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An Industry-Specific Investigation on Artificial Intelligence Adoption: The Cases of Financial Services and Manufacturing

Mathis Hoffmann
Software Business & Information Management, Technical University Darmstadt, mathis.hoffmann@stud.tu-darmstadt.de

Maren Mehler
Technical University of Darmstadt, maren.mehler@tu-darmstadt.de

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Mathis Hoffmann
Technical University of Darmstadt
Hochschulstr. 1, 64289 Darmstadt
m.hoffmann@hoffdoc.de

Maren F. Mehler
Technical University of Darmstadt
Hochschulstr. 1, 64289 Darmstadt
mehler@is.tu-darmstadt.de

Abstract

Artificial Intelligence (AI) has a lasting transformational effect on industries worldwide. Former research has primarily focused on AI adoption as a business phenomenon without considering different industries. Those are characterized by unique attributes that may influence how modern technologies are implemented. In order to initiate non-generalized research in that field, industry-specific drivers and barriers to firm-level AI adoption in the financial services and the manufacturing industry are analyzed. Drawing on the Technology-Organization-Environment (TOE) framework, it was possible to paint a holistic picture of use cases and unique, but also general drivers and barriers of AI adoption for each industry. Ultimately, by bringing these two viewpoints together, a theory of hard (generalizable) and soft (industry-specific) AI adoption factors was developed. Therefore, the findings serve as a basis for further industry-specific research and provide business stakeholders and executives with a transparent handbook about industry insights and AI knowledge.

Keywords: Artificial Intelligence, Adoption, TOE Framework, Financial Services Industry, Manufacturing Industry

Introduction

Most companies know that Artificial Intelligence (AI) offers great potential for saving time and costs, thus increasing profits. For example, 34% of companies worldwide are already using AI in 2022, and 42% are exploring AI (IBM, 2022). AI is estimated to contribute $15.7 trillion to the global gross domestic product (GDP) in 2030 (PwC, 2017). AI embraces several disciplines and techniques in computer science, but business leaders' focus has also shifted to how the technology's capabilities can be leveraged to create economic value. Despite the many opportunities AI offers, many companies are – if at all – still exploring and have not yet adopted AI. Two reasons can explain this: First, barriers, if they exist, hinder the implementation, and second, potentially missing drivers will not support the adoption process of AI in organizations (Pumplun et al., 2019; Zöll et al., 2022).

Research on organizational and individual technology adoption is not new. The most established frameworks are the Technology Acceptance Model (TAM) (Davis, 1989) and Technology-Organization-Environment (TOE) (DePietro et al., 1990[1]). In the last years, the investigation of the so-called 'AI readiness factors' has also become established, i.e., the organizational 'chassis'

[1] The TOE framework was actually developed by DePietro et al. (1990) in chapter 7 of Tornatzky and Fleischer, but is often cited as Tornatzky & Fleischer (1990).

embracing all prerequisites for enablement of successful AI adoption. Respective contributions have been performed by Jöhnk et al. (2021) and Pumplun et al. (2019) with qualitative, interview-based methods. Readiness factors can be seen as a preceding level before the organizational adoption of AI itself. However, the results were aggregated and generalized across all industries.

Fundamental strategic management science, like Porter's five forces (Porter, 1980), argues that a company's industry structure is characterized by different, maybe even unique industry parameters. This is why technology adoption factors might also be affected and differ between industries, opening up the need to zoom in on selected industries. This need has also been recognized by authors of previous studies (Cubric et al., 2020; Kar et al., 2021; Pumplun et al., 2019; Zöll et al., 2022). However, industry-specific research on drivers and barriers to AI adoption only exists in a few cases, and a cross-industry comparison is missing. Kruse et al. (2019), for example, answered the question about the challenges and barriers of AI in banking and insurance by conducting interviews with AI experts from the German finance industry and supporting industries. Kinkel et al. (2021) defined a questionnaire-based survey and collected responses from over 600 industry stakeholders to investigate factors of AI adoption in the manufacturing industry.

Thus, this paper seeks to contribute to the research on AI adoption in financial services and manufacturing from separate viewpoints. The financial services industry offers great potential (Hentzen et al., 2021). Manufacturing is very diverse and constantly in transformation and, therefore, has many use cases (United States Department of Labor, n.d.; de Propris & Bailey, 2020; Zhang et al., 2019). The holistic perspective on drivers and barriers in both industries intends to exert an industry-specific reality check of generalized, industry-aggregated research. Therefore, we seek to answer the following research questions (RQs):

RQ1: *What factors drive AI adoption in the financial services and manufacturing industries?*

RQ2: *What factors curb AI adoption in the financial services and manufacturing industries?*

RQ3: *How do drivers and barriers of AI adoption relate to each other across industries?*

To answer the research questions, we conducted an interview-based multiple-case study. The process of qualitative data collection aims to establish verified causal findings and explanations for the described phenomena. The TOE framework, a widespread theory in technology adoption research, supports the research. With this paper, we urge future research on the adoption of technologies to consider industry-specific factors by showing that the financial service industry and manufacturing industry have different drivers and barriers and vary from known general factors.

This paper is structured as follows: After the introduction with our motivation and research questions, we present the TOE framework, fundamentals of AI, and related work. We then describe our case study methodology in chapter three and provide the results of our research according to the TOE framework in the next chapter. Finally, we discuss the results, give theoretical and practical contributions and limitations, and conclude our paper.

Theoretical Background

Technology-Organization-Environment (TOE) Framework

Technology adoption is not an isolated phenomenon but represents "a series of decisions that are not visible to all [involved] participants" (DePietro et al., 1990, p. 178). To ensure that all influencing factors are taken into account, it is established in research to use technology adoption frameworks, which can support a complexity-reducing abstraction. The TOE framework is one of the most common technology adoption frameworks in information systems (IS) research (Kinkel et al., 2021) focusing on firm-level and including firm-external influences (Oliveira & Martins, 2011). It was utilized, for example, for adoption technologies such as Big Data (Bremser, 2018), of AI (Pumplun et al., 2019), but also for specific AI adoption barriers in finance (Kruse et al., 2019). The TOE framework identifies three different contexts in and surrounding a company that influence technology adoption: the technological context, the organizational context, and the environmental context (DePietro et al., 1990) (see Figure 1).

