Deus ex Machina

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An Organizational Perspective on Artificial Intelligence Adoption

Dissertation

zur Erlangung des akademischen Grades eines

Doktors der Wirtschaftswissenschaft der

Rechts- und Wirtschaftswissenschaftlichen Fakultät

der Universität Bayreuth

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Tag der mündlichen Prüfung:	04.07.2023

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The following sections are partly comprised of content taken from research articles included in this thesis. To improve the readability of the text, I have omitted the standard labeling of citations at these points.

Abstract

Information Systems (IS) research has intensively investigated the adoption of information technologies (IT). However, the literature presents little about adopting AI, which is a challenging intention that differs from what is known about the adoption of other IT. AI's technological nature enables machines acting autonomously and intelligent, which continuously triggers the growth of its scope of application and its performance at a high pace. Consequently, organizations must perceive AI adoption as a continuous task, challenging decision-makers due to missing knowledge on how to manage such an ongoing phenomenon. Therefore, the latest research engaged by AI's peculiar continuous characteristic calls for reworking our existing models for IT adoption, so that organizations can use the new theory to guide AI adoption. So far researchers have been focusing on AI applications, but due to its enormous number of potential fields of application they have not been able to derive holistic insights on the technology characteristics and how an organization can approach AI adoption holistically.

This thesis approaches the missing holistic perspective on AI adoption. The academic target is to provide a framework which contextually connects existing knowledge on AI use cases to the technology's characteristics. Through this connection, the framework has the ambition to inform AI adoption with an organizational perspective. Therefore, this thesis has three research goals (RG). The first RG is to extend the knowledge on AI technology (AIT) characteristics by pointing out which kinds of intelligent machines there currently are and by delivering an overview on the existing components and configurations of machine learning (ML) applications. The second RG is to investigate the connection of the organizational value creation logic to the adoption of AI by investigating the business model of organizations. The final third RG investigates the operation of AI adoption by examining how organizations can understand the ongoing process.

The thesis approaches the three RGs by using the Technology-Organization-Environment (TOE) framework as a guiding principle to develop an AI specific IT adoption model. Four research articles present the results of this thesis. The first article follows the RG 1 and presents two types of intelligent machines. The second article also follows the RG 1 by delivering an ML application taxonomy. To add to RG 2, the third article demonstrates a business model taxonomy. Finally, the fourth article targets RG 3 using the TOE

components to explain how continuity appears when adopting AI. With the findings from the articles the thesis presents a holistic model for AI adoption.

With the results the thesis contributes to the field of IT adoption. It shows that and how IT adoption, in the case of AI, appears with a continuous character. The results furthermore hold practical contributions since the developed model informs and guides AI adoption. Another theoretical contribution appears for the TOE theory. With the third article this thesis demonstrated that the term business model, so far, was not adequately met within its previous state and presents a generally valid extension of the TOE frame.

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1 Introduction

Artificial intelligence (AI) offers organizations various disruptive potentials in numerous domains (Enholm et al., 2022; Jöhnk et al., 2021; Legner et al., 2017). AI technologies (AIT), due to their characteristics, are highly adaptable to many settings (Hong and Tam, 2006). With their adaptability, AIT can create autonomy and intelligence in almost countless applicational settings, making AI a general-purpose-technology (GPT) (Cockburn et al., 2018). Its ascribed general-purpose value forces decision-makers from almost every organization of nearly every sector globally to consider the adoption of AI. However, due to its peculiar characteristics, AI adoption is a completely different topic than earlier information technologies (IT), necessitating the reworking of the existing IT adoption models for AI adoption (Ågerfalk, 2020).

Amid the variety of existing attempts at defining AI, the current information systems (IS) discourse recognizes AI predominantly as a "frontier of computational advancements" (Berente et al., 2021: 1437), which grows perpetually in terms of performance and scope (Berente et al., 2021). This recognition derives from the prevalent phenomenon that technologies that can be explained by mathematical algorithms as soon as their function is unveiled are no longer perceived as *intelligent* technologies. AIT identify and differentiate themselves from other IT by three main facets: autonomy, learning, and inscrutability (Baird and Maruping, 2021; Berente et al., 2021; Glikson and Woolley, 2020; Kellogg et al., 2020; Lyytinen et al., 2021; Rahwan et al., 2019). These three facets together represent and capture the current knowledge on AIT. Accordingly, for AI adoption, that means the adoption of AI will continue perpetually, which has far-reaching consequences for organizations seeking to adopt AI.

Adopting IT such as AI means "implementing a technology new to the organization and the acceptance and use by the users in the society" (Radhakrishnan and Chattopadhyay, 2020: 89). From an IS perspective, one can perceive an organization as a system of several sub-IS, each on its own consisting of technological as well as social components (Ågerfalk, 2020; Boaden and Lockett, 1991). Accordingly, the adoption of IT is either an extension of the current technological components of an IS, or as a replacement of a formerly included one. Logically, the characteristics of every sub-IS of an organization grow from their comprised technological and social components, and the characteristics of the organization's overarching systemic IS grows from the entirety of characteristics comprised within its sub-IS. Considering this coherence, IT adoption by the task-related implementation of new technologies changes organizations on several levels (Dong et al., 2021).

In the light of AI adoption, AIT provides the sub-IS and, consequently, the systemic IS with intelligence, qualitatively growing with every new AIT implementation. Nevertheless, from an IS perspective for the context of AI adoption, this means that organizations, from the moment of starting AI adoption, put themselves into a never-ending process of development. This is because the three facets per definition theoretically always allow the existence of a more mature and better version of the currently used AIT, which, can create the demand for continual improvements through competitive pressure.

Knowing about the imminent challenge of a never-ending adoption is of central importance for every organization. In today's organizations, information is a critical key to success (Schmidt et al., 2009). Hence, the importance of IS to manage the information within organizations became inevitable. Since IT offers more and more opportunities to increase the quality, processing, collection, allocation, and storage of as well as access to information, the use of IT to upgrade the organizations' IS became not just important, but vital (Schmidt et al., 2009). Due to the role of IT within IS enabling the use, creation, transmission, and manipulation of data and information (McKinney and Yoos, 2010), organizations must keep their IT up-to-date, to avoid the aging of their IS.

To inform the strategically important decision of organizations whether to adopt IT or not, research has intensively studied impacts on IT adoption. Nevertheless, the literature remains fragmented on the subject of AIT adoption (Jöhnk et al., 2021). So far, there is much knowledge on the potential value the technology application can create (Nam et al., 2021). Furthermore, the literature presents several different streams researching, e.g., the readiness of organizations for AI adoption (Jöhnk et al., 2021), the management of AI implementation at task-level (Alsheibani et al., 2018), or the management of AI strategies (Li et al., 2021). Nevertheless, research currently lacks a systemic IS perspective that can inform AI adoption decision-making through a model which can explain the imminent IS transformation when adopting AIT. The target of this thesis, hence, is to shed light on the impacts of AI adoption and to explain how organizations can approach AI adoption while being aware of its ever-developing character. This thesis does this by developing a model that contextually bundles AIT adoption impacting factors, which can then be used to explain the AIT adoption caused IS transformation under consideration of AITs peculiarities.

Within the IS domain, researchers have for decades predominantly used the Diffusion of Innovation Theory (DOI), Technology Acceptance Model (TAM), and the Technology-Organization-Environment Framework (TOE) (Oliveira and Martins, 2011; Radhakrishnan and Chattopadhyay, 2020) to explain IT adoption. To grasp the connection from a granular task-related technology implementation to high-level IS adaptions, this thesis seeks an approach which considers both technological as well as organizational aspects. Since TAM is on an individual level (Oliveira and Martins, 2011), and DOI sets its focus on explaining how and why innovations diffuse by relying on internal and external organizational components without considering the technological characteristics, and in line with, e.g., Jöhnk et al. (2021), Nam et al. (2021), or Alsheibani et al. (2018), this thesis will use the categories of TOE from DePietro et al. (1990) as a guide and answer our three research goals:

1. Extend the knowledge within the Technology context of AIT adoption by delivering theoretical ex-post insights about AIT applications.
2. Extend the knowledge within the Organization context of AIT adoption by examining the consideration of business models.
3. Explain AI adoption process by TOE application.

Our results deliver a model informing AI adoption decision-making as well as the AI adoption process using the TOE frame. Our findings on the one hand contribute to the knowledge about the technological characteristics of AIT and on the other hand develop the organizational TOE frame theoretically by generally extending the Organization context. For AI theory, our results present a contextual connection of distinct existing AI research streams by structuring those into the contexts of TOE. In addition, the results extend the state-of-the-art in AI research with four artifacts that practitioners can use for

AI adoption purposes. In the field of IT adoption research, the results open the AI-specific perspective which is the first that has a continuous and ongoing character.

