5-15-2019

A NEW ORGANIZATIONAL CHASSIS FOR ARTIFICIAL INTELLIGENCE - EXPLORING ORGANIZATIONAL READINESS FACTORS

Luisa Pumplun
Technische Universität Darmstadt, pumplun@is.tu-darmstadt.de

Christoph Tauchert
Technische Universität Darmstadt, tauchert@is.tu-darmstadt.de

Margareta Heidt
Technische Universität Darmstadt, heidt@is.tu-darmstadt.de

A NEW ORGANIZATIONAL CHASSIS FOR ARTIFICIAL INTELLIGENCE - EXPLORING ORGANIZATIONAL READINESS FACTORS

Research Paper

Pumplun, Luisa, Technische Universität Darmstadt, Darmstadt, Germany, pumplun@is.tu-darmstadt.de

Tauchert, Christoph, Technische Universität Darmstadt, Darmstadt, Germany, tauchert@is.tu-darmstadt.de

Heidt, Margareta, Technische Universität Darmstadt, Darmstadt, Germany, heidt@is.tu-darmstadt.de

Abstract

In 2018, investments in AI rapidly increased by over 50 percent compared to the previous year and reached 19.1 billion USD. However, little is known about the necessary AI-specific requirements or readiness factors to ensure a successful organizational implementation of this technological innovation. Additionally, extant IS research has largely overlooked the possible strategic impact on processes, structures, and management of AI investments. Drawing on TOE framework, different factors are identified and then validated conducting 12 expert interviews with 14 interviewees regarding their applicability on the adoption process of artificial intelligence. The results strongly suggest that the general TOE framework, which has been applied to other technologies such as cloud computing, needs to be revisited and extended to be used in this specific context. Exemplary, new factors emerged which include data – in particular, availability, quality and protection of data – as well as regulatory issues arising from the newly introduced GDPR. Our study thus provides an expanded TOE framework adapted to the specific requirements of artificial intelligence adoption as well as 12 propositions regarding the particular effects of the suggested factors, which could serve as a basis for future AI adoption research and guide managerial decision-making.

Keywords: Artificial Intelligence, Adoption, TOE Framework, Organizational Readiness.

1 Introduction

"The world's most valuable resource is no longer oil, but data" – proclaimed by The Economist (2017) and a plethora of other articles, the business value of data is widely accepted. If data is the new oil of our economy and artificial intelligence (AI) is fuelled by data, then AI can analogously be referred to as the engine (Agrawal et al., 2018). Thanks to improved algorithms in deep learning and ample access to historical datasets as well as cost-effective computing power and storage space, AI applications are on the rise and receive increasing attention from both technology companies and more 'traditional' companies that anticipate competitive advantages (MSV, 2018). Despite inconspicuous short term impact, long term commitment is important since AI represents a paradigm shift for organizations (Hosanagar and Saxena, 2017). According to Gartner, "85 percent of CIOs will be piloting AI programs through a combination of buy, build, and outsource efforts" by 2020 (Andrews et al., 2017, p. 2) – however, just like a new engine for electric vehicles requires a new chassis, approaching an organizational AI project requires an assessment whether the focal organization possesses the necessary prerequisites and framework to enable successful AI initiatives.

Despite ever increasing organizational (and governmental) investments in AI (Bughin et al., 2017), less than 39 percent of all companies have an AI strategy in place, only 20 percent of companies have actually incorporated AI in some offerings or processes, and merely 5 percent have extensively incorporated AI (Ransbotham et al., 2017). The easiest explanation for this apparent hesitance are prominent examples of AI projects gone awry, like the Microsoft Chatbot Tay tweeting racist slurs (Reese, 2016) or IBM's Watson failing to diagnose cancer as promised in their advertising campaign (Flam, 2018). However, most so-called AI failures cannot be attributed to AI itself but rather to the underlying processes and the involved people. Current AI research has focused predominantly on technical advancements (e.g., Monroe, 2018; Lu et al., 2018) but largely factored out the necessity to analyse the readiness of the 'organizational chassis' to successfully support AI initiatives. In this regard, AI initiatives cannot be approached like yet another new technology trend since several aspects distinguish these projects from previous technology initiatives, e.g., cloud computing adoption or social media marketing: in its essence, AI refers to a broad and complex set of approaches that do not have to confine themselves to methods that are observable and have thus been often compared to a black box (McCarthy, 2007). In accordance with McCarthy (2007, p. 2) we understand AI as a "science and engineering of making intelligent machines, especially intelligent computer programs", which tries but is not limited to simulate human intelligence and which includes underlying technologies like machine learning, deep learning and natural language processing (Elliot and Andrews, 2017). AI differs from non-AI technology as it learns to make decision based on incoming data, rather than being based on an explicitly defined set of rules (Crowston and Bolici, 2019). This self-adaptive property allows AI to learn from user behaviour, react to its environment, and make complex decisions automatically. These properties result in human attributes being assigned to AI (Rzepka and Berger, 2018). However, the technology is also perceived as a threat because the algorithm's decision is not transparent (i.e., black box behaviour) and is likely exceeding human capabilities in a particular task due to its efficiency and scalability (Brundage et al., 2018).

In an information systems (IS) context, researchers have only recently begun to examine organizational readiness factors for AI (e.g., Alsheibani et al., 2018) but have as of now not yet expanded frameworks like TOE (technological-organizational-environmental) to cover the specific characteristics AI initiatives entail across industries and adoption stages. Due to the scarce extant literature, this study explores organizational readiness factors through a qualitative interview approach with 14 experts from both user and provider firms at various adoption stages. Building on TOE as conceptual framework, our approach thus aims to identify:

(1) Which factors influence the decision and the ability to adopt AI in organizations? And sets out to shed further light onto (2) What explicitly distinguishes the introduction of AI from other technologies?

The remainder of this manuscript is structured as follows: To begin with, we provide a brief overview of the related work and theoretical background (TOE) to mark off the research area before the qualitative study design is presented. After introducing our study sample comprising 14 interviewees, we derive empirical results which are integrated to expand the TOE framework. The results of our paper are a first step in providing a holistic view of the factors that are relevant for adoption of AI in the nascent research landscape. Thereby, the discussion of our key findings illustrates contributions to research and practice and an approach to future work. Finally, we conclude the manuscript by pointing out the limitations of our study and providing specific avenues for future research.

2 Theoretical and Conceptual Background

2.1 Artificial Intelligence and Adoption

The nascent ubiquitous adoption of AI in companies is currently omnipresent in research and practice which indicates the potential attributed to AI. However, only few studies have dealt with the organizational aspects of AI adoption like the implementation of the technology into organizational processes and governance structures (e.g., Ransbotham et al., 2017). Extant published studies rather focus on the improvement of this technology and its underlying algorithms (e.g., Monroe, 2018; Yan et al., 2016) or the impact of AI on specific industries and departments (e.g., Huang and Rust, 2018; Kruse et al., 2019;

Moncrief, 2017) – whereas overarching aspects like the influence on AI applications exerted by an organization's strategy or the macro-environment, have scarcely been taken into account in information systems (IS) literature (Nascimento et al., 2018).

