006; Möller & Halinen, 2017). Likewise, it adds to the discussion on managing data from the point of view of privacy concerns (see Alhassan et al., 2018; Corso & Paolucci, 2001). This study therefore contributes to the innovation management and network orchestration literatures in the context of connected health, where data-driven innovations such as AI-based decision support solutions need to be continuously developed in order to improve the quality of care and cost-effectiveness (Pikkarainen et al., 2018).

This study took as its starting point a search for answers to the question: "where do data access challenges in AI-based connected health stem from, and how can they be addressed by means of innovation network orchestration? A key finding of the study is that healthcare providers and health technology providers already now identify quite well the challenges in terms data access and use in data-driven connected health innovations. However, they struggle with identifying the best solutions to overcome the challenges. Based on theoretical and empirical examination, it was suggested that the challenges in data access for AI companies can be considered at three levels: individual, organizational and institutional.

In many cases, challenges seem to emerge especially from diverging perceptions, or misinterpretation of factors that reside on varying levels. Individual level obstacles for data access may start from individuals' earlier organizational collaboration failures, lack of organization specific guidelines for data use or from different interpretations.. Lack of organizational level guidelines, may, in turn, result from uncertainty regarding institutional level regulations and policies.

Our study shows that the greatest challenges in connected health and in creating innovative data-driven and patient-centric solutions, stem from tightening data privacy regulations that reside at the institutional level (that is, beyond individual organization) and, in particular, interpret in different ways at the individual and organizational levels. Likewise, the lack of processes and data strategies at an organizational level is an important contributor to how challenges are faced. Their absence tends to limit access to data especially in hospitals. As such, this is not surprising. However, when connected more directly to the different levels, the challenges change, and become more difficult and less solvable.

This leads us to the second part of the research question: It seems that innovation network orchestration holds the most potential when it is focused on the organizational level, and on inter-organizational relationships. The research above suggests that solutions for data access challenges are mainly organizational, which means covering actions such as improving the processes and data strategy of the hospital. While there is also a need for national level interpretations of institutional regulations and guidelines for healthcare organizations so that the data access and data management policies do not differ between organisations, it is a matter of organizations making this information visible among their members and collaborators. In this, orchestrators can be relevant intermediaries. However, more indirect elements are also present.

Individual level challenges and solutions may take quite different forms, and be even irrational if they build solely on beliefs and perceptions rather than facts. The above findings point towards personal connections, discussions, and relationships having a crucial role in breaking down barriers and finding solutions to create innovative connected health solutions in collaboration with hospitals and AI companies. This means, on one hand, that carefully selected orchestrators may be in a position that allows development to start on data access systems, and to move from there to actual innovation generation; individual-level issues are brought to the organizational level. On the other hand, an orchestrator has a central task of building the premises for discussions among network actors, so that the beliefs and perceptions of participants can come closer to each other. This approach may be much more discrete than coordinating for data access systems, but nevertheless relevant for an institution's ultimate goals.

This study leads to managerial implications that may impact AI companies targeting the healthcare market. It is important for AI companies to understand that in order to succeed with data access they need to, 1) find the right orchestrators, 2) build personal connections and trust among hospital personnel, 3) understand and follow the rules, regulations, and guidelines related to data protection, transfer and storage.

One of the key managerial findings of our study is that the greatest challenges among healthcare providers and health technology companies lay at the organizational level, covering issues such as a lack of data strategy and guidelines in a hospital. Network orchestration can therefore be approached efficiently at this level. Creating and communicating clearly about hospital level rules and protocols for data use and access in a hospital can be a first step to creating connected health innovations in collaboration with AI companies. Companies, in turn, can be provided with educational materials about regulations concerning health care data access, so that expectations can be adjusted realistically. If requests for data are already suited within the existing legislation, this means they will have more success in proceeding.

Additionally, orchestrators need to be aware of varying perceptions and expectations, understand the resource limits, and be able to target the discussions and activities efficiently. Understanding the central factors across different levels allows them to promote practices that ease data access challenges without jeopardizing confidentiality and privacy needs. Excessive access restrictions can thus be avoided, and data management eased so that innovative solutions can emerge and function properly. Indeed, we suggest that privacy issues in data management are problems only if they are problematized, which means that they can also become part of the solution.

In practice, the central issues are selecting the orchestrator carefully (a neutral translator and intermediary may be needed), bringing the central actors together to increase common understanding, and placing the challenges (and solutions) at the organizational level, rather than the institutional or individual level in order to avoid overly abstract institutional elements, misconceptions and personalization of issues.

The limitations of this study lie in the single case context. Examining one specific network is bound to bring up one set of aspects while perhaps not showing signs of others. However, we believe that the general framing can be adapted to other research contexts, in a way that allows for testing the ideas presented here, as well as finding relevant new issues.

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Connected Health Innovation: Data Access Challenges in the Interface of AI Companies and Hospitals

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