2 Artificial Intelligence Adoption Theory

2.1 Intelligent Information Systems

From a technological viewpoint, the current AI discourse often confuses AI with Machine Learning (ML) by using both terms synonymously (Abdel-Karim et al., 2021; Ågerfalk, 2020). ML is the method which most of the current AIT use (Ågerfalk, 2020), but in fact is only one out of various methods AI comprises. Researchers from the field of IS have used various approaches to define the term AI. Collins et al. (2021) investigated which AI definitions exist in the articles from the Senior Scholars' Basket of Eight Journals[1] from 2005 until 2020. The most frequently used definitions appeared in the formulations of Russel and Norvig (2010), calling AI the exhibition of human intelligence in machines through mimicking humanoid cognitive functions, such as to learn, speak, problem-solve, perceive, reason, and interact. Another commonly used approach depicts AI as a broad spectrum of technologies which meet or overarch humans' ability in cognitive tasks such as learning or problem solving (DeCanio, 2016). Rai et al. (2019), finally, perceive AI "as the ability of a machine to perform cognitive functions that research associates with human minds, such as perceiving, reasoning, learning, interacting with the environment, problem solving, decision-making, and even demonstrating creativity" (Rai et al., 2019: iii)

Comparing the definitions, there are three main aspects they have in common. Every definition connects AI to (1) computer programs, which can (2) act, and (3) perform their actions intelligently. Especially the latter aspect, however, creates disagreements among researchers since intelligence on its own is still lacking a commonly agreed upon definition (Hassani et al., 2020). As a logical consequence, this lack of clarity in terms of defining intelligence is a barrier to a clear understanding about which technology actually

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[1] The Scholars' basket collects the eight top journals from the IS domain to "provide more consistency and meaningfulness" (https://aisnet.org/page/SeniorScholarBasket).

represents intelligence that is created by humans (Hassani et al., 2020). The current solution to this lack of precision is perceiving AI in general as a *computational target* of creating intelligent machines (Benaich and Hogarth, 2022; Berente et al., 2021). AIT, accordingly, are the methods and techniques which researchers and practitioners use to build those machines (Stone et al., 2022; Weber et al., 2022) which autonomously perform functions that typically would benchmark biological intelligence (Collins et al., 2021; DeCanio, 2016; Rai et al., 2019; Russel and Norvig, 2010).

However, the object of this thesis is not to define AI, but to shed light on the IS perspective of its adoption on an organizational level. An IS is "a system which assembles, stores, processes, and delivers information relevant to an organization (or to society), in such a way that the information is accessible and useful to those who wish to use it" (Avison and Myers, 1995; Buckingham et al., 1986). IS can appear in several different configurations. The two counterparts of an IS are a social (i.e., humanoid) and a technological component (Ågerfalk, 2020; Boaden and Lockett, 1991). The goal of such constructs is to theoretically depict the manipulation and the exchange of information inside and between the counterparts of the IS as well as with other IS (Ågerfalk, 2020). Information in this regard is like a token, which each counterpart of an IS can manipulate (create, transform, analyze, delete) or exchange (receive, store, and distribute) (McKinney and Yoos, 2010). Holistically, an organization comprises various IS, which all interact with each other and manipulate information independently.

This thesis considers AI adoption as the task-related implementation of AIT providing IS with (machine) intelligence, growing by every AIT application implementation. AI adoption comprises but is not limited to the implementation of AIT to a single or certain tasks, which represents a use case, application, or task-related implementation (McKinsey, 2018). Instead, AI adoption has the target to empower an organization's systemic IS with autonomy and learning capabilities holistically (Weber et al., 2022), while considering technological inscrutability (Berente et al., 2021). In this regard, AI adoption is a paradigm that organizations realize through the implementation of task-related AI use cases (Ågerfalk, 2020; Berente et al., 2021). Following, this thesis defines AI adoption as the attempt to create intelligent IS by integrating AIT into IS (Ågerfalk, 2020; Agrawal et al., 2021; Hassani et al., 2020). Through the inclusion of AIT, a non-AI

IS empowers itself with the AIT's peculiar capabilities of autonomous intelligent actions. This creates novel phenomena within the social as well as the technical component, which distinguishes intelligent IS from earlier IS in social as well as technological regards.

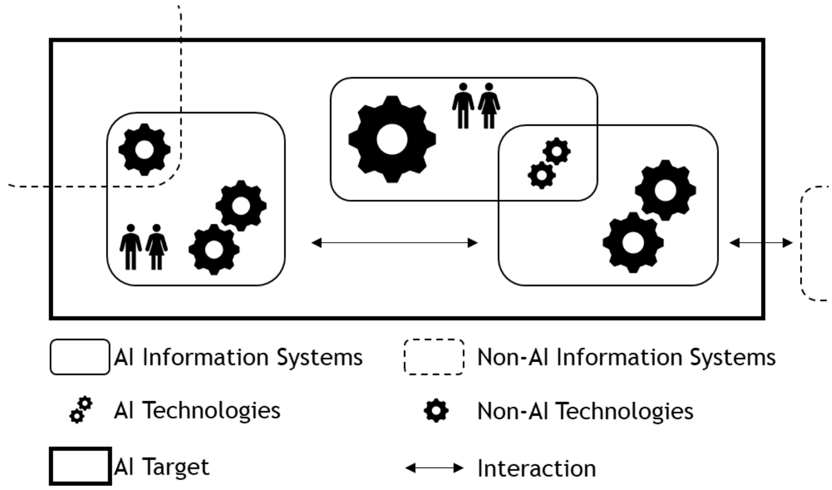

Figure 1. Intelligent Information Systems

2.1.1 Social Component

IS are constituent of social and/or technical components (Buckingham et al., 1986). There are two different ways a social component can appear. First, the existence of a social component can basically mean that the IS under consideration comprises human beings. But there is a second rationale integrated into the nature of IS that the existence of human beings brings in, which is social action (Ågerfalk, 2020). Following Weber (1979), such action is "*social* which in its meaning as intended by the actor or actors, takes account of the behaviour of others and is thereby oriented in its course." Social actions, accordingly, comprise intentions and considerations which, due to our definition, AI enables for machines (Russel and Norvig, 2010). Formerly, such behavior was exclusively reserved for human beings, implicating that IS requires humans to comprise a social component. Logically, with intelligence in IS, the social component is no longer bound to the existence of humans. Instead, there is a social component also in the interaction of machines (Ågerfalk, 2020), which non-AI machines would not be able to fulfill. From a social perspective, intelligent IS are the first IS which comprise three kinds of social interaction: Human-human, human-machine, and machine-machine.

The second phenomenon with intelligent IS that is strongly related to the novel perspective on the social component regards the role of the technical component in human-machine interfaces. Before the ability of machines to socially interact, humans used machines for information purposes (Weber, 1979). A machine's capability for social interaction enables the machine's autonomy within tasks, which leads to machines not just augmenting humans, but even replacing them in terms of responsibility. That is a relocation of the social role between human and machines. Due to sociality, the role of machines shifts from simple task operations to assuming knowledge and responsibility (Weber, 1979).

2.1.2 Technological Component

Theoretically focusing on the emergence of AIT's ability of autonomous intelligent actions there are two main technological logics. The difference between both can be best explained via the concept of agents as introduced by Russel and Norvig (2010).

AI for us is the target of building machines which perform autonomously such functions that typically would benchmark biological intelligence (Collins et al., 2021; DeCanio, 2016; Rai et al., 2019; Russel and Norvig, 2010). Machines in this regard comprise cyber as well as physical systems (Berger et al., 2018). The control center (the "brain") of these machines consists of software performing tasks such as perceiving, visioning, or sensing, which are considered as AIT (Stone et al., 2022; Weber et al., 2022). These technologies function in such a way that research considers their *data processing* or their *output* as action and, therefore, designate these algorithms as *agents*. AI/computer agents surpass the action of other non-AI computer programs by their intelligence, which is expressed through autonomous operation, perception of their environment, prolonged timely persistence, adaption to change, and the creation and persecution of targets (Russel and Norvig, 2010).

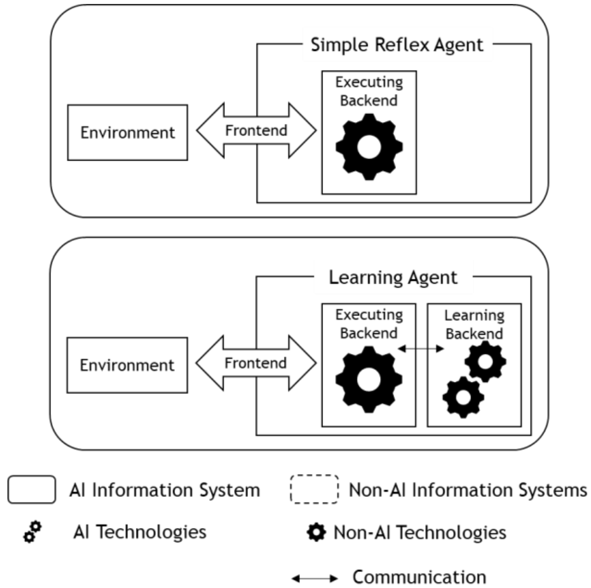

Figure 2. Artificial Intelligence Agents (Kühl et al., 2022; Russel and Norvig, 2010)

Using the agent perspective, research distinguishes between two kinds of AI agents. Both differ according to the perception of their intelligence. For the first agent, only the output is considered as intelligent action. Kühl et al. (2022) with reference to Russel and Norvig (2010) depict these agents as *simple reflex agents*. The counterpart to simple reflex agents are *learning agents*, which draw their intelligence from their data processing (Kühl et al., 2022; Russel and Norvig, 2010). The former agent relies on external predefined rules and only acts according to these. The latter agent learns, meaning that these agents, based on different learning methods, create their own rules which they then use to orientate their action. Expert Systems, Rule Engines, and Decision Graphs are examples for simple reflex agents, whilst Artificial Neural Networks, for example, represent learning agents. The interplay of both types of agents then opens up the way towards AI.

2.2 Technology Adoption Decision in Information Systems

IT adoption is one of the main instigators of change in organizations (Dong et al., 2021). Research explains this impact by the power IT has in handling the extensive use of information. Every production process of each organization, whether physical or not, requires some sort of information. This can be by supporting the processing workers or machines, or even by information itself being the commodity or product for processing (Ghobakhloo et al., 2012). Since, accordingly, information is required for every process within each organization, the structuration and organization of information with the help of IS became inevitable (Ghobakhloo et al., 2012). Digital IT helped to increase the capacity of these IS drastically, which is why organizations started to upgrade their IS with several purpose-oriented IT (Ghobakhloo et al., 2012). Every IT brings with it novel and peculiar challenges for the IS. Therefore, organizations are required to adjust their existing IS according to the new IT. Hence, from an IS perspective, organizational change is the adjustment of an organization's logic of creation, allocation, and manipulation of information (Dong et al., 2021).