Indeed, a literature review by Nascimento et al. (2018) demonstrates possible avenues for future studies by identifying specific aspects which should be considered when adopting AI technologies (i.e., high commitment to the area, human requirements to deal with the techniques), but they do not integrate their findings into a theoretical framework. Similarly, Rzepka and Berger (2018) focus on the interaction of AI systems and users and address important factors (e.g., the fit between the user, system and task), but do not apply a distinct adoption framework. There are some further, rather practice-oriented contributions analysing or discussing the adoption of AI. For example, vom Brocke et al. (2018) state that new job profiles have to be created, resulting in the necessity of adequate skill development of employees and the adjustment of corporate strategies.

However, the aforementioned findings are still rather disparate and do not provide a concise framework that could guide future organizational studies regarding AI and the actual implementation of AI in companies. To the best of our knowledge, there are only two contributions that consider the adoption of AI in organizations from a more theoretical perspective and across various industries (Alsheibani et al., 2018; Rana et al., 2014). Alsheibani et al. (2018), a research-in-progress publication, draw on the TOE framework (DePietro et al., 1990) to explain an organization's readiness to introduce AI into their organization. In line with the existing theory, they constitute technological (T), organizational (O), and environmental (E) factors which influence AI adoption and propose a quantitative, thus confirmative, approach. Accordingly, influencing factors are selected on the basis of assumptions from past studies, which are not specified in more detail, and on the basis of previous technologies, which do not have the same specific characteristics as AI. Rana et al. (2014), on the other hand, use the Technology Acceptance Model (TAM) to explain the organizational adoption of machine learning techniques in the specific context of software defect prediction. Again, the unique characteristics of AI are not sufficiently addressed. Instead, existing concepts (e.g., perceived benefits) are examined based on a sample of only four interviewees from two companies. Given that AI differs from previous technologies in several ways, an all-embracing framework needs to take these differences into account (Zhu and Kraemer, 2005): AI is considered both efficient and scalable, is able to exceed human capabilities and comprehension (Brundage et al., 2018), derives its own rules from added data (Crowston and Bolici, 2019) and shows a distinctive black box behaviour (Adadi and Berrada, 2018). In addition, recent developments affect the organizational use of AI (e.g., improvement of deep learning algorithms) making it necessary to collect comprehensive, up-to-date data.

Since no current exploratory study investigates the adoption of AI across various industries, an explorative approach is necessary to provide further insights that potentially deepen and extend the proposed TOE framework to account for the novelty regarding the organizational implementation and adoption of AI.

2.2 TOE Framework and Diffusion of Innovation

In general, the TOE framework represents a useful and somewhat flexible starting point to study innovations as it provides a generic theory for the diffusion of technologies (Zhu and Kraemer, 2005). Therefore, it has been widely applied to other contexts and technologies like cloud computing (e.g., Lian et al., 2014), big data (e.g., Bremser, 2018) and business intelligence systems (e.g., Hatta et al., 2017). In essence, the TOE framework comprises three main elements that influence the adoption process of technological innovations: (a) the technological context describing the internal and external relevant technologies available, (b) the organizational context that depends on internal structures and processes measured by various factors such as company size and free resources and (c) the environmental context, which describes the business related field of action, taking into account industry, competitors, government, and suppliers (DePietro et al., 1990). Following Zhu and Kraemer (2005) the TOE framework can be extended by using the innovation diffusion theory of Rogers (1995), which states different technological factors including relative advantage and compatibility. Relative advantage is described as the degree to which an organization perceives an innovation better compared to the previous solution. The second factor, compatibility, is the degree to which an innovation matches the actual needs of the potential user organization. Both factors are positively related to its rate of adoption (Rogers, 1995). Looking at the organizational readiness, DePietro et al. (1990) postulate a positive influence of the strategic behaviour of management, organization's size and slack resources. They also point out the relevance of the intensity of competition as a positive factor on adoption as well as governmental regulations, which can have both, negative and positive effects on innovation implementation. Since there is only little research on AI adoption, a general TOE framework as described above is used as an initial conceptual starting point (see Figure 1), which will be expanded in the course of the study.

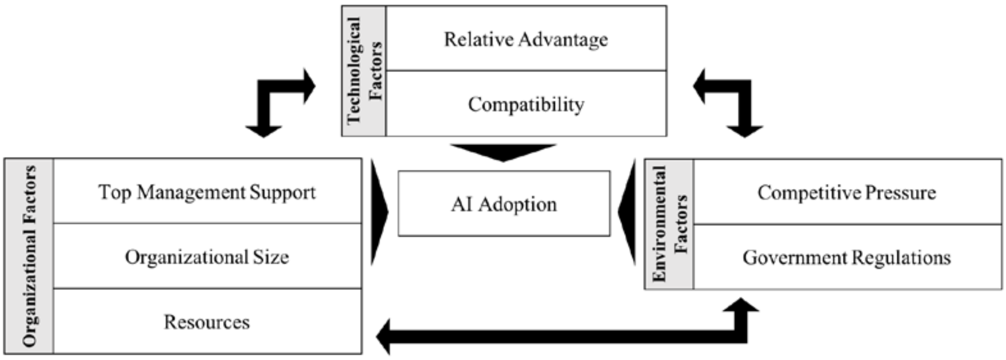

Figure 1. TOE Framework as Conceptual Base (based on DePietro et al., 1990; Rogers, 1995)

3 Qualitative Research Methodology

The aim of the study is to expand the current state of IS research concerning AI application in organizations by questioning experts who work on managerial and operational levels for AI provider and user firms. Organizational AI adoption is a complex topic and has not yet been fully explored. Therefore, an explorative approach using interviews with experts seems appropriate to investigate the problems occurring in this particular context (Flick et al., 2004). According to Weber (1990), content analysis can be used to assess open-ended questions, making the approach suitable for evaluation of the collected qualitative data. Thus, in order to develop an organizational adoption framework, this paper follows the steps of content analysis (see Figure 2): Based on the TOE framework, which serves as a conceptual framework, seven initial categories were derived from relevant literature (e.g., factors "compatibility" or "top management support" in Figure 1). By analysing the interviews, these categories are examined and extended gradually, resulting in 23 categories and subcategories of the final framework for AI adoption. The interviews are transcribed, coded and analysed taking into account relevant practice-oriented studies through triangulation (Hsieh and Shannon, 2005). In particular, we use a combination of directed and conventional analysis, where the directed approach uses codes derived from theory (i.e., TOE framework) and the conventional analysis takes into account information obtained directly from the data since the applied theory is not specifically adjusted to AI technology and therefore should be supplemented and deepened inductively (Hsieh and Shannon, 2005).