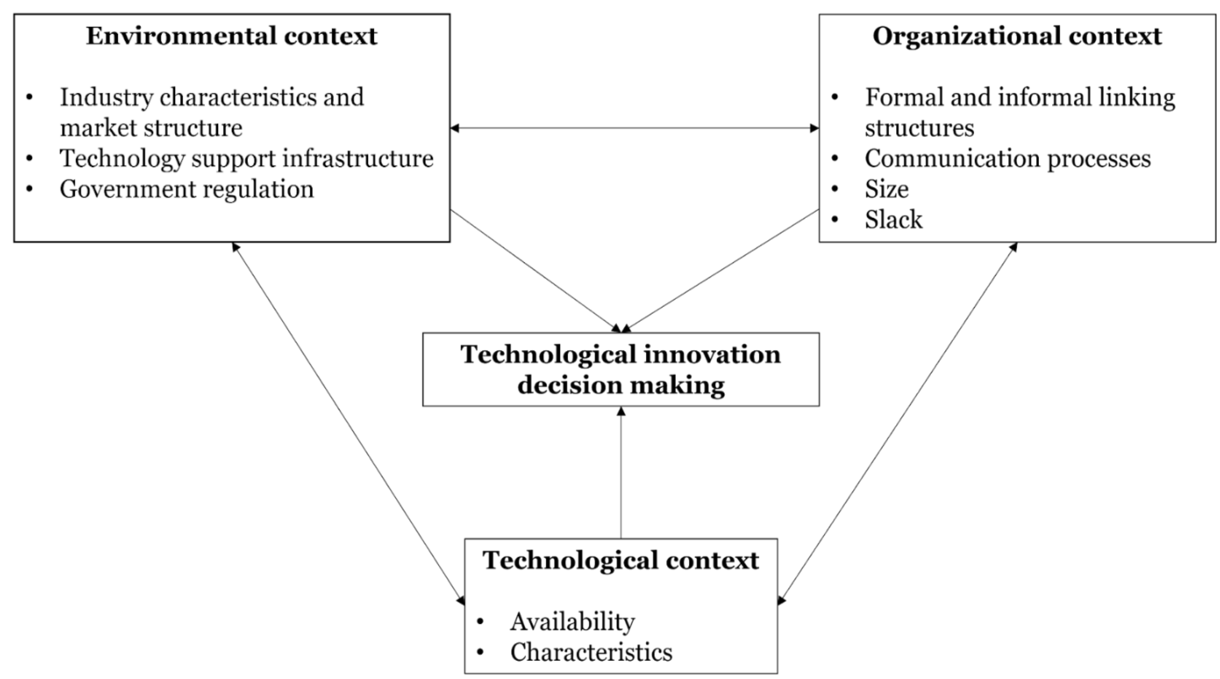

Figure 1. Technology-Organization-Environment (TOE) Framework, According to DePietro et al. (1990)

The **technological context** embraces internal and external technologies that are or may be relevant to a firm. The focus is on how an innovative technology itself can influence a company's adoption process. This includes AI and its technical requirements, respective sub-disciplines, but also alternative technologies, and the holistic enterprise IT infrastructure. The **organizational context** covers a firm's descriptive measures: e.g., firm size, managerial structure, or human resources. The **environmental context** is the 'arena' in which a company operates, bringing opportunities and constraints for technological innovation (DePietro et al., 1990). The TOE framework has a solid theoretical basis and consistent empirical support in IS research (Oliveira & Martins, 2011). In AI adoption research, the TOE framework was already applied multiple times: Kruse et al. (2019), for example, based their analysis of AI adoption challenges in the financial services industry on the TOE framework. Kinkel et al. (2021) even explicitly concluded that the framework was suitable for AI. Other applications can be found, for example, in the area of AI readiness factors (Jöhnk et al., 2021; Pumplun et al., 2019). Therefore, the TOE framework is expected to be useful also for this study in arranging the findings, interpretations and disclosing connections.

Artificial Intelligence

Artificial Intelligence (AI) is seen as a major innovative technology for businesses in almost every industry and will likely force companies to transform their core processes, value proposition, and business models (Brynjolfsson & McAfee, 2017; Sjödin et al., 2021). We follow Russell and Norvig (2021), describing AI as "intelligent agents that receive percepts from the environment and take actions that affect that environment" (Russell & Norvig, 2021, p. 7). They also define Machine Learning (ML) as a subcategory of AI which gives predictions based on experience. While companies mainly adopt ML, other types of AI should not be neglected here. Therefore, the term AI will be used in the following in order to remain more generic.

To understand AI adoption as a transformational journey, drivers and barriers can be distinguished. Former research has already investigated these adoption factors but has left some gaps open: first, most research did not include an industry-specific focus (e.g., Pumplun et al., 2019), leading to generalized findings. Second, the little existing industry-specific research has not produced a holistic view of both drivers and barriers (e.g., Kinkel et al., 2021; Kruse et al., 2019). Third, specific ways of looking at at least two industries have not yet been brought together to reveal relations, interdependencies, and commonalities. This paper will analyze the financial service and manufacturing industries, as many AI use cases can be found (Hentzen et al., 2021; Zhang et al., 2019). Also, different use cases exist: While the financial services industry has a focus on customers and intangible products and services, the manufacturing industry focuses on physical products. Thus, different drivers and barriers are expected.

Financial services companies are subject to special regulatory requirements (Kapsis, 2020; Freudenstein et al., 2019). In addition, the IT infrastructure is dominated by technologies from the last decades, so-called 'legacy IT' systems (Freudenstein et al., 2019). Furthermore, the industry is characterized by strong competition among other FinTech start-ups offering personalized services and achieving lower costs through AI (Kruse et al., 2019; Sinn et al., 2021; Lee & Shin, 2018). The potential of AI ranges from the back-end, noncustomer-facing operations to front-end, customer-facing scenarios, e.g., detecting consumer credit delinquencies (Khandani et al., 2010); assess customers' credit-worthiness (Dastile et al., 2020); chatbots to automate customer interaction (Riikkinen et al., 2018) or as 'robo-advisors' for automated portfolio and investment management (Buchanan & Wright, 2021; Hentzen et al., 2021).

Influencing effects on the adoption at the firm level have barely been analyzed in the industry alone and especially not as a comparison between industries. Kruse et al. (2019) assessed the challenges that financial services companies face when planning to adopt and implement AI. Strong similarities to generic barriers to AI adoption can be found, but challenges in the financial services industry seem more diverse (see Table 1).

The manufacturing industry is in constant transformation, as 'industrial AI' – mapping AI application scenarios onto manufacturing use cases (Zhang et al., 2019) – enables process optimization (Peres et al., 2020), quality control (Ding et al., 2020; Ojer et al., 2020), predictive maintenance and human-robot collaboration (Peres et al., 2020). Thus, just like in financial services, the question arises of how AI adoption is accelerated and hindered in the industry. Kinkel et al. (2021) analyzed manufacturing companies' use of AI and TOE-classified adoption variables through a survey among more than 600 participants from the manufacturing industry.

Table 1 shows generic drivers (D) and barriers (B) according to Kar et al. (2021), specific barriers for the finance industry according to Kruse et al. (2019), and specific factors in the manufacturing industry according to Kinkel et al. (2021) (G – General, FS – financial services and M – manufacturing) that former research comprised. Additionally, these factors were clustered according to the TOE framework (T – Technology, O – Organization, and E – Environment).