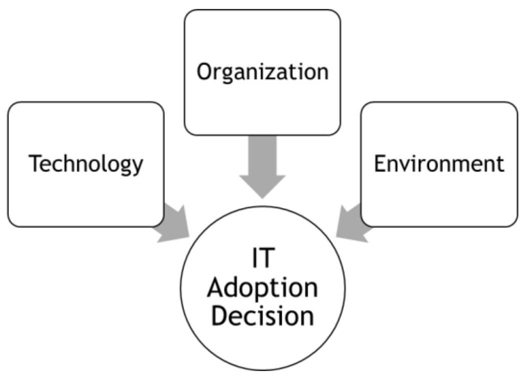

Figure 3. Impact on IT Adoption Decision (DePietro et al., 1990)

The highest possible degree of information quality is the key for a successful venture in the today's digital era. Hence, for organizations, one of the main intentions to adopt IT is to exploit increased information quality by strategically changing the common organizational IS environment (Dong et al., 2021). However, IS literature has shown sufficiently that IT adoption does not automatically increase information quality but can also drastically destruct it (Aggarwal, 2013). To avoid value destruction through mistaken IT adoption decisions, IS research guides decision-makers with the TOE framework. Accordingly, decision-makers generally must consider impacts from the three contexts of TOE when deciding about IT adoption (DePietro et al., 1990) (Figure 3).

2.2.1 Technology

In the first context, Technology, both the *availability* and the technology-specific *characteristics* impact the adoption decision (DePietro et al., 1990).

Availability means that an organization must have access to the resources of the considered technology. Access can be gained via two ways: Either there are external suppliers which provide the technology to the adopting organizations (i.e., software-as-a-service), or the organization can become a first mover or early adopter by adopting the technology via in-house development. For each existing technology, either of the two ways creates several different business cases, and organizations need to assess and accommodate their decision-making process on the calculated case-specific chances and challenges. In the case of enterprise resource planning (ERP) systems, for example, external availability has grown to such an extent that there are providers for almost each individual demand, leaving no room for gaining competitive advantages by in-house development. Nevertheless, the wide diffusion of ERP systems among competitors also set a standard for information quality in the organizations' master data and, therefore, can push the need for adoption.

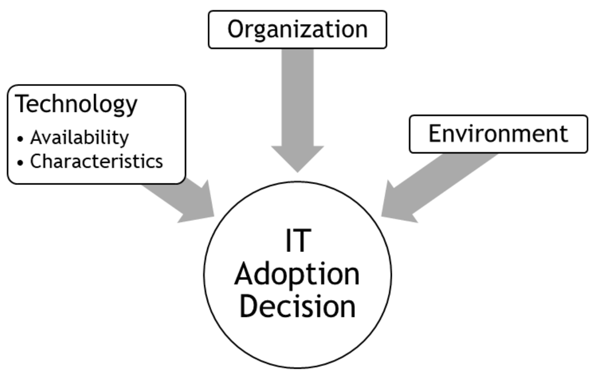

Figure 4. Technology Context (DePietro et al., 1990)

By the means of technological *characteristics*, the TOE framework addresses the compatibility of the new IT with the existing organizational-internal IT landscape (Al-Hujran et al., 2018). Since every different IT on its own comprises several capabilities and key tasks (Ågerfalk, 2020), it is necessary that an organization's IT adoption is purpose-driven (Baker, 2012). Hence, to be able to distinguish use cases that create value from those which would destroy value, organizations must know and understand how a technology distinguishes itself and how it interacts with remaining technologies. To inform decision-makers, technology characteristics are the unique and general features of a technology considering, e.g., design, capabilities, applications, architectures, concepts, components, behavior, or potentials (Berger et al., 2018). One common way to define the characteristics of IT is by using the four layers[2] service (human involvement), content (data treatment, input, output), network (multiplicity, direction), and device (role of technology, scope) (Berger et al., 2018), which this thesis will also use.

2.2.2 Organization

The context Organization considers the formal and informal linking structures, communication processes, size, and slack of an organization (DePietro et al., 1990).

Linking structures impact the IT adoption decision regarding the connection of the inner-organizational stakeholders. Representing the degree of interdisciplinarity within teams and departments, the existence or absence of linking structures (product owners, gatekeepers) pushes or hinders IT adoption decisions (Baker, 2012; Galbraith, 1973; Tushman and Nadler, 1986). For example, decentralized and organic structures increase the interdisciplinarity within organizations and, therefore, support innovativeness by pushing IT adoption (Baker, 2012; Burns and Stalker, 2001; Daft and Becker, 1978).

In the light of communication processes, TOE addresses aspects like management support and acceptance, which impacts the attitude of the whole organization's stakeholders against the technological adoption (Alshamaila et al., 2013; Low et al., 2011; Oliveira et al., 2014). In the context of communication processes, the top-level management impacts IT adoption decisions by providing strategic innovation alignments (Baker, 2012).

Finally, the last two components impacting the IT adoption decision in the Organization context comes from size and slack. Measures such as the number of employees or the financial return represents the size of an organization and can impact the decision whether to adopt IT or not. Strongly related to the size, Baker (2012) citing DePietro et al. (1990) mentions slack as the last Organizational component impacting the adoption decision. The slack represents the freely available resources an organization has and can

[2] A detailed description of the layers and subdimensions can be found in Berger et al. (2018).

therefore push adoption decisions, but is not a required factor (Baker, 2012; DePietro et al., 1990).

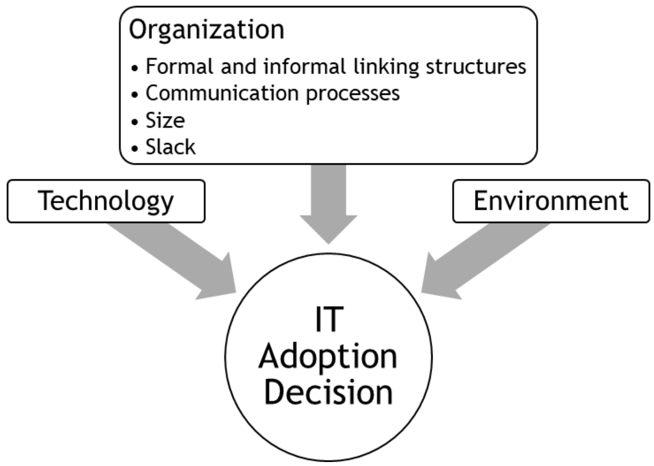

Figure 5. Organization Category (DePietro et al., 1990)

2.2.3 Environment

The Environment category of the TOE framework addresses the impact of the surrounding environment the adopting organization finds itself in. Impacts on an IT adoption decision arise from the surrounding government, market, industry, sector structures, and geographical aspects (Borgman et al., 2013; Fryer et al., 1979; Kamath and Liker, 1994; Lian et al., 2014; Oliveira et al., 2014; Prais and Mansfield, 1968).

According to its rules and regulations, the government may hinder as well as push IT adoption for organizations. In the case of AI, e.g., on the one hand, governments seeks to create laws which can limit or even prohibit the use of AI, but on the other hand, governments may endeavor to aid the development of the state of art in AI by offering public promotion (Beiker and Calo, 2012; DePietro et al., 1990; Schreurs and Steuwer, 2015).

Peculiarities of markets and industries extend over various aspects such as dynamism, volume, innovativeness, etc. Each organization, due to their participation within that market, somehow reflects these peculiarities. For this reason, the market itself also impacts the IT adoption of organizations (Ghobakhloo et al., 2012). The mobile phone market, for example, develops quickly, which puts pressure on the organization by requiring a high degree of competitiveness which impacts the IT adoption decision of the participating organizations (Al-Hujran et al., 2018).

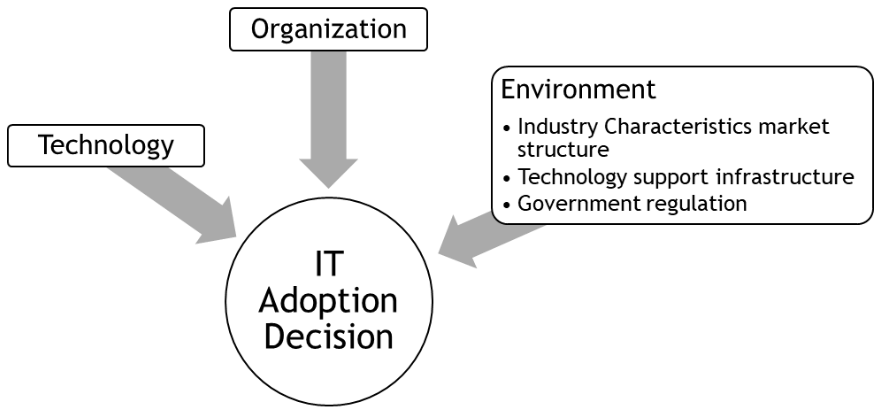

Figure 6. Environment Category (DePietro et al., 1990)

The TOE framework has already proven its theoretical robustness multiple times. The IS literature has used the framework to explain the adoption of, e.g., interorganizational systems (Baker, 2012; Grover, 1993; Mishra et al., 2007), e-business (Baker, 2012; Zhu et al., 2003; Zhu et al., 2004; Zhu et al., 2006; Zhu and Kraemer, 2005), electronic data interchange (EDI) (Baker, 2012; Kuan and Chau, 2001), open systems (Baker, 2012; Chau and Tam, 1997), or enterprise systems (Ramdani et al., 2009).