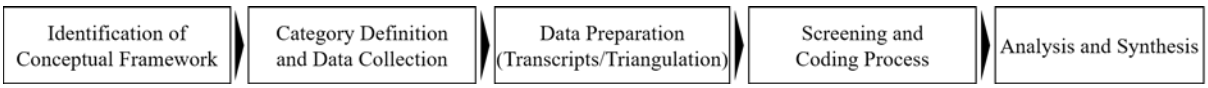

Figure 2. Content Analysis Process (based on Hsieh and Shannon, 2005)

3.1 Research Design

Our main information source were in-depth expert interviews, which were conducted in a semi-structured way. Thereby, the guiding principles of Sarker et al. (2013) were considered by preparing an interview protocol and questioning key informants in different companies. In order to avoid typical pitfalls of semi-structured qualitative interviews, contact was established with the interview partners via e-mail and telephone before the interviews were carried out (Hermanns, 2004). While conducting the interviews we kept our questions open in order to enable participants to speak freely.

The interview guide comprises three different sections. The first section comprised general questions about the position and responsibility of the interviewee and their previous experience in the field of AI and related technologies in an operational or managerial context. The second and most comprehensive section considered advantages and risks of using AI (i.e., the possible results of AI initiatives) and the triggers, prerequisites and limitations of using this technology in organizations. In addition, we inquired the criteria used by the companies to assess the general potential of AI. The last set of questions dealt with the actual use of AI and the strategic and tactical challenges it poses. For example, we asked the interview partners which AI-based applications are currently being used and which specific actions were associated with the introduction and implementation of these projects. Due to the semi-structured approach, initial questions were subject to a gradual adjustment in order to account for the individual expertise and position of the participants and to develop the focus during the interviewing process.

3.2 Sample and Data Collection

We provide an overview of the participants in Table 1 (see below) and further details in the following.

Participants (UF): Participants of firms that are predominantly users of AI products and services					**Participants (PF):** Participants of firms that are predominantly providers of AI products and services				
ID	**Position**	**Job-Exp.**	**Interview Method**	**Adoption Stage**	**ID**	**Position**	**Job Exp.**	**Interview Method**	**Core/ Non-core**
P-01	Digital Growth Manager	16 years	Face-to-face	Adoption	P-08	Founder	10 years	Face-to-face	C
P-02	Head of Marketing & Analytics	10 years	Face-to-face	Consideration	P-09	Development Manager	6 years	Face-to-face	C
P-03	Head of Digital Communications	14 years			P-10	Solution Manager	15 years		
P-04	Asset Management Strategist	3 years	Telephone/ Face-to-face	Adoption	P-11	Development Manager	7 years	Face-to-face	C
P-05	Chief Product Owner	8 years	Face-to-face	Continued use	P-12	Managing Director	19 years	Written answer	NC
P-06	Product owner	8 years	Face-to-face	Continued use	P-13	Consultant	2 years	Telephone	C
P-07	Account Executive	3 years	Telephone	Adoption	P-14	Managing Director	11 years	Telephone	C
Awareness: Org. becomes aware of AI **Consideration:** Org. considers to adopt AI **Intention:** Org. intends to adopt AI **Adoption:** Org. begins to adopt AI **Continued use:** Org. continues to use AI					**Core (C):** AI capabilities and products differentiate company strategically from others **Non-Core (NC):** AI capabilities and products are no strategic factor for company				

Table 1. Participant overview

The interview partners were selected on the basis of a key informant approach. Following the rules of data triangulation, both user (UF) and provider firms (PF) were surveyed (Flick, 2004). The answers were collected over a six-month period and took place between May and October 2018. In total 12 interviews with 14 highly involved participants were conducted within two European countries (Germany and Ireland), taking into account seven experts from provider firms and seven experts of companies, which mainly purchase AI products. After the 12th interview, data collection was discontinued as a further contribution of additional qualitative data was considered unlikely (i.e., theoretical saturation was assumed) (Flick, 2004).

Among the 14 interviewees were eleven male and three female participants. The total number of respondents is comparable to other qualitative studies that consider the adoption of similar technologies (e.g., Bremser et al., 2017; Mallmann and Gastaud Maçada, 2018). In order to avoid an elite bias, both IT staff and managers were interviewed (Miles and Huberman, 1994). Therefore, three of the participants were managing directors or founders, eight identified as middle managers or heads of departments, while the remaining respondents were either consultants or strategists. For the purpose of potentially achieving more generalizable research results and identifying sector and enterprise size-specific differences (Flick, 2004), companies across various industries and of differing sizes were selected, including large (75 %), medium-sized (17 %) and very small enterprises (8 %) (European Commission, 2003) from industries like electricity, gas, steam and air conditioning supply (D), information and communication (J), manufacturing (C) as well as wholesale and retail trade (G) (United Nations, 2008). At the time of the interviews, the organizations were in different phases of implementation regarding AI. Based on the classification according to Frambach and Schillewaert (2002), user firms are divided into the following stages of adoption: awareness, consideration, intention, adoption and continued use, while provider firms were classified according whether they offered AI as a core competence or not (Leonard-Barton, 1992).

The interviews lasted on average 58 minutes and were mainly held face-to-face because of the complexity, scope, and sensitivity of the topic. Nevertheless, a total of four interviews were conducted using telephone calls and one participant replied in a written form due to geographical distance. An overview of the surveyed participants can be found in the table above (see Table 1).

3.3 Coding Concept

Most of the interviews were recorded and transcribed after agreement by the interviewees. In a single interview only notes were taken and in another case a written answer was submitted. Subsequently, the transcripts were assessed by using the NVivo 12 software and by conducting two coding cycles as recommended in Saldaña (2009). The first coding cycle comprised a mixture of attribute coding, descriptive coding and hypothesis coding. The former is performed to obtain essential insights about the data and its descriptive information (e.g., UF/PF, size of organizations). In addition, hypothesis coding was carried out to account for the initially conceptualized factors from the TOE framework (see Figure 1). These factors mentioned in the existing theory form the focus of the hypothesis-based approach and are deductively tested (Greener, 2008). Finally, descriptive coding is used to extract additional aspects that go beyond the previously identified factors (e.g., relative advantage, competitive pressure, and top management support) and thus potentially extend the existing framework. In a second cycle, the formerly created codes are combined into a smaller number of sets using pattern coding (Saldaña, 2009). By discussing and assessing the coding process with a group of four IS researchers and students, an investigator triangulation helped to ensure rigor and trustworthiness. Furthermore, an ongoing data triangulation process took place while coding the interviews by utilizing multiple sources of evidence (Flick, 2004). For example, additional corporate resources as well as current practice-oriented AI studies and reports were considered (e.g., Ransbotham et al., 2017, Andrews et al., 2017).