Variable	**Description**	**Industry**	**Factor**	**TOE**
Accuracy	Improved accuracy in decision-making and forecasting.	G	D	O
Cost-reduction	Automated business processes, efficient decision-making, and reduction of human error.	G	D	O
Decision-making	Automated, data-driven decision-making.	G	D	O
Productivity	Improved productivity and efficiency in business processes.	G	D	O
Speed	Improved time-to-decision due to automation.	G	D	O
Well-being	Less workload and reduced stress for employees.	G	D	O
Sustainability	Sustainable processes and supply chains.	G	D	O, E
Customer experience	Service improvement by learning customer preferences.	G	D	E
Data	Lack of data quality and data quantity.	G, FS	B	T

Variable	Description	Industry	Factor	TOE
Infrastructure	Infrastructure support is required for wide-scale implementation. Legacy IT needs to get replaced.	G	B	T
Model reusability	Reuse of the AI model for different problem scenarios is difficult.	G	B	T
AI strategy	Lack of an AI strategy defining how AI should be used to meet business goals.	G	B	O
Job security	Streamlining of routine-based job profiles.	G	B	O
Leadership	Lack of leadership commitment towards AI adoption.	G	B	O
Trust	Lack of trust in AI-generated decisions.	G	B	O
Use case identification	In some cases, AI solutions are less effective than traditional ones. Return on investment is at risk.	G	B	O
Know-how	Labour market gap or lack of budget to attract AI talent.	G	B	O, E
IT infrastructure	Legacy IT needs to get replaced.	FS	B	T
Vague market	Low availability of suitable AI software.	FS	B	T
AI characteristics	Risk, compliance, ethical standards.	FS	B	T, O
Agility to adapt	Adapt firm resources (financial, technical, human).	FS	B	O
Changing process competencies	Change management, changing environment.	FS	B	O
Know-how	Professional expertise regarding AI skills.	FS	B	O
Organizational hierarchy	Lack of organizational agility.	FS	B	O
Top management support	Lack of support by decision-makers.	FS	B	O
Competitive pressures	Especially driven by FinTechs.	FS	B	E
Data protection	Data protection is part of the core business.	FS	B	E
Governmental regulation	Regulatory requirements (BCBS239, MiFID).	FS	B	E
Lack of customer support	Moral concerns by customers.	FS	B	E
Company size	Measured by the number of employees.	M	D	O
Design	Role of product design as a competitive strategy.	M	D	O
Digital skills	Corporate technological know-how.	M	D	O
Product quality	Role of product quality as a competitive strategy.	M	B	O

TOE elements: T - Technology, O - Organization, E - Environment;
Factor: D - Driver, B - Barrier;
Industry: G - General, FS - Financial Services, M - Manufacturing

Table 1. Drivers and Barriers of AI Adoption from Literature

Overall, drivers and barriers of adoption variables exist (see Kar et al., 2021; Kinkel et al., 2021; Kruse et al., 2019), but their focus is on general AI adoption instead of individual industries and a cross-industry comparison. The next chapter describes how the qualitative research design of this study intends to target this gap.

Methodology

As the research questions require the construction of an exploratory and explanatory model, interview-based case studies provide the best opportunity to analyze phenomena regarding their causality and inherent interrelationships. The structure is oriented on the combination of the five case study design components of Yin (2014) and the step-by-step chronological framework by Eisenhardt (1989).

Getting started. A case study should have clear, predefined research questions to be used for theory-building (Eisenhardt, 1989), serving as the first out of five central case study design components (Yin, 2014). Therefore, the research questions were developed iteratively by reviewing existing literature in scientific databases and a forward and backward search. The state of research on both generalized and industry-specific AI adoption was derived. These account for the so-called 'theoretical study propositions', the second design component (Yin, 2014).

Selecting cases. A multiple-case study offers analytical generalization of the findings by deriving substantiated theories between cases (Yin, 2014). This results in external validity (Yin, 2014). While a case study cannot reflect variation in every possible dimension (Yin, 2014), some degree of environmental and characteristic variation should be considered while planning the investigated cases instead of applying random selection (Eisenhardt, 1989). Thus, the definition of the study's unit of analysis (i.e., the 'case') was set up as the third research design principle (Yin, 2014). In this paper, a case is defined as an individual with expertise in topics related to organizational AI adoption, working for either a private company within a focus industry (manufacturing and financial services) or holding profound stakes and insights about it. This strategy makes use of potentially different perspectives on the topic and supports the idea of replication logic. A detailed list of cases in the data collection is presented in Table 2. This table includes information about the current role, overall job experience, experience in current role, location, and company size. The interviews were conducted in July and August 2022; the average duration was 27 minutes (min 24, max 32 minutes), and written answers were given for one interview.

#	Industry	Role	Experience (in current role)	Location	Size
		Financial Services			
I.1	Management consulting	Managing consultant – AI in financial services	10 (4) years	UK	L
I.2	Insurance	Head of AI solutions	15 (5) years	Germany	M
I.3	Insurance	Head of AI and data development	24 (1.5) years	Germany	S
		Manufacturing			
I.4	Management consulting	Senior consultant – AI in manufacturing	7 (5) years	UK	L
I.5	Management consulting	Senior consultant – digital operations	4 (Unknown)	UK	L
I.6	Management consulting	Managing consultant – intelligent automation and AI	13 (2.5) years	Germany	S
I.7	Mechanical and plant engineering	Product manager – pre-sales digital solutions	8 (3) years	Germany	M
Size: S - < 5,000 employees, M - 5,000 - 50,000 employees, L - >50,000 employees					

Table 2. Interview Partners

Crafting instruments and protocols. The next steps are a clear definition of the sources for data collection, the types of collected data, and the number of investigators performing research (Eisenhardt, 1989). This paper's data collection only included qualitative data without any additional case-related documents. One author performed the collection.

Entering the field. All interviewees received the questionnaire in advance to ensure a smooth interview. In case study research, data collection and data analysis are not strictly separated (Eisenhardt, 1989). Thus, writing down field notes and impressions during the investigation is required to enable adjustments to the interview question protocol and provide flexibility to respond to emerging trends (Eisenhardt, 1989). These adjustments in interview questions were essential in the early stages of data collection, as some optional questions turned out to be obsolete. In contrast, additional questions in the following interviews could deepen other emerging and surprising topics.

Analyzing the data. The analysis was prepared by defining an analytical strategy and choosing analytical techniques. The setting of these parameters forms the fourth design component. An analytical strategy is important for the fair treatment of evidence and for producing logical analytical conclusions (Yin, 2014). Out of four common strategies in case study science (Yin, 2014), three can be ruled out based on the scope of this study. The chosen strategy lets the theoretical propositions lead the study and is the most common one in research (Yin, 2014). This strategy uses the theoretical foundations as external sources of knowledge to relate the findings of this study. This makes it possible to fit new data into the findings from the literature. Conceptually, the pattern-matching technique has been applied as a guide for qualitative analyses. This technique relies on using codes, i.e., categories representing a piece of thematic content. First, the interview transcripts were divided into two groups according to the industry. Consequently, the following steps were performed for each group separately. Second, several deductive codes (main categories) were brought to the interview data, yielding a content-related structure and logical parts. This was followed by deriving inductive codes, born out of the specific content of the interviews, and breaking the main categories down into subcategories. These subcategories enabled mapping sets of cross-case interview statements onto sole findings within an industry group. However, starting this process again for each case resulted in new subcategories for each interview transcript. To ensure that no later-defined subcategory was missed in already-reviewed transcripts, steps 3-5 were repeated iteratively until the number of codes converged (Kuckartz & Rädiker, 2022).