Although TOE delivers a general applicable frame for the adoption of IT, each IT is unique due to its nature. The numerous different applications of the framework have shown that within each of the three dimensions there are both contextual categories which exist only explicitly for a certain technology as well as contextual categories which exist for each IT adoption consistently (Zhu et al., 2004). Nevertheless, the configuration even within consistent categories varies across different technologies (Baker, 2012). Therefore, there is huge potential in applying the TOE framework to the context of AIT adoption. These potentials come up, e.g., by testing those elements of the categories which researchers currently perceive as consistent, by finding new persistent category elements, by defining the technology-specific configuration of persistent category elements, or by finding new technology-specific category elements.

2.3 Artificial Intelligence Adoption

The adoption of AI holds special challenges for organizations (Weber et al., 2022). The scope of this thesis focuses especially on the organizational and technological aspects of AI adoption. Research from the Technology as well as the Organization context of TOE so far has presented several factors affecting the adoption decision of AI as a specific type of IT. In the following section, this thesis describes the state-of-the-art AI research in the contexts Technology and Organization and will indicate existing research gaps in the literature, which this thesis aims to close. Within the Technology context, this thesis explicitly focuses on the characteristics of AI, since the characteristics explain the source of a technology's explicit features. Within the Organization context, this thesis addresses business model aspects as well as transformational aspects which occur within an organization when adopting AIT.

2.3.1 Technology Context

In the Technology context, state-of-the-art research on AIT characteristics has reached several milestones. To summarize and structure the characteristics of AIT, this thesis uses the four-layer perspective of Berger et al. (2018) (Table 1). This perspective uses the four layers service, content, network, and device, to structure the dimensions and characteristics of IT as presented in Table 1. The fields highlighted in grey indicate the characteristics, which accord to AIT.

Within the *service* layer, AIT is characterized through offering task-related value directly to human beings through active usage (Berger et al., 2018), which the field of AI research depicts as human-machine-interaction. AIT research has exposed this human-machine-interaction via the two phenomena of augmentation and automation (Raisch and Krakowski, 2021). In an AI-augmented human-machine interaction, for example, the processing power of the AIT will directly support the human worker. This is present in use cases such as AI supporting human beings in text creation through, i.e., suggestions, translations, and corrections (Cagle, 2019). In an automated context instead, AIT will not support human workers but replace them. There are examples for AI-empowered automation, e.g., in the automotive industry, where manufacturers use AI agents to automate and streamline their production processes (IBM, 2023).

Table 1. Technology Characteristics of Artificial Intelligence (Berger et al., 2018)

Layer	Dimension	AIT				
Service	Human Involvement	Active Usage	Passive Usage			
Content	Data Treatment	Collection	Aggregation	Analysis	Execution	Transmission
	Input	Digital	Physical			
	Output	Digital	Physical			
Network	Multiplicity	One-to-One	One-to-Many	Many-to-Many		
	Direction	Uni-directional	Bi-directional			
Device	Role of Technology	Application	Infrastructure			
	Scope	Cyber	Cyber-Physical			

Especially in the *content* layer, the framework captures the adaptability of AIT's capabilities to various purposes. Perception, comprehension, action, and learning (Bawack et al., 2019; Bawack et al., 2021; Ransome Bawack et al., 2019) are the four capabilities of AIT which enable it to either collect, aggregate, analyze, execute, or transmit data[3] (Berger et al., 2018). According to its capabilities, AIT can comprehend contexts and can, therefore, automatically collect, e.g., real time customer data (Cornelissen, 2021). Its capabilities of learning and comprehending are ideal for analysis purposes, which enable advanced data-based decision-making, as already shown, e.g., in motor sports (Aversa et al., 2018).

From a network layer perspective, AIT extends its flexible adaptability by being able to appear as bi- as well as uni-directional technologies (Berger et al., 2018). Its uni-directional characteristic, for example, appears in autonomously driving vehicles, which perceive their environment via sensor data, but do not feed any information back to its environment (Berger et al., 2018). The bi-directional information flow, on the other hand,

[3] Other IT rarely provide each part of data treatment.

appears within ML agents, which give back their formulated rules (trained model) learned from data externally received (Berger et al., 2018).

Finally, the device layer addresses the function of the AIT within considered systems (Adomavicius et al., 2007). AIT "provide a set of functions that directly address and satisfy users' needs" (Berger et al., 2018). This satisfaction of need is the most important dimension of the technology, which`s use cases, especially in innovation literature, play a special role in that they transfer the state of a novel artifact from being an invention into an innovation (Thompson, 1965). Accordingly, the utility in use cases is the deciding metric which requires AIT to prove its value.

The growing diffusion of AIT across every business sector led to a huge diversification between the technological models, components, and use cases. Nevertheless, GPTs such as AIT (Cockburn et al., 2018) distinguish themselves from remaining IT by their multivariate applicability (Hong and Tam, 2006). This means that such a GPT can create value in completely different environments by fulfilling various purposes with similar configurations. GPTs are thus highly adaptable with varying use cases due to the utility of their key capabilities. In the case of AIT, the high adaptability of a single key capability multiplies by the increasing number of technology configurations. This multiplying effect again leads to a wide field of use cases, which is even more difficult to oversee.

So far, researchers' interest is seemingly concentrated on expounding the extent of variability of applications (Buck et al., 2021). However, research has missed building ex-post models from existing AIT applications describing what the main purpose of applied AIT is and how AIT appears in an applied manner. Especially for AIT implementation, though, it is necessary that research derives theoretical generalizations on AIT use cases. Currently, researchers have no specific insights about the types of intelligent machines exist and which purposes AIT serves applied in use cases. This thesis, hence, sets its purpose in addressing this research gap to inform decision makers. To do so, the first research goal of this goal of this thesis is to address the missing ex-post theorization of AIT applications.

Table 2. Research Goal 1

RG 1: Extend the knowledge within the Technology context of AIT adoption by delivering theoretical ex-post insights about AIT applications.				
Research Articles	No.	Title	Publication Outlet	Publication Status
	1	Raiders Of The Lost Ark - A Review about the Roots and Application of Artificial Intelligence	International Journal of Innovation and Technology Management	Published
	2	Machine Learning Application Archetypes: Insights from the Complex System of Professional Sports	Journal of Sport Management	Under Review

2.3.2 Organization Context

The Organization context of TOE considers formal and informal linking structures, communication processes, size, and slack. Although this frame has been adequate for previous IT adoption decisions, there is a difference in the light of AI. In its current state, TOE framework misses to consider the value creation logics of an organization. Due to its GPT characteristic as well as its application purposes, AI can transform both the processual functioning and the value creation logic of an organization (Weber et al., 2022). Nevertheless, what TOE missis within the established components of the Organization context is the impact coming from a transformed value creation logic.

AI adopted to transform the value creation logic of an organization alters the business model by integrating AIT into their inner core, considering AI as a product and value component (Brynjolfsson, 2017). These AI business models distinguish from other IT-enabled business models regarding novel AIT-enabled value propositions and changed data relation in the value creation process (Weber et al., 2022). Unlike previous IT business models, AIT-based business models are able to propose values that "shift the application of IT toward the domain of knowledge and service work" (Weber et al., 2022). This AIT peculiarity appears e.g., in medical applications where AIT agents detect diseases (Brynjolfsson, 2017). However, so far it is not clear, if TOE does comprise a component in any of the three existing contexts which is able to represent business model perspectives. It is, therefore, necessary to consider the business model logic for AI adoption.

Table 3. Research Goal 2

<table>
<tr><td colspan="5">RG 2: Extend the knowledge within the Organization context of AIT adoption by examining the consideration of business models.</td></tr>
<tr><td rowspan="2">Research Article</td><td>No.</td><td>Title</td><td>Publication Outlet</td><td>Publication Status</td></tr>
<tr><td>3</td><td>Toward an Enduring Football Economy: A Business Model Taxonomy for Europe's Professional Football Clubs</td><td>European Sport Management Quarterly</td><td>Published</td></tr>
</table>

2.3.3 Transformation Aspect

However, whether the adoption decision is driven by the intention of integrating AIT into the value provision or by the intention of optimizing organizational functions, the adoption decision in every case depends on the effects the decision likely causes. These resulting effects are the answer to the question of how an organization can approach the transformation AIT adoption requires depending on the difference between the business model's current state and its targeted AIT-enabled status. Research has shown progress in analyzing which role AIT can take over in business models (Weber et al., 2022). However, the transformational procedure, which according to its extent also impacts the adoption decision, has not yet been investigated intensively. Research has shown that AIT adoption requires transformation across the different levels of an organization beyond technological aspects to unfold its whole potential (Agrawal et al., 2021). What researchers currently do not know is where to start from specifically and how this transformational process goes on (Weber et al., 2022). This thesis, therefore, addresses the missing consideration of the AI transformation by extending knowledge on the sector-related business models and general AI transformation.

Table 4. Research Goal 3

RG 3: Explain AI adoption process by TOE application.				
Research Article	No.	Title	Publication Outlet	Publication Status
	4	Artificial Intelligence Adoption and Management – An Evolution-Theoretical Model	Information & Management	Under Review

3 Main Results

3.1 Impacts from Technology Characteristics

The following section provides the results this thesis delivers for the Technology-enforced impacts on the AIT adoption decision. The results focus on the characteristics of AIT and deliver ex-post knowledge on the use case application of AIT. The first article investigates which kinds of use cases for AIT generally exist regarding the focus of action (moving vs. knowing). The second article explores which behavioral patterns, especially ML applications, comprise key tasks.