4 Results and Discussion

While validating the proposed TOE framework for adoption of AI (see Figure 1), we found evidence that the established factors do not fully reflect the challenges that companies face when they want to introduce AI to their companies. The presented TOE framework merely includes fundamental factors that are also applicable to other technologies such as cloud computing. Therefore, the findings that do not go beyond these basics are summarized in tabular form (Table 2). Aspects that supplement or contextualize the original framework will be examined in more detail below.

El.	Fact.	Results	Statements
Technological Factors	Relative Advantage	With the help of AI it is possible to learn from the data over time. However, AI is not a panacea, but should be compared to the use of robust conventional systems for the specific application. The combination of both approaches should also be considered in order to solve the overall problem. This assumption is strengthened by Rzepka and Berger (2018), who indicate that AI is better suited for particular use cases than others. In addition, it is demanded that the results of AI be made comprehensible and no longer represent a black box. The demand for more transparency of AI based systems is also demanded in the current IS literature (e.g., Rzepka and Berger, 2018; Crowston and Bolici, 2019).	"But that one adapts, that one learns based on collective knowledge, no matter if one provides it now at the beginning or continuously, that one adapts there then, that is actually the strength of this AI." – P-11 "And it may well be that you get on with workflows or get on with fixed processes. Or that you say, you know what, we just run AI in the background. And we just take a look at which needles the system still brings us. But it's by no means a panacea […]." – P-01 "We know that we can't really understand machine learning. […] And that there must be procedures that show that exactly this one feature was responsible for it." – P-13
	Compatibility	For the successful use of AI, the work processes must be adapted to the technological requirements. Furthermore, there must be a fit between the desired application and technology.[a]	"If I then ask [...] why do the projects fail? You then realize that the need was not clearly communicated, the use case was not right, that it was too big. That you say you want to do something, but you don't know what." – P-01
Organizational Factors	Top Management Support	In principle, the support of top management can facilitate the introduction of AI. However, a certain understanding of the technology and its applications is required. Currently, decision makers in middle management are particularly problematic, as they are very KPI-driven and thus inhibit AI use.	"Someone, a top manager or someone comes from some conference, has picked up something like Big Data or Predictive Maintenance as buzzwords and then says, 'yes, let's do it'. Yes? And then you start to code somehow and you start to collect and somehow you notice then hey, actually we don't know exactly what we are supposed to do now." – P-14
	Organizational Size	It is unclear whether larger companies have a better chance of adopting AI. Basically, a high budget and a large volume of customer data enables and justifies the use of AI. However, the slow group structures are also hampering further development in this area.	"Now are you going to [...] I'd rather say a niche area. Niche in the sense of, you have maybe only 10,000 users. Then it's not worth the effort that data scientists, Computational Linguists develop something for five years." – P-11
	Resources	The resources can be divided into the factors budget, employees and data that affect the use of AI.[a]	"I think obstacles […] are certainly the initial expenditures. At the beginning, you'd need a small one-off budget, a bit of know-how as a starting point […]." – P-02
Environmental Factors	Comp. Pressure	Competitive pressure leads companies to increasingly deal with AI in order to gain a competitive advantage.	"They [the costumers] challenge us too. They say, look at the competition, the start-up does that, we've already looked with them. Why can't you do that yet?" – P-10
	Gov. Regulations	Many laws complicate the introduction and use of AI. In this context a renewal of the legal situation is demanded. Especially the GDPR and the employees' council are a particular hurdle for companies.[a]	"And innovation and law are two words that I think rarely appear in one single sentence." – P-04

[a]: Further details on the subcategories are discussed below

Table 2. Findings: Examination of proposed factors in TOE framework

In addition to the 'classic' TOE assumptions, the experts also mention prerequisites for the implementation of AI that result from the special properties of AI and therefore have only been insufficiently addressed or have not been examined in general TOE literature at all before. These new findings are described comprehensively in the following section.

Technological Factors

Technological factors comprise two main aspects: Relative advantage, which was already considered in Table 2 in detail, and compatibility, which can be divided into two subcategories on the basis of expert interviews: business processes and business cases. Therefore, we will revisit the second factor compatibility in the following and explain it in more detail.

Compatibility. According to experts, the *business processes* in the company must be adapted to the new requirements that arise from the use of AI. In the context of AI, it is therefore no longer useful to use existing KPIs of other projects, since AI projects have differing properties. For example, the results that arise from such projects can no longer be planned to an extent that would be necessary regarding traditional, common KPIs (e.g., ROI) as demonstrated by the following quote:

> "The interesting thing about how we implement these projects here is that we didn't define KPIs […]. That means for us, we learn with the information we get back through the system. That's a very important point. If you apply old KPIs to new technologies and approaches, you run the risk of only digitizing old KPIs." – P-01

Instead, it becomes necessary to introduce agile forms of work. Particularly in the field of data science, it is important to continuously evaluate the progress of projects, since the feasibility of ideas in this area cannot be proven from the outset. There are only a few, incomplete criteria to evaluate the existing data at the very beginning. Within the framework of agile, flexible working models for software development, the current status and the data can always be viewed in terms of new findings, thus reducing the risk of investing the wrong amount of time and money. The relevance of agile working methods is underlined by the following statement:

> “And in IT you had very, rigid waterfalls, that is classic traditional IT project management. Which is not, how shall I say, very beneficial regarding the uncertainties when using data and artificial intelligence. […] Because you just plan a concept somehow, that's actually this classic process, over half a year and then you look into the data and notice ‘oh God, that's all wrong!’. And you can actually throw the concept away! So half a year, more or less, not as much progress has been made as if one had looked at the data in advance." – P-14

In addition to the work processes, however, further factors must also be checked for compatibility. Another very frequently mentioned aspect is the formulation of a concrete *business case*. Experts believe that AI can only be used successfully if there is a clear problem. AI must be seen as a tool for a purpose and cannot be viewed in isolation. The problem of prioritizing possible use cases appropriately is known from literature on big data use (e.g., Bremser, 2018), which also deals with an underlying technology that can be used in a variety of ways in organizations.

> “But you really need to know, ‘where can you solve a problem with that?’. Just because you can do AI, it doesn't bring you anything, zero, honestly not. […] They don't buy it because it's AI. So really, also corporate customers, they don't buy it because there is AI in it now. They buy it because it must have a benefit.” – P-08

In line with these factors influencing AI adoption, we formulate the following propositions:

Proposition 1*: Compatibility between AI technology and business processes (e.g., agile forms of work) as well as the development of a dedicated business case will have a positive effect on adoption of AI in companies*

Organizational Factors

In addition to technological readiness, factors must also be taken into account that reflect the overall organization's ability to implement AI. The factors culture and organizational structure were newly discovered by examining the expert interviews, while the factor resources was subdivided into the aspects budget, employees, and data.