Shaping hypotheses. The explanation-building technique was applied to summarize and report the findings (Yin, 2014). Therefore, an iterative process was applied between adapting and comparing a statement with the qualitative data (Yin, 2014). The following order facilitated this: A list with all text segments within the group carrying the focal code was generated for each code. With this code-relevant overview, it was possible to analyze derivable key messages iteratively and identify to what extent summarizing was possible and where separation was needed.

Closing research. Research is considered complete when saturation of results is achieved and incremental growth is minimal. Although only three (respectively four) interviews were conducted within the industries, hardly any new insights resulted from the last interviews (in both industries, only one, respectively two new inductive codes could be assigned in the analysis of the last interview in each case, and it became increasingly difficult to separate the content from existing codes), thus, saturation was achieved.

Enfolding literature. Identifying and dealing with literature conflicting with one's findings – so-called 'rival explanations' – is a central step in establishing internal validity and assessing its generalizability (Eisenhardt, 1989), yielding in the implementation of the fifth and last research design principle (Yin, 2014). Generalizability needs to be understood as the question of whether the study findings are scientifically complete. This was tested by using a two-sided strategy. First, an outside-in technique was used to identify previous research findings in this study's results. Afterward, an inside-out technique was used to identify this study's results in previous research findings. As a result, gaps and differences were disclosed and enabled a basis for critical reflection.

Besides the five fundamental design components, case study research should comply with four general quality tests (Yin, 2014). Each test can be complied with by realizing a set of techniques and tactics inside the research design (Yin, 2014). Table 3 gives a respective overview together with a summary of their implementation in this study.

Test	Theoretical case study tactic	Tactic implementation in this paper
Construct validity	Use multiple sources of evidence.	Cases included internal and external industry stakeholders to use different perspectives.
	Establish chain of evidence.	Detailed, chronological description of the method enables to trace back all steps and conclusions.
	Have key informants review the draft case study report.	Transcript review was optionally offered for review to the interviewees, but the offer has not been used.
Internal validity	Pattern matching.	Iterative text coding.
	Explanation building.	Iterative shaping of conclusions out of the data.
	Address rival explanations.	Addressing former research and identifying gaps.
	Use logic models.	Not applicable.
External validity	Use replication logic in multiple-case studies.	Iteratively shaping conclusions out of the data.
Reliability	Use case study report.	See Results chapter.
	Develop case study database.	Composition of case overview (see Table 2), interview transcripts and case study report.

Table 3. Case Study Quality Tests According to Yin (2014)

Results

This chapter is divided into four parts. First, the interviewees' perspectives on AI adoption and use cases are assessed for both the financial and manufacturing industries. In the second and third sections, the drivers and barriers of each industry are presented and categorized according to the TOE framework. In the fourth section, the drivers and barriers of both industries are compared.

State of AI Adoption and Use Cases

Financial Services Industry

Financial services companies seem to be aware of AI's business potential, as I.2 and I.3 both are the heads of official AI-specialized organizations within their company. Also, I.1 believes that most companies at least state to target AI capabilities in their corporate strategy. However, the actual state of implementation seems to be in its infancy. Many financial services companies are experimenting with AI in so-called 'sandbox environments' (I.1), that is, in isolated systems where software can be tested safely. Only one respondent mentions that his company is leading in AI adoption compared to others he is in touch with through several cross-company AI committees (I.2).

AI use cases can be classified into two categories: 'Offensive' use cases transform the way business is run, e.g., how market interaction looks like and which services are being offered (I.1). In contrast, 'defensive' use cases target improving existing processes and due diligence activities and making them more secure (I.1). Overall, many use cases focus on customer analytics and customer behavior, such as risk management, or business operations, such as algorithmic trading (I.1; I.2; I.3).

Manufacturing Industry

The manufacturing industry structure is more diverse compared to financial services. As a result, the identified use cases and process applications are wide-ranging. Some interview partners state that the use of AI is in its infancy and is treated cautiously – including large, established companies that are still completely at the beginning (I.5). Here, AI is applied only in selected individual cases, which may even be separate from one another (I.6). Others have witnessed a wide range of AI in various use cases (I.4; I.6). The most common scenario is the field of quality control by combining hardware, software, and intelligent algorithms to automate the manual and labor-intensive inspection of manufactured parts (I.4). Besides that, the respondents presented applications of predictive maintenance or scheduling tasks on shop floors (I.4; I.7). However, a holistic approach of extracting, processing, analyzing, and using data along the entire value chain is hardly found in any manufacturing company (I.6).

Drivers of AI Adoption

Next, the drivers of AI adoption derived from the interviews shown in Table 4 are presented. Eleven drivers are found for the financial services industry and nine for the manufacturing industry. In the following two sections, these factors are categorized and explained according to the TOE framework.

Financial Services Industry

Technological drivers. As financial services providers are confronted with extensive demands on their data management, these regulatory requirements do naturally exist as part of their business models and significantly increased after the global financial crisis of 2008/2009 (I.1). However, they transparently highlight possibilities of automation and other uses of AI, making its application easier (I.1). AI adoption is also driven by standardizing processes for scalable, reusable, and flexible AI systems (I.3). That means building a technological baseline in the form of a system that can be used again in another context. Hand-in-hand with this effect is the opportunity of realizing leverage effects (I.3), which occur when the implementation of a single use case offers the ability to have a disproportionately bigger advantage to the organization compared to the development effort.

Organizational drivers. Almost all organizational drivers can be summarized as business decisions aimed at either growth or cost reduction. According to the interview partners, the organizational intention to reduce costs can primarily be found in defensive use cases. This can be achieved by optimizing, automating, and streamlining existing processes (I.1; I.2; I.3), for example, by using intelligent recommendation systems to minimize search times in internal systems for clerks (I.2). A company's effort to maximize profits, in particular, is reflected in the offensive applications of AI (e.g., customer analytics, recommendations and cross-selling, algorithmic trading). Moreover, AI adoption is accelerated by the trend toward data-driven decisions. Forecasting models, in particular, can serve as decision support systems in order to help executives back up their decisions with numbers and facts rather than relying on belief and gut feeling (I.3).

Environmental drivers. Compared to the organizational context, environmental drivers are far more diverse, as they originate from several actors within the market. First, the use of AI is accelerated by the desire to improve customer experience (CX) (I.2). Again, a kinship with defensive use cases can be noticed, as these can be leveraged to optimize CX journeys by improving or automating processes and reducing execution times. Besides the customers, the market environment and competition could be identified as having accelerating effects on AI adoption. However, this aspect must be considered from two perspectives: On the one hand, the respondents referenced competitive pressure within the market (I.2; I.3). On the other hand, cross-company exchange (e.g., through committees and conferences) allows theoretical ideas to bear fruit (I.2; I.3). Surprisingly, also regulatory requirements imposed by the legislator have an accelerating effect on AI adoption. These requirements can be so overwhelming that companies hope to be able to handle them by using AI (I.1). *"For example, there is a large bank [...] [facing the problem] of money laundering. They are hoping to get a better handle on their money laundering problem by using AI because they realize that it's just too gigantic. These are too gigantic of an undertaking for humans to do."* (I.1)

Manufacturing Industry

Technological drivers. Not a single technological driver for AI adoption could be identified in the manufacturing industry.