3.1.1 Raiders of the Lost Ark - A Review about the Roots and Application of Artificial Intelligence (Buck, Ifland, Stähle, and Thorwarth, 2021)

Whether AI appears as an innovative product or if its adoption increases the productivity of processes (Makridakis, 2017), the various potentials AIT offers for organizations has led to a vast field of different applications. The increased processing power of the last decade has led AIT to take over various roles across almost every sector. Whilst the wide variety of use cases has grown to an unmanageable extent, research has equally lost ground in extending AIT theory.

To support academia as well as researchers in keeping the overview of the purposes AIT can fulfill, this article especially focuses on the nature of AIT use cases. Technology use cases, especially in the innovation literature, play a special role in that they transfer the state of a novel artifact from being an invention into an innovation (Thompson, 1965).

Accordingly, the use case is the deciding factor that an invention requires to prove its value.

Indeed, research can no longer consider AIT as an invention due to its extensive use cases. But it is similarly important to extract theoretical knowledge about use cases covered within the vast number of existing applications. With this article, it was our target to investigate a broad field of existing AIT use cases to formulate a general valid conceptualization of which kind of AIT use cases exist.

Due to the vast number of existing use cases, this article decided to focus on the most deeply embedded ones. For this article, the authors regarded a use case as deeply embedded as soon as the use case article cites at least one of the most cited AIT articles ever. To verify this criterion for the articles under consideration, the researchers first conducted a citation network analysis to determine the most referenced AIT articles. Within the articles which grew from the streamline of those 13 articles ("roots of AI"), the authors searched for existing use case clusters representing generally valid use case scenarios.

Overall, this work investigated 13,547 articles. Out of that basket, the authors started with the 13 most cited articles and obtained 100 use case articles directly citing the most referenced ones. From those 100 use cases, the researchers extracted a theoretical construct describing types of existing application scenarios. Our results first show a separation between *theoretical and algorithmic development* and *use case applications*. Use cases, furthermore, divide into the two types of machines: *Sensor-Related Hardware* (SRH) and *Virtual Machines* (VM). Both categories differ regarding their purpose of application. While SRH uses AIT to enable AIT physical movements and interactions, a VM, instead, has the target of knowledge creation and decision-making (Buck et al., 2021).

From a theoretical perspective, this article contributes to the understanding of the nature of AIT use case scenarios and supports increasing the purpose-adoption-fit. It therefore contributes to the AIT adoption theory by extending the state-of-the-art of AIT characteristics in the Technology context.

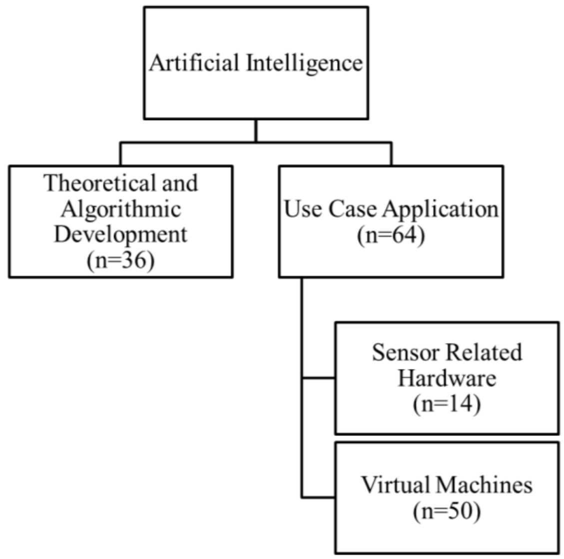

Figure 7. Types of Intelligent Machines (Buck et al., 2021)

3.1.2 Machine Learning Application Archetypes: Insights from the Complex System of Professional Sports (Ifland, Protschky, Schüll, and Buck, 2023)

Recently, especially the sports domain has increasingly adopted AIT applications, e.g., for player scouting and recruitment (Mathew et al., 2018; Rani P. et al., 2020), to increase athlete workout outcomes, to increase the health of the athletes (see e.g., Stetter et al. (2019), or Kautz et al. (2017)), for match strategy analysis (Parameswaran, 2013), or to dynamically adapt customer offerings (see e.g., Arslan et al. (2022), or Arti et al. (2019)). Most of these existing applications rely on ML methods (Ågerfalk, 2020) and, due to its wide diffusion within the sports domain, ML took over several purposes such as assisting athletes by their training activities as well es support customer behaviour analyses and, therewith, created various values for the different stakeholders of the sports industry. The sports sector, hence, was a fitting environment to collect and analyze existing ML use cases to extract general valid theoretical key tasks of ML application.

To extract ex-post theory on AIT, the authors developed machine learning application archetypes. They did this by creating a taxonomy which collects and structures the different configurations of the existing ML application within the sports sector. To regard the sector specifics of the sports domain in addition to the technology configuration, the taxonomy also comprised purpose-related as well as environment-related components. Following that, this article used the taxonomy as a data pattern to analyze 494 real-life ML applications. Consequently, the researchers received a data set which described the configuration of each of the 494 objects through the taxonomy pattern. Finally, to derive ML application archetypes, the authors clustered the 494 objects due to their taxonomy configurations. The six resulting clusters represent general valid ML application patterns.

Table 5. Machine Learning Application Archetypes

ML Application Pattern	Generally Valid Description
Internal Innovation Enabler	An ML application that enables individuals to recognize new solutions to a given problem and thus improve their ability to tackle the problem. Based on classifying internal textual data.
Human Performance Driver	An ML application that supports human individuals and groups by using organization-internal textual data to classify the performance-related output of an executed solution approach.
Internal Foreseer	An ML application that enables organizations to make predictions about possible future internal (value-adding) effects of organizational activities. Based on classifying textual data external to the organization.
External Foreseer	An ML application that enables organizations to make predictions about possible future external (sales-related) effects of organizational activities. Based on classifying textual data external to the organization.
Machine Performance Driver	An ML application that either supports or enables operating machines to autonomously improve their capabilities. Based on classifying visual data internal to the organization.
External Innovation Enabler	An ML application that supports organizations in applying tools by showing alternative approaches of using the tools. Based on classifying textual data external to the organization.

The six application patterns show that the key tasks ML delivers accord to the internal as well as to the external level of organizations. Our findings show ML can enable innovation externally or internally, drive the performance of human and machines, and can either internally or externally predict circumstances relevant to the organization.

Our ML application patterns generally explain the adaptable key tasks of ML AIT. The results therefore extend the theory of ML application and especially complement the understanding of the ML technology currently in use. This extends the knowledge on the

Technology characteristics of AIT and, with that, helps organizations to decide about the adoption of AIT in an informed manner.

3.2 Impacts from the Organization Context - Toward an Enduring Football Economy: A Business Model Taxonomy for Europe's Professional Football Clubs (Buck, and Ifland, 2021)

Section 3.2 provides the results this thesis adds to the Organization category of impacts on the adoption decision of AIT. The first article takes over a sector-specific perspective and provides knowledge about business models in professional sport. The second article delivers ex-post knowledge on organizations' components and the mechanisms of the AI transformation arising when adopting AIT.

Since the adoption decision of AIT is impacted by both the architectural as well as the value creation perspective, the authors extract the business model of professional European sports clubs to show which further components the TOE Organization category requires to adopt. The authors take the sector of professional European sports as a domain of application, since AIT adoption is growing vastly in the sector of professional sports (Diel et al., 2021).

Business model research in the sports domain, however, compared to other business sectors, is missing a theoretical basis to build AIT adoption decisions on (Buck and Ifland, 2022). Consequently, the sports sector's stakeholders' adoption decision may be biased due to missing information in the Organizational category. To address this problem, the researchers prepare the decision-making process for AIT in the sports domain by delivering business model insights for professional European football clubs.

This article investigates the business model of professional football clubs by analyzing their behavior within the market. Following the taxonomy development process of Nickerson et al. (2013), the authors explored the existing literature as well as knowledge from practice by observing football clubs as real-world objects. During the analysis, the researchers identified the counterparts which the 98 professional football clubs from the five European top leagues (Bundesliga, LaLiga, Premier League, Ligue One, Serie A) during the 2018/19 season used for their value creation. The results structure the identified business models components in a business model taxonomy (Table 6), which the authors evaluated through five case study applications.

The 13 dimensions of our developed business model taxonomy structure 63 business model components. The professional football clubs on a meta level operate within the three dimensions operations, marketing and communications, and finance and economics. Our results prove the existence of differences between the business models of the football clubs and deliver a theoretical approach for the Organizational category for AIT adoption decision-making.