Culture. After evaluating the interviews, it became evident that the adoption of AI in a company is strongly influenced by the culture in the company. In addition to top management support the introduction and implementation of an innovative culture in the company are also relevant. In this context, aspects of *change management* to achieve an innovative culture within the company were mentioned frequently by the interviewees. The functionality of an intelligent application is based on the input of already existing, high-quality data as well as the training which has to be carried out by the employees over time (Crowston and Bolici, 2019). Only if there is a willingness to use the technology in the long run, the quality of the answers and decisions made by the machine will improve.

> "In the beginning the model is bad. You have few answers that reach this threshold. But by constantly saying as an employee that this was right or by correcting, you are building a knowledge base." – P-08

If the path to an *innovative culture* is not successful, there is a danger of missing out on new, important technologies and trends. The factor of missing an absorptive capacity to adopt new technologies is evidenced by the following statement:

> "In such a large corporation you have the tendency to say again and again 'well, we make money with the model we have! Why should I come up with something new now?'." – P-05

Resources. The adoption of AI in a company does not only depend on the culture, but also results from slack resources, which should be further subdivided. Comparable to other innovations (e.g., Bremser et al., 2017), the available financial resources through a *budget* are an important aspect that generally determines the implementation of new technologies in projects. A high budget can enable capacities, create financial freedom and help to build know-how. On the other hand, obligations also arise from financial resources. This problem can in turn jeopardize the successful introduction of AI, since the course of projects with AI is unpredictable and strongly dependent on the data used. The restricting influence of budget is demonstrated by the following statement:

> "The second point is the budget. The moment your management or the person responsible for the budget asks the question 'what is the return on investment?'. And 'what happens if I don't do it?' You are no longer on the move agilely, but you are immediately arrested in a major project. The demand or the requirements are already defined, there's a price tag on it and there's a timeline on it. No more room for adjustments." – P-01

In addition to the budget, a second aspect should be considered as one of the most frequently discussed factors within the sample: the *employees* of a company who have the necessary know-how to apply the technology. Basically, it should be noted that the staff should have both, the professional qualifications and programming knowledge in the field of AI (e.g., utilizing libraries such as TensorFlow, PyTorch or Keras) as well as a domain understanding of the respective organization. It should also be considered that many companies have problems recruiting professionals such as data scientists, who demand high salaries and are potentially disloyal to their employers due to a high demand on the labour market. The necessity of these occupational groups for implementation of AI is also addressed by previous studies (e.g., Kruse et al., 2019). Additionally, interviews show that AI projects cannot simply be outsourced as they require the company's domain knowledge as described. Therefore, an expert suggests to train the employees in the company who already have a domain specific knowledge (e.g., controller, statisticians) in the field of machine learning. The problem set is evidenced by the following statement:

> "This is one of the most important things: you need the people! In this day and age you can no longer outsource. Especially not with machine learning and artificial intelligence. That doesn't work. You need the experts. You need the people – who actually don't have the time." – P-01

The third subcategory that can be seen as a resource is the *data* used to train the AI. Data was among the factors most often mentioned by all interviewees across firms and positions and is also frequently considered in current literature (e.g., Crowston and Bolici, 2019). Various problems have been extracted while examining the qualitative interviews: Data must first be made accessible. Both *data availability* and data protection play an important role. Often the data must be made usable from different old systems. Furthermore, it is necessary to extract the data in a scalable form, because AI projects require as many data records as possible. According to the experts, these requirements can account for up to two thirds of the workload of an AI project. The following statement illustrates how time-consuming and difficult the provision of data can be:

> "We also often […] first had to think about 'where does the data actually come from?' […] We actually had to deal with three or four different legacy systems from which we had to get the data out." – P-05

In addition to the technical aspects of data availability, *data protection* also plays an important role. Often, it is mainly larger corporations that experience difficulties implementing an open data policy. In these kind of companies, a deliberate isolation of the individual departments takes place, which makes the successful introduction of AI more difficult:

"We're going to have to make sure that we stop pursuing a silo mentality." – P-01

Once the data is available, the quality of the data becomes relevant. This aspect was brought up very often by the interviewees, who point out that *data quality* is regularly a problem, as it is not fully possible to assess the data sets before the project is indeed implemented. Only a few incomplete metrics exist to evaluate the data in advance. This is particularly problematic because historical data often does not have the required quality and degree of detail due to time and cost pressure when data was generated.

"We also have customers who say yes, we have the CRM here, our system here, our old system. Maybe an old application. But we don't really want to take the data with us, because we know that the service staff often just entered something hurriedly due to a lack of time, and that it's not right." – P-10

Organizational Structure. The culture of the company is closely linked to its structure. As in the statement above, large corporations have problems setting up new AI projects because of their "everything is fine" mentality. Many companies therefore go the way of circumventing old, inhibiting structures by establishing a lab or hub within the organization. However, problems can also arise as a result of this procedure, which is made clear by the following statement by an expert:

"Is this somehow a lab in Silicon Valley, where clever people are all sitting around building something without being subject to the restrictions of the traditional company? The advantage of this is that they are very fast. This has the disadvantage that the integration into the slow company will fail later. [...] On the other hand, if you try it out of the existing IT, which is historically very cost-driven and very innovation-free, then it won't work either." – P-14

Therefore, it is suggested to use a hybrid model, in which a hub serves as a starting point for new ideas and technologies, but where an intense communication between the lab and the company still exists.

As shown above, organizational readiness factors influence decisions regarding AI adoption of companies strongly. Hence, we posit:

Proposition 2: *A dedicated AI budget, which does not entail any obligations to meet performance targets, will have a positive impact on the adoption of AI in companies*

Proposition 3: *The availability of data scientists and developers with appropriate expertise, domain knowledge as well as the willingness of users to train AI systems over time will have a positive impact on the adoption of AI in companies*

Proposition 4: *The availability of extensive, meaningful and high quality data will have a positive effect on adoption of AI in companies*

Proposition 5: *Departments who keep relevant data to themselves, an overreliance on status quo as well as slow and bureaucratically shaped corporate structures will have a negative effect on the adoption of AI in companies*

Environmental Factors

Looking at environmental readiness, the known factor government regulations is divided into two main aspects (GDPR and employees' council) and the categories industry requirements as well as customer readiness are newly filtered out by coding the expert interviews. The extensions of the original framework are explained in more detail in the following section.