Organizational drivers. Implementing AI started with curiosity a few years ago. In fact, curiosity towards AI and its hype as a revolutionary technology with value-adding potential was and still is one main driver for AI adoption (I.5; I.7). This is intertwined with the sheer will to become digital leaders, resulting in a high degree of intrinsic commitment to AI (I.7). One of the effects that manufacturing companies hope to achieve when applying AI is increasing productivity (I.4). This is accompanied by other factors that have a similar impact on business operations. These include efforts to reduce or automate labor-intensive, repetitive, manual, complex, and expensive operations (I.4; I.6). For example, the application of predictive maintenance falls into this category, as downtimes, and thus costs can be reduced (I.7). In addition, manufacturers also strive for consistent quality of the products produced (I.6), which again can also be simplified or improved with the help of AI – as described earlier in the quality inspection use case. *"Maybe another driver here is to look at 'what are the low-hanging fruits?' And I will assume to some extent that this is one of the reasons why AI is used so often in quality control. You are not actually designing the process. All you are doing is adding an intermediate station, so to speak, that takes a quick look with a camera to see if everything looks okay. That does not affect the business and can only be a win."* (I.6) In conclusion, organizational drivers stem almost entirely from economic intentions. As a rule, a business case serves as the basis, which in the case of a positive return on investment (ROI) is the clear leader among the AI adoption drivers (I.7).

Environmental drivers. Surprisingly, competitive pressure and the goal of achieving competitive advantages seem to play a minor role when it comes to AI adoption in manufacturing (I.5). However, the company's ambition to become part of a circular economy (CE) is crucial for the transformation to a data-driven company with a holistic AI approach (I.6).

Barriers of AI Adoption

In this section, the barriers to AI adoption derived from the interviews shown in Table 4 are presented. 13 barriers are found for the financial services industry and 17 for the manufacturing industry.

Financial Services Industry

Technological barriers. Adopting AI and implementing use cases starts with creating the technological conditions in the first place. In the financial services industry, I.1, I.2, and I.3 all mentioned being confronted with problems related to legacy IT as being highly self-contained and written in ancient programming languages. These systems are not suitable for integration with modern AI applications based on programming languages like Python, as they do not meet the novel idea of microservices architecture and therefore are a blocker for free and dynamic data flows (I.2). Also, cloud-based technologies, which can facilitate AI deployment, have not gotten through to financial services companies either (I.1). This, but also the cultural influence (see organizational barriers), might be the reason why the interviewees experienced a lack of tools to develop intelligent applications as another barrier of adopting AI (I.1; I.3). Data is also the central requirement for training AI. One problem is data processing into a desirable state regarding their form and quality (I.1). In addition, AI projects are hard to plan due to the unpredictability of training processes. (I.2). This makes it more difficult to forecast project milestones and estimate governance, approval, and coordination processes (I.2). I.2 argued that the technical implementation itself does also hold its challenges, but still is more plannable and forecastable than project timelines. Moreover, after implementation, it is still possible that an AI model does not live up to its expectations due to a lack of accuracy (I.2). What also hinders financial services companies from implementing highly autonomous intelligent decision-making systems is the issue of explainability (I.1; I.2). An AI system is defined to be 'explainable' when it can explain the rationale behind its decision (Samek et al., 2017). It is important for humans to verify the system, improve it, and learn from it, but also comply with legislation regarding the exact context of the application (Samek et al., 2017) instead of being treated as a black box algorithm. However, implementing explainability can be complex (I.2).

Organizational barriers. In the organizational context, the status quo of a risk-averse corporate culture is not only a barrier itself but also a root for several other challenges (I.1). *"So when you are working with a new technology like [...] [AI], then maybe you also have to try things out a bit faster, i.e., fail-fast, also fault tolerance. Banks and insurance companies work with data, figures, and risks every day. Rough generalization, but they tend to be more risk-averse than many other companies"* (I.1). This might be a reason why outdated but reliable legacy IT is hardly getting replaced and using open-source software standards for AI development is a hurdle. Also, the collision of work types is a barrier, as data scientists and IT professionals tend to move in an agile environment, which is unfamiliar to many executives and business teams (I.1). The corporate culture may also cause a barrier to AI adoption on an even higher level, as I.1, I.2 and I.3 have experienced a lack of leadership commitment toward AI. In general, the organizational approach to the topic and identifying the strategic value of AI are key to successful adoption, which necessitates the need for an AI strategy to find company-specific answers to a variety of questions (I.1). Smaller companies, in particular, tend to struggle with answering these questions (I.2) and, above all, with answering the question of the sense of using AI at all (I.1). Finally, there are also challenges regarding the field of corporate know-how (I.1). Especially in banks, there is a trend of outsourcing most AI projects, which may be a strategic maldevelopment, as it will keep data science and AI know-how excluded from the firm (I.1).

Environmental barriers. In financial services, the biggest hurdle regarding the implementation and use of AI software consists of government-imposed regulatory requirements and compliance standards (I.1). EU-based banks and insurance providers face additional complexities regarding their data management in order to comply with European General Data Privacy Regulation (GDPR) and to make data protection processes efficient (I.2; I.3). For this reason, financial institutions have set up entire units within the company to deal with data management (I.1).

Manufacturing Industry

Technological barriers. A special issue for manufacturing companies is the development of AI applications near physical infrastructure, such as machines or robots in the real world. This also has organizational implications, as intra- or even inter-organizational collaboration is required (I.7). Another issue is the procurement of complete smart systems. In particular, such systems apparently would be either very expensive or very inflexible (I.4). Moreover, in order to make AI models work in the first place, manufacturing companies face the issue of data availability (I.7). A lack would result in low accuracy in the model and might even make the application of the model completely useless for the specific use case (I.4). Moreover, AI may not even be the best solution for certain problems. This follows the plea of I.6 for thoughtful use of AI. Separately from this, one of the interviewees also feels that the revolutionary speed of technological developments can be too much for companies to cope with (I.4). Beyond AI algorithms, this applies above all to complementary technologies, such as hardware (I.4). Lastly, the development of AI through the use of cloud services – especially through infrastructure-as-a-service solutions – *"has become so easy thanks to the existing tools. As a result, I no longer believe that this will be a major hurdle in the future"* (I.6). However, the realization via the cloud becomes more difficult when robots generate high-resolution data (e.g., one data frame at a rate of four to eight milliseconds), yielding such large volumes of data that transferring them to the cloud and processing them there is hardly feasible in these cases (I.7). I.7 has an even more drastic view on the issue of cloud governance and user security concerns: The lion's share of his customers (mainly automotive companies and suppliers) do not want to deploy via the cloud and therefore are rather looking for on-premise and on-edge solutions. In conclusion, deployment seems to remain a challenge for AI adoption in the manufacturing industry.