Table 6. Business Model Taxonomy (Buck and Ifland, 2022)

Meta-dimension	Dimension	Characteristics					
Operations	Arriving players	Come back and hold	Come back and loan	Youth and hold	Youth and loan	Buy and loan	
		Receive loan abroad	Receive loan intern	Loan and buy	No fee		
	Leaving players	Give loan abroad	Give loan intern	Come back and free agent	Come back and sell		
		Youth and sell	Leave as free agents	End of career	No fee		
	Sporting performance	Relegation from domestic first class	Hold domestically	Participate internationally	Win nationally	Win internationally	
	Strategic cluster	Inexperienced B-players	Experienced B-players	Inexperienced A-players	Experienced A-players		
	Stadium	0	1	2			
Marketing and communication	Industry of jersey sponsor	Other	Automotive	Finance	Food	Flights and tourism	Betting and sport media
	Sponsor strategy	Local	Regional	Continental	Global		
	Market share of kit supplier	Subordinated manufacturer	Market leader				
	Social media stage	Traditional	Experimental	Integration	Multiplatform	Multichannel	Ecosystem
	International identity	Domestic	International	Global			
	Target markets	Only domestic	Middle East	South America	Asia	Russia	English/UK /US/Canada
Finance and economics	Spending on player recruitment	Deliberate	Moderate	Offensive	Extravagant		
	Transfer balance	Spending	Balanced	Earning			

3.3 Applying TOE to the Adoption Process – Artificial Intelligence Adoption and Management – An Evolution-Theoretical Model *(*Ifland, Stähle, and Buck, 2023*)*

The adoption of AIT for organizations is a process of bilateral adaption (Agrawal et al., 2021). Due to implicit multiplying effects the value an AIT use case creates increases the wider the perspective of consideration gets (Agrawal et al., 2021). For AIT it is, therefore, necessary to take a holistic perspective. In this regard, organizations must perceive an AIT-augmented or -automated task as a component impacting downstream and upstream contexts, which may start domino effects. The perception, though, only gets holistic as soon as organizations permit change to tasks which in the forefront have not been part of the AIT application consideration. Accordingly, AIT is not one technology that an organization adopts for a specific task. Instead, the power of AIT especially unfolds when considered as a transformation agenda adopting AIT for several interacting purposes. This article specifies the organizational components as well as AIT-specific logics with which these components are manipulated under the creation of an intelligent IS through the adoption of AIT for several applications.

To structure the components and explain the logics of the AI transformation, the authors explored the AI initiative of one of the leading energy suppliers of Germany via an embedded single case study (Yin, 2009). In the context of its AI initiative, the explored organization created intelligent IS through the application of AIT in 28 different use cases. For the case study, the authors considered each of the 28 cases via an interview study. The qualitative data analysis following Gioia et al. (2013) led us to a holistic AI-specific model picturing the logic and components of the organization's AI transformation (Figure 8).

Our resulting model consists of the three major contexts: AI-Operations, AI Organizational Change, and Performance. Our case study revealed that the adoption of AIT changes the way humans operate in specific tasks. These task adaptions can be captured within several organizational contexts that change. At this point, the embedding of AIT applications takes effect in that it multiplies the development by offering new AIT application opportunities. This back coupling creates a circle of development characteristics for the AI transformation. The third context, finally, captures the effects of the organizational process adaptations, which come up as increased business performance.

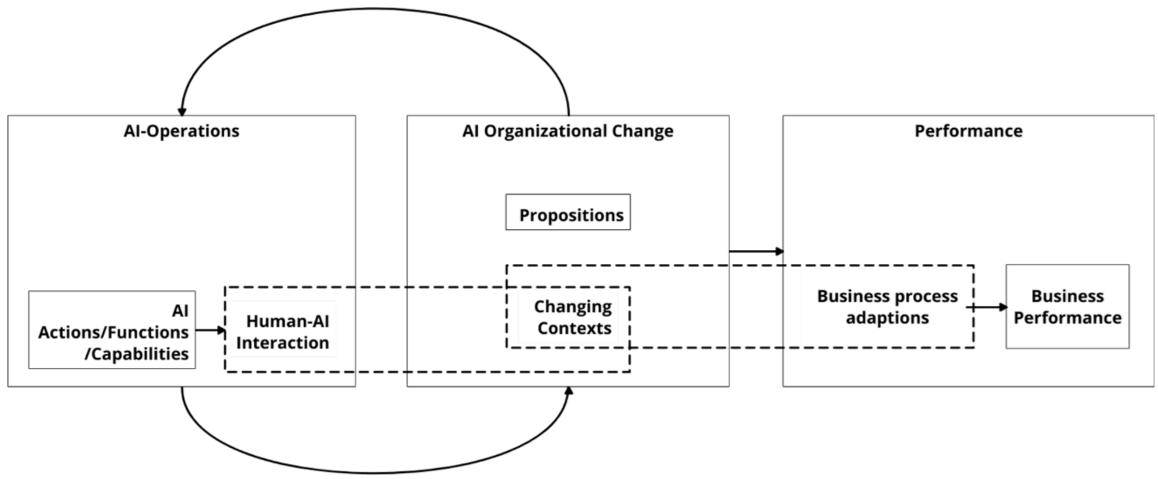

Figure 8. Artificial Intelligence Transformation Model

The results of this article extend the knowledge about AI transformation. The authors explicitly spot and structure the components of an organization affected by AIT adoption. The model, developed under the consideration of 28 AIT application use cases of a single group, also explains the interaction of the affected components. This article, hence, contributes to AI adoption theory by delivering a model, which explains the process of AI adoption by considering the AI specific phenomenon of continuity.

4 Discussion

4.1 Summary of the Results

The IS literature so far has investigated the adoption of IT with the help of the TOE framework (Baker, 2012; DePietro et al., 1990; Nam et al., 2021). This thesis used this theoretical lens as a starting point to inform AI adoption decision-making by investigating the factors impacting AI adoption. The general goal of this article was to contribute to the understanding of the impact of Technology and Organization on the AI adoption decision and how TOE appears within the adoption process. This thesis did this with three main research goals. The first goal was to extend the knowledge about the characteristics of

AIT, which the results of the two articles *Raiders of the Lost Ark – A Review About the Roots and Application of Artificial Intelligence* and *Machine Learning Application Archetypes: Insights From the Complex System of Professional Sports* did. The second goal was to expand the insights within the Organization category by extending the comprising components with the topic business model. This thesis did this by showing that business model components of organizations have not been covered by the previously used definition of the Organization category with the article *Toward an Enduring Football Economy: A Business Model Taxonomy for Europe's Professional Football Clubs*. The final research goal three of this thesis aimed to investigate the adoption of AI from a processual adoption. Therefore, with the fourth article *Artificial Intelligence Adoption and Management – An Evolution-Theoretical Model,* this thesis explained the process of AI adoption and management and how TOE offers a structured approach for guidance and informed decision-making.

For the first research goal, our results present a theoretical understanding of the nature of AI use cases. AIT enable machines which perform autonomously such functions that typically would benchmark biological intelligence (Collins et al., 2021; DeCanio, 2016; Russel and Norvig, 2010; Stone et al., 2022; Weber et al., 2022). Examples of use case applications, nevertheless, show that machines can range from software to hardware applications. This article, hence, investigated existing use cases. The results show that there are basically two types of machines: SRH and VMs. Those types of machines indicate two main use cases for AI. Knowing which kinds of machines AIT synthesizes, our results further deepened the understanding of those machines regarding their actual purpose. Considering 494 AI machines mainly from the field of virtual machines, the results from the second article present six archetypes of applications. Those archetypes generally represent the purposes VMs have been used for in various use cases so far.

The second research goal explicitly focused on the definition of the Organization category. Research so far has defined the Organization impacts on technology adoption through linking structures (formal and informal), communication processes, size of the organization, and slack, which altogether accord to the architectural perspective of an organization. Despite this, the literature indicated that AI adoption is strongly related to the value creation logic of an organization. The results of our second research goal, hence, show the components of the business model of professional European sports clubs, for which AIT are currently an important development to investigate. As expected, the former definition of the Organization category of TOE cannot cover the taxonomy components and, even more importantly, cannot cover the value creation logics. This thesis already outlined the importance of the business model for AI adoption. However, interestingly, there is already evidence for the need to extend the Organization category with the business model for other IT, too. From an IT adoption perspective, there are several conclusions why an organization's business model impacts the IT adoption decision. As the adoption of IT will either excessively or slightly change the organization's resources and their composition (Hartmann et al., 2016; Spiegel et al., 2016; Weber et al., 2022), the initial situation of the organization can either be a barrier or a catalyst. Depending on which IT an organization considers adopting, IT can either act as an automated interface to the customer, increase the productivity of process, or appear as a product itself (Steininger, 2019). Therefore, IT adoption can alter business models holistically, which in an innovation perspective represent the organization's value creation, delivery, and capture logics (Osterwalder and Pigneur, 2010). The current state of composition of the organization's resources, however, due to its current degree of innovativeness, determines if the adoption of the considered IT either increases or decreases the value creation power of the organization (Aggarwal, 2013). These obsolete business model components require some existing business models from the payment sector to rethink (Holotiuk et al., 2017) by also considering IT innovations and, therewith, push adoption decisions. As a logical consequence to this, our results suggest extending the definition of the Organization category of the TOE framework with *business model*.

For the final third research goal, this thesis investigated the AI adoption of a German energy supplier group within a case study. Our article pictures the AI adoption process and shows that the adoption of AI differs fundamentally from the adoption of other IT. The developed model found that TOE can grasp the AI adoption process with the help of the two contexts Technology and Organization, which appear as two of the main building blocks of the developed adoption process. The Environment category, per definition, accords to the externality of an organization, which is why Environment does not represent a specific building block of the framework, but instead represents the surrounding of the model, offering AI availability. The developed model shows continuous circles of adoption, which is exactly the phenomenon where AI differs from other IT. According to these results, because of these circles, research cannot depict the AI adoption process as an ending task. In contrast, and in line with the definition of the goal of creating intelligent IS, organizations can only start the process, which will continue as long as there is progress in AI development. Due to these circumstances, organizations cannot isolate the impacts of TOE on the adoption decision without considering the adoption itself, too. This has far-reaching consequences for the TOE framework. It means that in the case of AI decision-makers must also consider which impacts the adoption decision mirrors back to TOE categories.

This thesis, hence, suggests extending the TOE framework by arrows pointing back from the adoption decision to the two contexts Technology and Organization as shown in Figure 9. In the case of AI adoption extending the TOE framework with these two further arrows (dashed in Figure 9) helps to integrate the findings of the fourth article into TOE. Both arrows represent the phenomenon of continuity AI adoption brings with it and, therefore, is the crucial adaption which enables TOE to guide and explain the adoption of AI.