Government Regulations. As already indicated, the introduction of AI must also consider several legal aspects. A relevant regulation that was enforced in May 2018 is the *General Data Protection Regulation (GDPR),* which regulates activities like the processing of personal data. The handling of the new legal situation is addressed by many experts in the interviews as companies struggle to provide personal data for the training of their intelligent machines. In this context, many data sets need to be anonymized, which makes the use of intelligent, self-learning algorithms more difficult or even impossible. The following statement expresses the impact that such a regulation can have on the European economy:

"This shock with the General Data Protection Regulation […] to make everything bad per se and excessively laborious, that also contradicts any reality. Also, we have to be careful that we don't lose track of others with all these AI topics, because they will do it. We would like to, but we're getting a bit in ourselves' way." – P-11

In addition to legislation concerning the handling of personal customer data, the protection of employees must also be taken into account by firms. Many applications in the field of AI are based on learning from data. If intelligent software is used in the company to support employees, it can access a lot of information from their daily work routine. Thus, there is a danger that the personnel could be monitored. In addition, as a result of the progressive automation by AI, a large scope of duties is taken over gradually by machines. Although it was one of the less prominent constraints mentioned by all interviewees, these effects of intelligent algorithms ultimately lead to the fact that the introduction of AI is inhibited by *employees' council and employee representatives* in companies to protect employees' workplaces.

> "Because, of course, a system of this kind, which logs data without limits, could of course also store the information. That X makes three mails in one day and Y makes 30. And her completion rates are much higher. Okay? So the employees' council is definitely a key stakeholder." – P-01

Industry requirements. In addition, each industry has its own specific requirements, which also affect the adoption of AI. These are specific laws, external circumstances affecting the company, and the organization's interaction with the environment. For example, Kruse et al. (2019) examine the adoption of AI in financial sector taking into account its specific regulations, IT systems and customer group. These influences can encourage or inhibit the use of AI, depending on their nature. The necessary inclusion of the factor *industry* was evidenced, besides the related literature, by the following statement:

> "I also believe that our industry [electricity provision] is simply making a bit of an impact. The challenges facing our industry are simply more complex than what a small retailer might have to solve […]." – P-02

Costumer readiness. When a company is faced with the decision to introduce AI, the knowledge and acceptance of its customer base must also be taken into account. These requirements apply to B2B as well as to B2C companies, which should both focus on their customer's benefit. The interviewed experts currently see a development of their costumer's ability and willingness to deal with new technologies. Consumers in particular are increasingly demanding digital and intelligent offers and are acting as disruptors. This is consistent with other adoption literature, which points to changing customer expectations for individualized services and products (e.g., Bremser, 2018). But also corporate customers are beginning to innovate. The requirements they will have in the future can be seen from the following statement:

> "In 3 to 4 years, when the algorithms are mature, this will become the standard. Then the customers simply expect that such a function [intelligent service] is in the solution." – P-10

We thus posit that environmental factors, like the legislation or the readiness of industry and customers, affects AI adoption as follows:

Proposition 6*: Strict laws regarding the processing of personal data will hamper the training of intelligent machines and the review by a strong employee representative body will slow down and inhibit the introduction of new technologies. Thereby both will have a negative effect on adoption of AI in companies*

Proposition 7*: Industry specific properties (e.g., specific regulations, customer group) will, depending on their nature, have both positive and negative effects on the adoption of AI in companies*

Proposition 8*: Demanding customers will nudge the companies to design individualized, intelligent products and thus will have a positive effect on the adoption of AI in companies*

The previous findings will be used in the following to supplement the basic framework (see Figure 1) and to generate an overview of the experts' statements and thus the special features of AI (see Figure 3 on page 12).

After the proposed framework has been extensively investigated and extended, the next step is to showcase special features that occur during the introduction of AI in comparison to other technologies and which go beyond the theory of TOE. For this purpose, the statements of experts are investigated via crosstab queries (i.e., filter coded interviews simultaneously by a factor and company type) in order to get an idea about perceptual differences between provider and user firms, which eventually create a gap between supply and demand. The comparison inductively leads to different problem areas where the preconditions, views and attitudes of the provider and user firms differ.

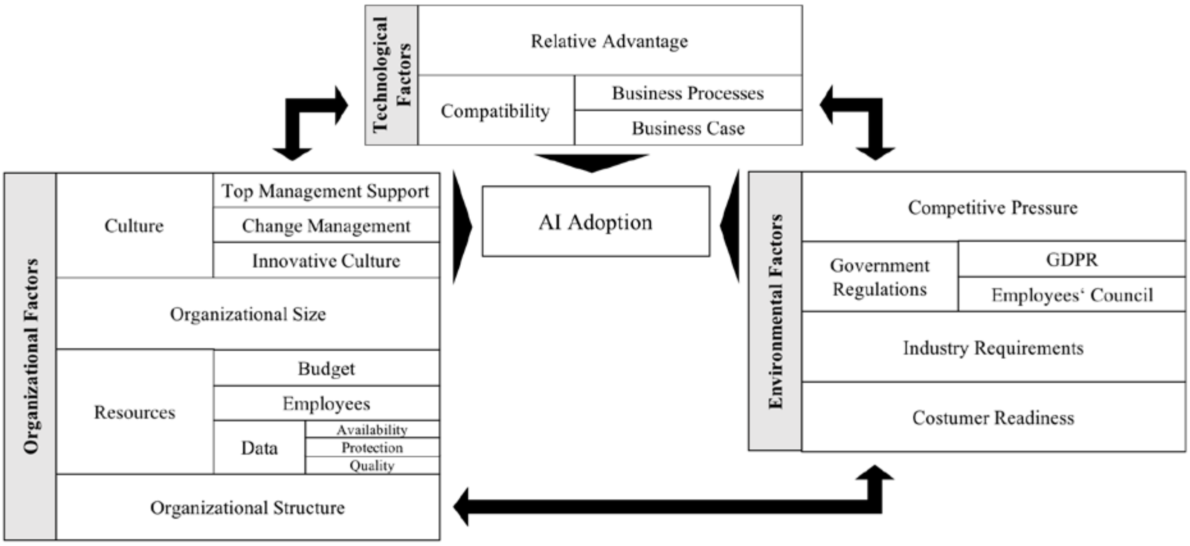

Figure 3. Extended and deepened framework for AI adoption

An example of this misconception between those two groups is the differing assessment of consumers. While user firms tend to view their costumers as sceptical about the acceptance of intelligent applications, providers see consumers as disruptors who explicitly demand innovations.

> "I believe we must not forget that our clientele is, to a large extent, rather conservative. And such a chatbot would not be suitable for everyone, not even for half of our target group." – P-02 (UF)

> "Very important, I have also become aware of this very often and very clearly, the customers are, as they say, the disruptors. They say exactly how they would like best to work with the brand." – P-10 (PF)

But it is not only the customers that are assessed differently by the respective category of the firm. There is also a divergence of ideas about the prerequisites within the companies. For example, user firms see the size and bureaucracy of their group as an obstacle to the acceptance of AI, while the provider designs their products primarily for large firms in mass markets which can generate sufficient amounts of data.

> "Because it has been said that we do not see it within our existing group structures, we cannot give the issue the attention it needs." – P-05 (UF)

> "That especially companies that have many service requests benefit from this. [...] I also believe that, for medium-sized companies or something, I do not know. Especially larger companies." – P-08 (PF)

The evaluation of the interviewees' statements also shows that the ideas regarding the availability of budget for AI projects diverge. While large user firms state that they have problems providing the required financial resources, the provider firms overestimate the possibilities of their customers.