Organizational barriers. The cautious approach to AI models running outside of the own organization (i.e., on cloud servers) likely stems from data sovereignty and internal privacy policies in manufacturing companies (I.7). In particular, a lack of standards can influence the internal development of a wide variety of solutions without transparent communication channels, resulting in a heterogeneous landscape of different AI solutions (I.6). There are also challenges at the management level. The statements here are mixed: I.4 emphasized the digitization efforts of international companies in particular, while I.7 experienced skepticism towards AI, especially among elderly and experienced managers. The unpredictability mentioned above of the success and accuracy of an AI model in the technological context has even significantly greater effects in the organizational context. These deployment imponderables are perceived as a risk and disruption to the operational process, as – in the worst case – a faulty AI system results in physical damage (e.g., *"defective/damaged/useless"* (I.5) goods) and thus in higher costs than in intangible application areas (I.5). In addition to this, a certain lack of failure culture is also the reason why manufacturing companies seem to be not more advanced in the field of AI (I.4). This means that executives tend to be reluctant to make an investment in the development of an AI system if the success of this system cannot be assessed from the outset (I.6). Moreover, non-acceptance or even fear from the workforce whose activities are the target of automation or workload reduction arises (I.7). This fear may be justified in some cases, but may also be due to a misunderstanding of AI itself in other cases (I.6). This concerns extreme cases in which there is no understanding of AI as a technology at all, but people rather have an undifferentiated conception (similar to science fiction) of what AI is capable of today (I.6). On the other hand, sometimes the wrong problems are solved with AI because decision-makers are unaware of which method is best suited for what (I.6; I.7). The latter again concerns the previously mentioned case of over-engineering. In conclusion, the lack of correct understanding, together with the need to build up respective know-how in the form of a data science workforce (I.7) that is merged into cross-functional, transparently communicating teams (I.4; I.7), can be an additional hurdle to adopt AI in the first place.

Environmental barriers. External regulation also seems to play only a small role for manufacturing companies. Still, regulatory requirements do affect AI adoption, but mainly in the areas of personal and customer data privacy policies – again due to the European GDPR (I.4; I.6). World affairs such as the war in Ukraine and the Covid-19 pandemic with their effects regarding sanctions on gas supply, materials shortages, drops in demand, worker unavailability, and reduced IT budgets seem to play a larger role in the environmental context (I.7). However, I.7 states that IT budgets seem to open up again soon.

Comparison between Industries

The sole presentation of the individual factors in Table 4 is not intended to suggest that each driver and barrier should be considered separately. It is clear from the results how related and correlated they can be. However, breaking them down into individual parts not only eases the understanding of AI adoption but also makes cross-industry differences and similarities apparent. This leads back to RQ3 from the first chapter.

Financial Services			**Manufacturing**		
Drivers					
# (FS-)	**Driver**	**TOE**	**# (M-)**	**Driver**	**TOE**
D1	Regulated data management	T	D1	Curiosity	O
D2	Scalability, reusability, flexibility	T	D2	Commitment to digitalization	O
D3	Realization of leverage effects	T	D3	Productivity and process efficiency	O
D4	Cost reduction	O	D4	Labour-intensity reduction	O
D5	Productivity and process efficiency	O	D5	Cost reduction	O
D6	Profit maximization	O	D6	Improving quality control	O
D7	Data-driven decision making	O	D7	AI 'quick wins'	O
D8	Improving CX	E	D8	ROI through AI investment	O
D9	Competitive pressure	E	D9	Sustainability / circular economy	E
D10	Cross-company knowledge exchange	E			
D11	Achieving regulatory compliance	E			

Financial Services			**Manufacturing**		
Barriers					
# (FS-)	**Barrier**	**TOE**	**# (M-)**	**Barrier**	**TOE**
B1	Legacy IT	T	B1	AI development intertwined with physical infrastructure	T
B2	AI development tools	T	B2	Inflexibility, expensiveness of buyable AI solutions	T
B3	Data	T	B3	Data	T
B4	Unpredictability of AI projects	T	B4	AI model accuracy	T
B5	AI model accuracy	T	B5	‘AI overengineering’ (AI not the best solution)	T
B6	Explainability	T	B6	Speed of technical development	T
B7	Industry culture and risk aversion	O	B7	Cloud-isolated deployment of AI solutions	T, O
B8	Cross-functionality and agility	O	B8	Internal data privacy policies	O
B9	Leadership commitment	O	B9	Lack of standardization	O
B10	AI strategy	O	B10	Leadership commitment	O
B11	Company and workforce size	O	B11	AI deployment as a risk of operational disruption	O
B12	Know-how	O	B12	Industry failure culture	O
B13	Regulation and compliance	E	B13	Fear and change management	O
			B14	AI understanding	O
			B15	Cross-functionality and agility	O
			B16	External data privacy regulations	E
			B17	World affairs (war, Covid-19)	E
TOE elements: T - Technology, O - Organization, E - Environment					

Table 4. Industry-specific Drivers and Barriers of AI Adoption

Drivers of AI adoption. In both industries, it turns out that technological factors do not primarily drive AI adoption. There are no drivers in the manufacturing industry (the experts did not provide an explanation), while there are a few in financial services. Therefore, we can conclude that AI does not serve an end in itself. Considering both the quantity but also their scope, the lion’s share of all drivers can be found in the organizational context – for both sectors. Here, it is noteworthy that AI in the manufacturing industry is driven by curiosity and commitment to digitalization. Even though these do not seem to be the strongest drivers, such aspirations in top-level management could not be found in the financial services sector. This circumstance could be related to financial services companies’ corporate cultures, meaning that technology curiosity and risk aversion are presumably negatively correlated. In addition, this is an example that not only drivers among themselves but even drivers and barriers are interrelated with each other. Moreover, strong similarities in the areas of productivity, cost reduction, and efficiency can be found between the industries. These factors, in particular, can be almost completely derived from economic aspirations, as in most cases, companies will just seek to achieve a positive ROI with single AI investments (I.7). This is relatively unsurprising, as a profit motive is the nature of a private company operating in the market. Other differences include the strive for data-driven decision-making (financial services) and AI-based quality control (manufacturing). The environmental context also reveals no further similarities regarding the drivers. These differ in terms of improving CX, competitive pressure, achieving regulatory compliance, and cross-company knowledge exchange on the one hand (financial services) and sustainability on the other (manufacturing).

Barriers to AI adoption. In contrast to the drivers, significantly greater heterogeneity can be observed in the barriers for both industries. One explanation could be that challenges are not decision-based but usually stem from many sources. Here, in particular, the TOE framework provides a plausible basis for classification. Second to witness is the high volume of technological barriers in contrast to the drivers. Similarities in this context only concern the challenge of lacking data, unsatisfactory AI model accuracy, and a lack of complementary tools, albeit with divergent manifestations of this barrier. In financial services, people tendentially shy away from new types of open-source technologies for development. In manufacturing, organizations often avoid using cloud technologies to simplify solution deployment. Strong correspondences in the organizational context only exist in the fields of know-how and AI understanding, and cross-functionality and agility. However, any similarities in leadership commitment and industry culture should be drawn carefully. In the manufacturing industry, in particular, this result must be viewed from two sides: Some companies have a low level of AI adoption due to a lack of commitment. Other companies, however, are characterized – as described in the drivers – by a strong desire for curiosity and digitization at the management level. Finally, the largest industry-specific differences can be found in the environmental context. Even if high data protection regulations exist, especially in Europe, the strict requirements for financial institutions cannot be compared with any other industry. It is precisely these compliance regulations that probably represent one of the biggest hurdles for financial services providers.