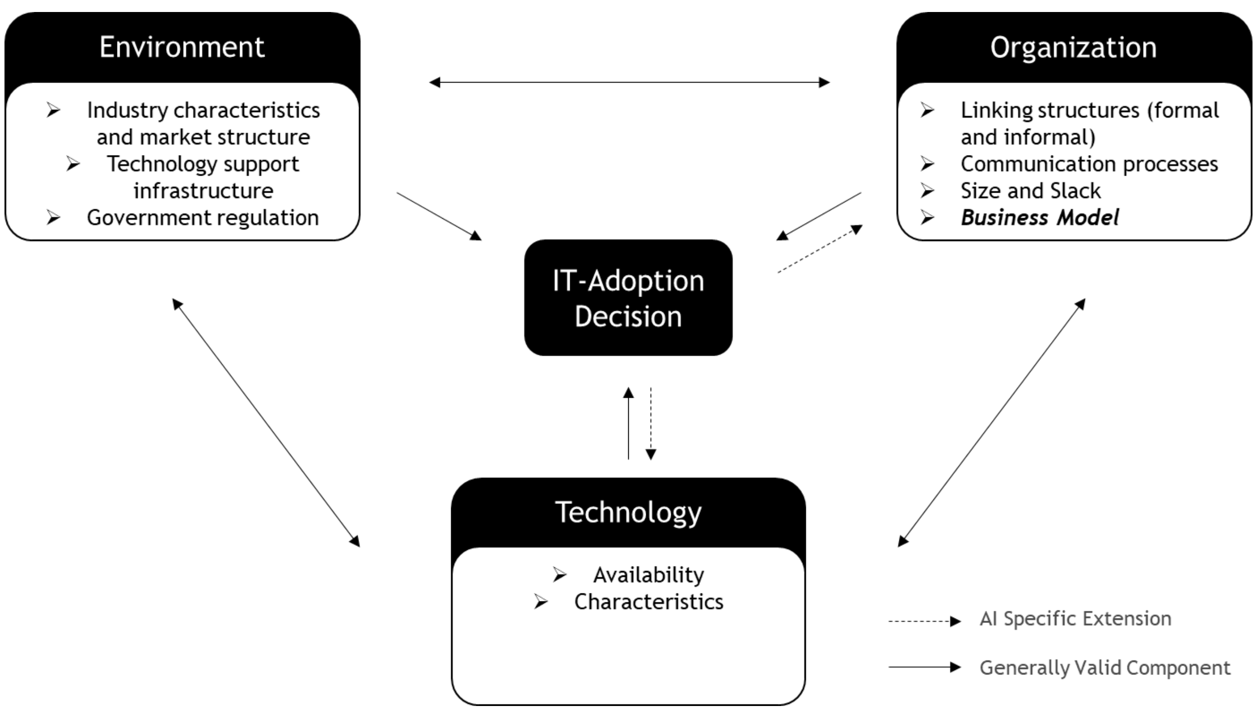

Figure 9. Extended TOE Framework

In summary, the TOE framework is an adequate theoretical frame to investigate and approach the adoption of AI. Nevertheless, our results suggest two adaptions. The first adaption concerns the AI-specific manifestation of TOE, by adding arrows pointing back to Technology and Organization. The second adaptation has much wider implications since our results found evidence for an extension of the Organization category generally valid for all remaining IT adoption decisions.

4.2 Theoretical Contribution

The results of this thesis offer several theoretical contributions to research. First, this thesis led the AI adoption under the application of the TOE framework. This is theoretically relevant regarding the need for reconsidering existing theory in the light of AI (Ågerfalk, 2020). TOE framework has proven its reliability by the application to the explanation of impacts on IT adoption decision many times before. Nevertheless, since AI, due to its described peculiarities, requires reconsidering every theory and model research has learned so far about IT adoption (Ågerfalk, 2020), it is necessary to test and confirm the applicability of TOE to AI adoption. With the results, this thesis can confirm that the TOE perspective is a proper theoretical approach to explain the AI adoption decision of organizations.

Second, our results touch and connect several distinct research streams of AI. Using the TOE framework our results structure and contextually connect these existing research streams. This shows that the TOE theory does not just explain the impacts on technology adoption theory but can also serve as a general theoretical basis to contextually connect existing research streams and theories on a technology.

Third, our results do not entirely address explicit direct impacts on the AI adoption decisions. Instead, our results are set in logical coherences, which at some point impact the adoption decision. Accordingly, the sources of impacts on the adoption decision are manifold and not always clear to define. However, the theoretical embedding of our results into the framework showed that one cannot distinguish clearly between the impacts on adoption decisions and the causing effects of the adoption decision. This thesis showed that especially with the embedding of the business model results. In this case, it is not explicitly the business model that impacts the adoption decision, but rather the effects decision-makers expect when deciding in such a way. In this respect, the TOE framework not only comprises the impacts on adoption decision but must also include the interrelation with the effects.

4.3 Practical Implications

Besides the theoretical contributions, our results have implications for practice, too. First, our results structure existing research streams into the holistic TOE frame. Therewith, this thesis gave a contextual connection to distinct existing AI research streams by structuring those into the contexts of Technology, Organization, and Environment. Practitioners can use this structuration to navigate through the field of AI research to support their strategic decisions according to AI.

Second, this thesis extended the state-of-the-art in AI research with four artifacts that practitioners can use for their purposes. The first two artifacts explicitly extend the knowledge on the characteristics of AIT. In this regard, the first artifact is a model which explains which general machines AIT comprises. The second artifact depicts the exact purposes of those machines. Together, both artifacts help practitioners to understand what AI can do and for which use cases AI can be applied. This knowledge helps to comprehensively diffuse AIT and in the long run promotes economic power. The third artifact helps practitioners to understand the business context of AIT. The business model analysis is required knowledge for the AI adoption decision-making process and, therefore, supports practitioners by analyzing their viewpoint. The fourth artifact, as a model explaining AI transformation, helps practitioners to grasp AI adoption holistically. Practitioners can use the model as guidance and orientation throughout the listed components. Therewith the fourth artifact substantially supports successful AI adoption and pushes the decision-making positively.

4.4 Limitations and Further Research

This thesis has some shortcomings. First, the TOE framework comprises a field that is too extensive to be considered completely within this thesis. AI adoption requires several further extensions to be understood well. So far, this thesis only contributed to the field of AIT characteristics in the Technology context and the components of business model and business transformation within the Organization context. We have not presented any contributions to the Environment context. Hence, to complete the TOE approach this thesis explicitly calls for research into the third category.

Furthermore, the current TOE framework states that each category comprises persistent components for each technology adoption. It is necessary to check that this consistency holds for AI, too. The research stream of AI readiness (see e.g., Jöhnk et al. (2021)), for example, offers a great chance to determine the consistency of components by using comparison to other technologies. Another valuable extension of the current state of research for example could consider the interrelationships of these persistent components. A persistent component which does not accord to AI adoption may hold interesting unique features for the definition of AI.

5 Conclusion

The adoption of IT is generally an important topic for IS research (Baker, 2012). Adopting IT changes the way an organization processes, transmits, creates, manipulates, or diffuses data and information. Therewith, it has impact on the organization's IS and is one of the most prominent reasons for change in organizations specifically or even holistically (Dong et al., 2021). The adoption of AIT requires special attention, since, due to its characteristics, research and practice cannot just apply our existing theories and models to explain AI adoption (Ågerfalk, 2020). This thesis gave AI adoption research a holistic structure integrating a wide field of distinct AI research streams. Our results also enhanced the understanding of AI adoption by adding two main use case-related articles as well as two main business model-related conclusions. Nevertheless, since research has now a holistic structure to approach the field of AI adoption, this is only a starting point. AI adoption is a phenomenon which affects organizations holistically. There are still several gaps until research reaches a full understanding about the challenges and chances of creating intelligent IS.

6 References

Abdel-Karim BM, Pfeuffer N and Hinz O (2021) Machine learning in information systems - a bibliographic review and open research issues. *Electronic Markets* 31(3): 643–670.

Adomavicius G, Bockstedt JC, Gupta A, et al. (2007) Technology roles and paths of influence in an ecosystem model of technology evolution. *Information Technology and Management* 8(2): 185–202.

Ågerfalk PJ (2020) Artificial intelligence as digital agency. *European Journal of Information Systems* 29(1): 1–8.

Aggarwal R (2013) Adjusting to BRICs in Glass Houses: Replacing Obsolete Institutions and Business Models. *Thunderbird International Business Review* 55(1): 37–54.

Agrawal A, Gans J and Goldfarb A (2021) AI Adoption and System-Wide Change. *National Bureau of Economic Research*. DOI: 10.3386/w28811.

Al-Hujran O, Al-Lozi EM, Al-Debei MM, et al. (2018) Challenges of Cloud Computing Adoption From the TOE Framework Perspective. *International Journal of E-Business Research* 14(3): 77–94.

Alshamaila Y, Papagiannidis S and Li F (2013) Cloud computing adoption by SMEs in the north east of England. *Journal of Enterprise Information Management* 26(3): 250–275.

Alsheibani S, Cheung Y and Messom C (2018) Artificial Intelligence Adoption: AI-readiness at Firm-Level. *PACIS 2018 Proceedings*.

Arslan HA, Tereyağoğlu N and Yılmaz Ö (2022) Scoring a Touchdown with Variable Pricing: Evidence from a Quasi-Experiment in the NFL Ticket Markets. *Management Science*. DOI: 10.1287/mnsc.2022.4588.