> "I think obstacles, why we have not done it [AI adoption] yet, are certainly the initial expenditures. At the beginning where you would need a small one-off budget, a bit of know-how as a starting point, which might not be there yet." – P-02 (UF)

> "It's also often the case that large corporations in particular have strategic investment pools, where even a CEO says 'yes, I have understood that in order to do something there, we now have to take three, four million in to our hands and we'll take that as play money and start making this initial investment'." – P-14 (PF)

Another point mentioned by the provider firms is the preference of user firms regarding on premise versus cloud-based solutions. As a result, providers are often unable to train and adapt the intelligent algorithms adequately since access to data and sufficient computing power is constrained.

Considering the differences between user and provider firms, we posit the following propositions:

Proposition 9: *The diverging assessment of consumer's AI readiness by provider and user firms leads to a different estimation of demand and thus will have a negative effect on adoption of AI in companies*

Proposition 10: *The fact that the companies that have sufficient data volumes and are addressed by provider firms are also trapped in slow structures of their corporations will have a negative effect on adoption of AI in companies*

Proposition 11: *Misconceptions about budget availability and willingness to pay between user and provider firms will have a negative effect on adoption of AI in companies*

Proposition 12: *Differing preferences of cloud-based and on premise applications between provider and user firms result in a negative effect on adoption of AI in companies*

5 Conclusion, Limitations, and Future Research

The explorative study showed that the TOE framework is applicable to the adoption of AI. However, some categories show results that are partially contradictory and require further research (e.g., organizational size). Furthermore, we were able to identify new, AI-specific factors (e.g., data) and subcategories for existing ones (e.g., GDPR and employees' council as part of government regulations). Moreover, evaluating the interviews allowed us to provide initial solution approaches to address the problems that could possibly arise while implementing AI. Altogether, a framework for the adoption of AI is proposed, which provides executives with a broad overview of AI related conditions in organizations. This enables companies to carry out a structured analysis of their status quo and identifying areas of improvements to adopt AI successfully in their processes and services. In addition, it is shown how a gap between supply and demand for AI technology can arise due to diverging assumptions of user and provider firms. In order to enable the top management to address this disagreement, it is necessary to expose them and to create the prerequisites needed for a successful implementation of AI in their company. Besides the practical implications, by conducting the first cross-industry exploratory study focusing on factors which enable and impede AI adoption in general, a basis for further research is introduced. This study can be seen as a starting point to conduct additional studies – for example focusing on or comparing special industries (e.g., healthcare, banking and finance) and associated requirements or looking at specific departments and use cases in depth (e.g., HR, Service).

Future research should consider a constitutive quantitative study, to review the given proposals and further examine existing inconsistencies within the factors. This will help to understand the factors' actual impact, making it possible to develop sound strategies and action plans for an integrated AI adoption. Moreover, a framework other than TOE might then be applied to better reflect the specific requirements of AI (e.g., conceptual framework of organizational innovation adoption by Frambach and Schillewaert (2002)). In addition, companies across the globe and of various cultures, should be included in the research, although a semi-multinational context already exists due to the fact that the interviewed firms are operating in several countries. Additionally, we have mainly considered large companies so far, as they currently already have dedicated positions for AI projects and could therefore be easily identified and contacted. However, future research should survey medium-sized and smaller companies, especially as contradictory results on the impact of company size were obtained in the study. Nevertheless, this study ultimately was able to conceptualize an 'organizational chassis' for the introduction of AI adoption that enables organizations to move forward in the field of AI.

References

Adadi, A. and M. Berrada (2018). "Peeking Inside the Black-Box: A Survey on Explainable Artificial Intelligence (XAI)." *IEEE Access* 6, 52138-52160.

Agrawal, A., J. Gans and A. Goldfarb (2018). *Is Your Company's Data Actually Valuable in the AI Era?* URL: https://hbr.org/2018/01/is-your-companys-data-actually-valuable-in-the-ai-era (visited on 11/18/2018).

Alsheibani, S., Y. Cheung and C. Messom (2018). "Artificial Intelligence Adoption: AI-readiness at Firm-Level." In: *Proceedings of Pacific Asia Conference on Information Systems (PACIS).* A-37. Yokohama: Japan.

Andrews, W., M. Sau, C. Dekate, A. Mullen, K. F. Brant, M. Revang and D. C. Plummer (2017). *Predicts 2018: Artificial Intelligence*. Technical Report. Gartner.

Bremser, C., G. Piller and F. Rothlauf (2017). "Strategies and Influencing Factors for Big Data Exploration." In: *Proceedings of Americas Conference on Information Systems (AMCIS).* A-4. Boston, Massachusetts: USA, p. 234.

Bremser, C. (2018). “Starting Points for Big Data Adoption.” In: *Proceedings of European Conference on Information Systems (ECIS).* A-32. Portsmouth: United Kingdom.

Brundage, M., S. Avin, J. Clark, H. Toner, P. Eckersley, B. Garfinkel, A. Dafoe, P. Scharre, T. Zeitzoff, B. Filar, H. Anderson, H. Roff, G. C. Allen, J. Steinhardt, C. Flynn, S. Ó hÉigeartaigh, S. Beard, H. Belfield, S. Farquhar, C. Lyle, R. Crootof, O. Evans, M. Page, J. Bryson, R. Yampolskiy, D. Amodei (2018). *The Malicious Use of Artificial Intelligence: Forecasting, Prevention, and Mitigation*. Technical Report. Future of Humanity Institute; University of Oxford; Centre for the Study of Existential Risk; University of Cambridge; Center for a New American Security; Electronic Frontier Foundation; OpenAI.

Bughin, J., E. Hazan, S. Ramaswamy, M. Chui, T. Allas, P. Dahlström, N. Henke and M. Trench (2017). *Artificial Intelligence: The Next Digital Frontier?.* Technical Report. McKinsey Global Institute.

Crowston, K. and F. Bolici (2019). “Impacts of Machine Learning on Work.” In: *Proceedings of Hawaii International Conference on System Sciences (HICSS).* A-52. Wailea: Hawaii, p. 5961.

DePietro, R., E. Wiarda and M. Fleischer (1990). “The Context for Change: Organization, Technology and Environment.” In: *The Process of Technological Innovation*. Ed. by L. Tornatzky and M. Fleischer. 4th Edition. Lexington: Lexington Books, 152-175.

Elliot, B. and W. Andrews (2017). *A Framework for Applying AI in the Enterprise*. Technical Report. Gartner.

European Commission (2003). “Commission Recommendation of 6 May 2003 Concerning the Definition of Micro, Small and Medium-Sized Enterprises (Notified under Document Number C (2003) 1422).” *Official Journal of the European Union* L 124, 36-41.