Discussion

First, the findings of drivers and barriers for financial services and manufacturing are discussed and connected to the literature. Then theoretical and practical contributions, limitations, and future research follow.

Theorizing and Generalization of Drivers and Barriers

In the results, one could be taken aback by the almost complete absence of technical drivers. In order to find a presumed explanation, we first take a look at the theoretical cross-industry generalization of drivers in the other two contexts. Productivity, accuracy, speed, and cost reduction are industry-independent drivers and, therefore, can be interpreted as 'hard' economic factors. This finding supports the findings of general factors from Cubric (2020) that value-related incentives primarily drive AI adoption. From an outside-in perspective (i.e., mapping the generic drivers/barriers from the theoretical background onto this study's findings), other drivers can be interpreted as 'soft' determinants since these could not be found at all (e.g., increasing well-being) or not to the same extent for both industries (e.g., decision-making, sustainability, CX). This stands under the proviso that some factors (e.g., sustainability) could not yet be verified as AI adoption drivers. From an inside-out perspective (i.e., mapping this study's findings onto the generic drivers/barriers from the theoretical background), the data of this study also show that, beyond the generic drivers, there are novel industry-specific factors that cannot be generalized to other industries (e.g., regulated data management as a driver, enhanced quality control, sustainability). The strong economic orientation of the drivers discussed could represent a possible causality for the absence of technical drivers. Conceivable drivers are presumably still too detached from organizational and environmental factors at present, so that at least the conscious existence of such technical drivers is not given.

In the context of barriers, generalization becomes much more difficult. Here again, a few 'hard' barriers can be found that apply to both industries. These primarily concern the technological context (e.g., data and tool availability, AI models' accuracy) and the organizational context (e.g., required expertise and know-how, cross-functionality, agility). Nevertheless, significantly more 'soft' barriers can be found – i.e., those challenges that are not universally applicable. A look into the environmental context shows that one who wants to infer from the generic challenges (see Table 1) to those of the specific industry will likely miss out on the industry's key AI adoption determinants. The role of regulation and compliance for financial services companies, for example, cannot be generalized over all industries.

Contributions, Limitations and Future Research

If a company adopts AI, it has great potential for saving time and costs, thus increasing profits. Therefore, many general drivers and barriers to AI adoption have been identified in the last years (e.g., Zöll et al. (2022); Kar et al. (2021); Cubric et al. (2020) and Pumplun et al. (2019)). However, these general factors cannot indicate why AI is utilized in some industries more than others. While AI offers great possibilities in the financial service and the manufacturing industries, and some use cases are already implemented in both, they still differ significantly. Thus, we first gave an overview of existing factors in AI adoption and clustered them according to the TOE framework. We then conducted interviews to identify industry-specific drivers and barriers to AI adoption. Those were again clustered into the three TOE categories and compared across industries. It was possible to derive hard (generalizable) and soft (non-generalizable) AI adoption factors.

Our case study provides several **theoretical contributions**. First, we present an overview of the drivers and barriers to AI adoption in financial services and the manufacturing industry. Comparing these determinants resulted in a classification into soft factors (industry-specific) and hard factors (generalizable). Soft drivers in the manufacturing industry are, for example, the curiosity of companies, while an exemplary barrier in the financial service industry is their legacy IT. More generalizable factors are especially technological barriers such as available data and AI model accuracy, i.e., factors that are specific to AI. By conducting interviews, it was possible to draw a picture beyond correlated AI adoption variables and identify dynamic cause-and-effect relationships. As a result, a holistic view close to organizational structures could be given. Second, by demonstrating unique factors (soft factors) and general drivers and barriers (hard factors), we extend the TOE framework by including industry-specific determinants in technology adoption. In addition, initial evidence suggests that these drivers and barriers influence the adoption of AI to a varying degree. Therefore, we contribute to the industry-specific research of AI adoption and provide a basis for the future development of AI applications. This is likely transferable to the adoption of other technologies as well. Third, to the best of our knowledge, we are the first to combine Eisenhardt (1989) and Yin (2014) into one methodology that can guide future research. The methodology allowed a deep insight into the industries to derive the different factors of AI adoption.

Besides that, we have **practical implications** for industry stakeholders, business decision-makers, and AI executives. First, having the research designed as a multiple-case study, all results can serve as a form of anonymized, cross-company knowledge-sharing, enabling market and technology transparency in several ways. Identifying use cases and the state of AI adoption provides the necessary information to understand the current industry situation and consider the underlying context. Second, the study can serve both as a starting point for market analyses and technological investigation of AI adoption. Any industry stakeholder in financial services or manufacturing who seeks to advance their organization in the direction of AI adoption will find a detailed summary of drivers and barriers in this study. Lastly, AI specialists or consultants can benefit from understanding their customers' needs, challenges, and motivating influences behind their AI adoption journeys.

This study is also subject to **limitations**. Due to the limited number of interviews, only two industries in Germany and UK were investigated, with only three/four interviews per industry. In addition, regarding the use of the TOE framework, it is not possible to separate the drivers and barriers strictly according to the three contexts, as many factors are intertwined, e.g., having enough data is considered a technological barrier, but a data-driven culture would support getting them as part of organizational context. Pumplun et al. (2019) classified the AI readiness factor 'data' into the organizational context with the argument that data must be available and accessible within a corporate organization in order to adopt AI.

Among other thoughts, these limitations provided the basis for the following proposals for **further research**. Thus, the same research design can also be applied to other industries. Thereby, the theoretical industry-specific contributions of this study may be extended, and valuable practical insights could be given. The investigation of AI adoption in the public sector is highly recommended, as respective drivers for AI adoption may differ from economic aspirations in business. In addition, qualitative methods can focus on overcoming adoption barriers, contributing to developing corporate AI strategy frameworks.

Finally, just like in previous research patterns, future studies are recommended to use quantitative methods to verify this study's findings and determine each factor's importance.

Conclusion

In this paper, we draw a holistic picture of AI adoption in the financial services and manufacturing industries. The research design enabled the elaboration of advanced and dynamic influences on AI adoption. The viewpoint has shifted from general AI readiness factors to an industry-specific perspective. The main point to emphasize here is that the driving factors for AI adoption are mostly economic aspirations. In contrast, barriers are heterogeneous, and different conclusions can be drawn for every TOE context. In the technological context, they exhibit many generic patterns across the sectors. However, the organizational context consists of a significant amount of industry-specific variations. Environmental barriers could be identified as specific and hardly generalizable. In the next step, additional industries will be added to our research to provide even more insights.

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References

Bremser, C. (2018). Starting Points for Big Data Adoption. *Proceedings of the 26th European Conference on Information Systems (ECIS).*

Brynjolfsson, E., and McAfee, A. (2017). The Business of Artificial Intelligence: What It Can - And Cannot - Do for Your Organization, Harvard Business Review (ed.).

Buchanan, B. G., and Wright, D. (2021). The Impact of Machine Learning on UK Financial Services, *Oxford Review of Economic Policy*, 537-563.