Flam, F. (2018). *IBM’s Watson Hasn’t Beaten Cancer, But A.I. Still Has Promise*. URL: https://www.bloomberg.com/opinion/articles/2018-08-24/ibm-s-watson-failed-against-cancer-but-a-i-still-has-promise (visited on 11/20/2018).

Flick, U. (2004). “Triangulation in Qualitative Research.” In: *A Companion to Qualitative Research*. Ed. by U. Flick, E. von Kardoff and I. Steinke. London: Sage, 178-183.

Flick, U., E. von Kardorff and I. Steinke (2004). “What is Qualitative Research? An Introduction to the Field.” In: *A Companion to Qualitative Research*. Ed. by U. Flick, E. von Kardoff and I. Steinke. London: Sage, 3-11.

Frambach, R. T. and N. Schillewaert (2002). “Organizational innovation adoption: A multi-level framework of determinants and opportunities for future research.” *Journal of Business Research* 55 (2), 163– 176.

Greener, S. (2008). *Business Research Methods*. London: Ventus Publishing ApS.

Hatta, N. N. M., S. Miskon and N. S. Abdullah (2017). "Business Intelligence System Adoption Model for SMEs." In: *Proceedings of Pacific Asia Conference on Information Systems (PACIS).* A-192. Langkawi: Malaysia.

Hermanns, H. (2004). “Interviewing as an Activity.” In: *A Companion to Qualitative Research.* Ed. by U. Flick, E. von Kardoff and I. Steinke. London: Sage, 209–213.

Hosanagar, K. and A. Saxena (2017). *The First Wave of Corporate AI Is Doomed to Fail*. URL: https://hbr.org/2017/04/the-first-wave-of-corporate-ai-is-doomed-to-fail (visited on 11/18/2018).

Hsieh, H.-F. and S. E. Shannon (2005). “Three Approaches to Qualitative Content Analysis.” *Qualitative Health Research* 15 (9), 1277-1288.

Huang, M.-H. and R. T. Rust (2018). “Artificial Intelligence in Service.” *Journal of Service Research* 21 (2), 155-172.

Kruse, L., N. Wunderlich and R. Beck (2019). “Artificial Intelligence for the Financial Service Industry: What Challenges Organizations to Succeed.” In: *Proceedings of Hawaii International Conference on System Sciences (HICSS).* Wailea: Hawaii, p. 6408.

Leonard-Barton, D. (1992). “Core Capabilities and Core Rigidities: A Paradox in Managing New Product Development.” *Strategic Management Journal* 13 (S1), 111-125.

Lian, J.-W., D. C. Yen and Y.-T. Wang (2014). “An exploratory study to understand the critical factors affecting the decision to adopt cloud computing in Taiwan hospital.” *International Journal of Information Management* 34 (1), 28-36.

Lu, B. Y., D. Qian, H. Fu and W. Chen (2018). “Will Supercomputers Be Super-Data and Super-AI Machines?” *Communications of the ACM* 61 (11), 82-87.

Mallmann, G. L. and A. C. Gastaud Maçada (2018). “Adoption of Cloud Computing: A Study with Public and Private Hospitals in a Developing Country.” *International Journal of Innovation and Technology Management* 15 (5), 1850044.

McCarthy, J. (2007). *What Is Artificial Intelligence?*. Interview. Stanford University.

Miles, M. B. and A. M. Huberman (1994). *Qualitative Data Analysis: An Expanded Sourcebook*. 2nd Edition. Beverly Hills, CA: Sage.

Moncrief, W. C. (2017). “Are sales as we know it dying … or merely transforming?” *Journal of Personal Selling & Sales Management* 37 (4), 271–279.

Monroe, D. (2018). “Chips for Artificial Intelligence.” *Communications of the ACM* 61 (4), 15-17.

MSV, J. (2018). *Here Are Three Factors That Accelerate The Rise Of Artificial Intelligence*. URL: https://www.forbes.com/sites/janakirammsv/2018/05/27/here-are-three-factors-that-accelerate-the-rise-of-artificial-intelligence/#639dff18add9 (visited on 11/19/2018).

Nascimento, A. M., M. A. V. C. da Cunha, F. de Souza Meirelles, E. Scornavacca and V. V. de Melo (2018). "A Literature Analysis of Research on Artificial Intelligence in Management Information System (MIS)." In: *Proceedings of Americas Conference on Information Systems (AMCIS)*. A-5. New Orleans, Louisiana: USA, p. 2613.

Rana, R., M. Staron, J. Hansson, M. Nilsson and W. Meding (2014). “A Framework for Adoption of Machine Learning in Industry for Software Defect Prediction.” In: *Proceedings of 9th International Conference on Software Engineering and Applications (ICSOFT-EA).* Vienna: Austria, p. 383.

Ransbotham, S., D. Kiron, P. Gerbert, and M. Reeves (2017). *Reshaping Business With Artificial Intelligence*. Technical Report. MIT Sloan Management Review.

Reese, H. (2016). *Top 10 AI failures of 2016*. URL: https://www.techrepublic.com/article/top-10-ai-failures-of-2016/ (visited on 11/20/2018).

Rogers, E. M. (1995). *Diffusion of innovations*. 4th Edition. New York: Free Press.

Rzepka, C. and B. Berger (2018). "User Interaction with AI-enabled Systems: A Systematic Review of IS Research." In: *Proceedings of International Conference on Information Systems (ICIS)*. A-7. San Francisco: USA.

Saldaña, J. (2009). *The Coding Manual for Qualitative Researchers*. 1st Edition. London: Sage.

Sarker, S., X. Xiao and T. Beaulieu (2013). “Qualitative Studies in Information Systems: A Critical Review and Some Guiding Principles.” *MIS Quarterly* 37 (4), ii-xviii.

The Economist (2017). *Regulating the internet giants: The world’s most valuable resource is no longer oil, but data*. URL: https://www.economist.com/leaders/2017/05/06/the-worlds-most-valuable-resource-is-no-longer-oil-but-data (visited on 11/03/2018).

United Nations (2008). *International Standard Industrial Classification of All Economic Activities*. 4th Edition. New York: United Nations Publication.

vom Brocke, J., W. M. Maaß, P. Buxmann, A. Maedche, J. M. Leimeister and G. Pecht (2018). “Future Work and Enterprise Systems.” *Business & Information Systems Engineering* 60 (4), 357–366.

Weber, R. P. (1990). *Basic content analysis*. 2nd Edition. Newbury Park, CA: Sage.

Yan, D., Q. Zhou, J. Wang and N. Zhang (2016). “Bayesian Regularisation Neural Network based on Artificial Intelligence Optimisation.” *International Journal of Production Research* 55 (8), 2266–2287.

Zhu, K. and K. L. Kraemer (2005). “Post-Adoption Variations in Usage and Value of E-Business by Organizations: Cross-Country Evidence from the Retail Industry.” *Information Systems Research* 16 (1), 61–84.