Cubric, M. (2020). Drivers, Barriers and Social Considerations for AI Adoption in Business and Management: A tertiary study, *Technology in Society, 62*, 1-12.

Dastile, X., Celik, T., and Potsane, M. (2020). Statistical and Machine Learning Models in Credit Scoring: A systematic literature survey, *Applied Soft Computing, 91*, pp. 1-21.

Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology, *MIS Quarterly*, 319–340.

DePietro, Rocco, Wiarda, Edith & Fleischer, Mitchell (1990). The Context for Change: Organization, Technology and Environment, in Tornatzky, L. G. and Fleischer, M. (Eds.) The Processes of Technological Innovation, Lexington Books: Lexington, MA., 151-175.

de Propris, Lisa; Bailey, David (ed.). (2020). Industry 4.0 and Regional Transformation. London. Routledge (Regions and cities).

Ding, H., Gao, R. X., Isaksson, A. J., Landers, R. G., Parisini, T., and Yuan, Y. (2020). State of AI-Based Monitoring in Smart Manufacturing and Introduction to Focused Section, *IEEE/ASME Transactions on Mechatronics, 25*(5), 2143-2154.

Eisenhardt, K. M. (1989). Building Theories from Case Study Research, *The Academy of Management Review, 14*, 532-550.

European Parliament. (2022). Circular Economy. Definition, Importance and Benefits. https://www.europarl.europa.eu/news/en/headlines/economy/20151201STO05603/circular-economy-definition-importance-and-benefits, accessed on 2022-08-11.

Freudenstein, G., Zies, I., and Busche, S. (2019). Der ewige Kampf der Banken mit der Legacy-IT, Bain & Company Germany Inc. and Bain & Company Switzerland Inc. (eds.).

Hentzen, J. K., Hoffmann, A., Dolan, R., and Pala, E. (2021). Artificial Intelligence in Customer-Facing Financial Services: A Systematic Literature Review and Agenda for Future Research, *International Journal of Bank Marketing, 40*(6), 1299-1336.

IBM. 2022. IBM Global AI Adoption Index (2022). https://www.ibm.com/downloads/cas/GVAGA3JP, accessed on 2023-01-30.

Jöhnk, J., Weißert, M., and Wyrtki, K. (2021). Ready or Not, AI Comes—an Interview Study of Organizational AI Readiness Factors, *Business & Information Systems Engineering, 63*(1), 5-20.
Kapsis, I. (2020). Artificial Intelligence in Financial Services: Systemic Implications and Regulatory Responses, *Banking & Financial Services Policy Report*, 1-21.
Kar, S., Kar, A. K., and Gupta, M. P. (2021). Modeling Drivers and Barriers of Artificial Intelligence Adoption: Insights from a Strategic Management Perspective, *Intelligent Systems in Accounting, Finance & Management, 28*(4), 217-238.
Khandani, A. E., Kim, A. J., and Lo, A. W. (2010). Consumer Credit-Risk Models via Machine-Learning Algorithms, *Journal of Banking & Finance 34*(11), 2767-2787.
Kinkel, S., Baumgartner, M., and Cherubini, E. (2021). Prerequisites for the Adoption of AI Technologies in Manufacturing: Evidence From a Worldwide Sample of Manufacturing Companies, *Technovation, 110*, 1-17.
Kruse, L., Wunderlich, N., and Beck, R. (2019). Artificial Intelligence for the Financial Services Industry: What Challenges Organizations to Succeed, *Proceedings of the 52nd Hawaii International Conference on System Sciences*.
Kuckartz, Udo; Rädiker, Stefan. (2022). Qualitative Inhaltsanalyse. Methoden, Praxis, Computerunterstützung, 5th ed., Beltz Juventa, Weinheim (Germany).
Lee, I., and Shin, Y. J. (2018). Fintech: Ecosystem, Business Models, Investment Decisions, and Challenges, *Business Horizons, 61*, 35-46.
Ojer, M., Serrano, I., Saiz, F., Barandiaran, I., Gil, I., Aguinaga, D., and Alejandro, D. (2020). Real-Time Automatic Optical System to Assist Operators in the Assembling of Electronic Components, *The International Journal of Advanced Manufacturing Technology, 107*(5), 2261-2275.
Oliveira, T., and Martins, M. F. (2011). Literature Review of Information Technology Adoption Models at Firm Level, *Electronic Journal of Information Systems Evaluation, 14*(1), 110-121.
Peres, R. S., Jia, X., Lee, J., Sun, K., Colombo, A. W., and Barata, J. (2020). Industrial Artificial Intelligence in Industry 4.0-Systematic Review, Challenges and Outlook, *IEEE Access, 8*, 220121-220139.
Porter, M. E. (1980). Competitive Strategy: Techniques for Analyzing Industries and Competitors, New York (USA): Free Press.
Pumplun, L., Tauchert, C., and Heidt, M. (2019). A New Organizational Chassis for Artificial Intelligence-Exploring Organizational Readiness Factors, *Proceedings of the 27th European Conference on Information Systems (ECIS)*, 1-15.
PwC. (2017). Sizing the Prize. What's the Real Value of AI for Your Business and How Can You Capitalise? https://www.pwc.com/gx/en/issues/analytics/assets/pwc-ai-analysis-sizing-the-prize-report.pdf, accessed on 2023-02-15.
Riikkinen, M., Saarijärvi, H., Sarlin, P., and Lähteenmäki, I. (2018). Using Artificial Intelligence to Create Value in Insurance, *International Journal of Bank Marketing*, 1145-1168.
Russell, S., and Norvig, P. (2021). Artificial Intelligence: A Modern Approach, Harlow (England): Pearson.
Samek, W., Wiegand, T., and Müller, K.-R. (2017). Explainable Artificial Intelligence: Understanding, Visualizing and Interpreting Deep Learning Models, *ITU Journal: ICT Discoveries*, 1-8.
Sinn, W., Thoben, S., and Graf, C. (2021). Deutschlands Banken 2021: Wie die Renditewende gelingt, Bain & Company Germany Inc. and Bain & Company Switzerland Inc. (eds.).
Sjödin, D., Parida, V., Palmié, M., and Wincent, J. (2021). How AI Capabilities Enable Business Model Innovation: Scaling AI Through Co-evolutionary Processes and Feedback Loops, *Journal of Business Research, 134*, 574-587.
United States Department of Labor (ed.). n.d. "SIC Manual". https://www.osha.gov/data/sic-manual, accessed on 2022-07-29.
Yin, R. K. (2014). Case Study Research: Design and Methods, London (England): SAGE.
Zhang, X., Ming, X., Liu, Z., Yin, D., Chen, Z., and Chang, Y. (2019). A Reference Framework and Overall Planning of Industrial Artificial Intelligence (I-AI) For New Application Scenarios, *The International Journal of Advanced Manufacturing Technology, 101*(9), 2367-2389.
Zöll, A., Eitle, V., and Buxmann, P. (2022). Machine Learning Adoption Based on the Toe Framework: A Quantitative Study, *PACIS 2022 Proceedings*, 1-17.