Arti, Dubey KP and Agrawal S (2019) An Opinion Mining for Indian Premier League Using Machine Learning Techniques. In: *2019 4th International Conference on Internet of Things: Smart Innovation and Usages (IoT-SIU):* IEEE.

Aversa P, Cabantous L and Haefliger S (2018) When decision support systems fail: Insights for strategic information systems from Formula 1. *The Journal of Strategic Information Systems* 27(3): 221–236.

Avison DE and Myers MD (1995) Information systems and anthropology: and anthropological perspective on IT and organizational culture. *Information Technology & People* 8(3): 43–56.

Baird A and Maruping LM (2021) The Next Generation of Research on IS Use: A Theoretical Framework of Delegation to and from Agentic IS Artifacts. *MIS Quarterly* 45(1): 315–341.

Baker J (2012) The Technology–Organization–Environment Framework. In: *Information Systems Theory:* Springer, New York, NY, pp. 231–245.

Bawack R, Fosso Wamba S and Carillo K (2019) Where information systems research meets artificial intelligence practice: towards the development of an AI capability framework. *DIGIT 2019 Proceedings*.

Bawack RE, Fosso Wamba S and Carillo KDA (2021) A framework for understanding artificial intelligence research: insights from practice. *Journal of Enterprise Information Management* 34(2): 645–678.

Beiker S and Calo R (2012) Legal Aspects of Autonomous Driving. *Santa Clara L. Rev.* DOI: 10.2139/ssrn.2767899.

Benaich N and Hogarth I (2022) A Report on the state of AI and its implication for the future. *Air Street Capital,* 11 October.

Berente N, Gu B, Recker J, et al. (2021) Managing artificial intelligence. *MIS Quarterly*.

Berger S, Marie-Sophie D and Röglinger M (2018) The Nature of Digital Technologies-Development of a Multi-Layer Taxonomy. *European Conference on Information Systems*.

Boaden R and Lockett G (1991) Information technology, information systems and information management: definition and development. *European Journal of Information Systems* 1(1): 23–32.

Borgman HP, Bahli B, Heier H, et al. (2013) Cloudrise: Exploring Cloud Computing Adoption and Governance with the TOE Framework. In: *2013 46th Hawaii International Conference on System Sciences:* IEEE.

Brynjolfsson E (2017) *Machine, Platform, Crowd*. [S.I.]: W. W. Norton & Company.

Buck C and Ifland S (2022) Toward an enduring football economy: a business model taxonomy for Europe's professional football clubs. *European Sport Management Quarterly*: 1–21.

Buck C, Ifland S, Stähle P, et al. (2021) Raiders of the Lost Ark — A Review About the Roots and Application of Artificial Intelligence. *International Journal of Innovation and Technology Management* 18(08).

Buckingham RA, Hirscheim RA, Land FF, et al. (1986) *Information systems education: recommendations and implementation*. Cambridge University Press.

Burns T and Stalker GM (2001) *The management of innovation*. Oxford: Oxford Univ. Press.

Cagle K (2019) AI Augmentation: The Real Future of Artificial Intelligence. *Forbes,* 30 September.

Chau PYK and Tam KY (1997) Factors Affecting the Adoption of Open Systems: An Exploratory Study. *MIS Quarterly* 21(1): 1.

Cockburn IM, Henderson R and Stern S (2018) The impact of artificial intelligence on innovation: An exploratory analysis: 115–146.

Collins C, Dennehy D, Conboy K, et al. (2021) Artificial intelligence in information systems research: A systematic literature review and research agenda. *International Journal of Information Management* 60: 102383.

Cornelissen J (2021) Google: 5 Ways AI and Machine Learning Could Impact Data Collection. *MRMW: the portal for your latest market research technology updates,* 6 September.

Daft RL and Becker SW (1978) *The innovative organization: Innovation adoption in school organizations*. New York: Elsevier.

DeCanio SJ (2016) Robots and humans – complements or substitutes? *Journal of Macroeconomics* 49: 280–291.

DePietro R, Wiarda E and Fleischer M (1990) The context for change: Organization, technology and environment. In: Tornatzky LG and Fleischer M (eds) *The processes of technological innovation:* Lexington: Lexington Books, pp. 151–175.

Diel S, Ifland S, Wytopil F, et al. (2021) How Digital Technologies Transform Football – A Structured Literature Review. *PACIS 2021 Proceedings*.

Dong JQ, Karhade PP, Rai A, et al. (2021) How Firms Make Information Technology Investment Decisions: Toward a Behavioral Agency Theory. *Journal of Management Information Systems* 38(1): 29–58.

Enholm IM, Papagiannidis E, Mikalef P, et al. (2022) Artificial Intelligence and Business Value: a Literature Review. *Information Systems Frontiers* 24(5): 1709–1734.

Fryer JS, Mansfield E, Rapoport J, et al. (1979) The Production and Application of New Industrial Technology. *The Academy of Management Review* 4(2): 295.

Galbraith JR (1973) *Designing complex organizations*. Reading, Mass.: Addison-Wesley.

Ghobakhloo M, Hong TS, Sabouri MS, et al. (2012) Strategies for Successful Information Technology Adoption in Small and Medium-sized Enterprises. *Information* 3(1): 36–67.

Gioia DA, Corley KG and Hamilton AL (2013) Seeking Qualitative Rigor in Inductive Research. *Organizational Research Methods* 16(1): 15–31.

Glikson E and Woolley AW (2020) Human Trust in Artificial Intelligence: Review of Empirical Research. *Academy of Management Annals* 14(2): 627–660.

Grover V (1993) An Empirically Derived Model for the Adoption of Customer-based Interorganizational Systems. *Decision Sciences* 24(3): 603–640.

Hartmann PM, Zaki M, Feldmann N, et al. (2016) Capturing value from big data – a taxonomy of data-driven business models used by start-up firms. *International Journal of Operations & Production Management* 36(10): 1382–1406.

Hassani H, Silva ES, Unger S, et al. (2020) Artificial Intelligence (AI) or Intelligence Augmentation (IA): What Is the Future? *AI* 1(2): 143–155.

Holotiuk F, Pisani F and Moormann J (2017) The Impact of Blockchain Technology on Business Models in the Payments Industry. *Wirtschaftsinformatik 2017 Proceedings*.

Hong S-J and Tam KY (2006) Understanding the Adoption of Multipurpose Information Appliances: The Case of Mobile Data Services. *Information Systems Research* 17(2): 162–179.

IBM (2023) What is Intelligent Automation? Available at: https://www.ibm.com/topics/intelligent-automation (accessed 18 January 2023).

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.

Kamath RR and Liker JK (1994) A second look at Japanese product development. *Harvard Business Review*.

Kautz T, Groh BH, Hannink J, et al. (2017) Activity recognition in beach volleyball using a Deep Convolutional Neural Network. *Data Mining and Knowledge Discovery* 31(6): 1678–1705.

Kellogg KC, Valentine MA and Christin A (2020) Algorithms at Work: The New Contested Terrain of Control. *Academy of Management Annals* 14(1): 366–410.

Kuan KK and Chau PY (2001) A perception-based model for EDI adoption in small businesses using a technology–organization–environment framework. *Information & Management* 38(8): 507–521.

Kühl N, Schemmer M, Goutier M, et al. (2022) Artificial intelligence and machine learning. *Electronic Markets* 32(4): 2235–2244.

Legner C, Eymann T, Hess T, et al. (2017) Digitalization: Opportunity and Challenge for the Business and Information Systems Engineering Community. *Business & Information Systems Engineering* 59(4): 301–308.

Li J, Li M, Wang X, et al. (2021) Strategic Directions for AI: The Role of CIOs and Boards of Directors. *MIS Quarterly* 45(3): 1603–1644.

Lian J-W, Yen DC and Wang Y-T (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.

Low C, Chen Y and Wu M (2011) Understanding the determinants of cloud computing adoption. *Industrial Management & Data Systems* 111(7): 1006–1023.

Lyytinen K, Nickerson JV and King JL (2021) Metahuman systems = humans + machines that learn. *Journal of Information Technology* 36(4): 427–445.

Makridakis S (2017) The forthcoming Artificial Intelligence (AI) revolution: Its impact on society and firms. *Futures* 90: 46–60.

Mathew V, Chacko AM and Udhayakumar A (2018) Prediction of suitable human resource for replacement in skilled job positions using Supervised Machine Learning. In: *2018 8th International Symposium on Embedded Computing and System Design (ISED):* IEEE.

McKinney and Yoos (2010) Information About Information: A Taxonomy of Views. *MIS Quarterly* 34(2): 329.

McKinsey (2018) The impact of artificial intelligence on innovation: An exploratory analysis. *McKinsey Global Institute*(2).

Mishra AN, Konana P and Barua A (2007) Antecedents and Consequences of Internet Use in Procurement: An Empirical Investigation of U.S. Manufacturing Firms. *Information Systems Research* 18(1): 103–120.

Nam K, Dutt CS, Chathoth P, et al. (2021) The adoption of artificial intelligence and robotics in the hotel industry: prospects and challenges. *Electronic Markets* 31(3): 553–574.

Nickerson RC, Varshney U and Muntermann J (2013) A method for taxonomy development and its application in information systems. *European Journal of Information Systems* 22(3): 336–359.

Oliveira T and Martins MF (2011) Literature Review of Information Technology Adoption Models at Firm Level. *Electronic Journal of Information Systems Evaluation* 14(1): pp110-121-pp110-121.

Oliveira T, Thomas M and Espadanal M (2014) Assessing the determinants of cloud computing adoption: An analysis of the manufacturing and services sectors. *Information & Management* 51(5): 497–510.

Osterwalder A and Pigneur Y (2010) *Business model generation: A handbook for visionaries, game changers, and challengers*. New York: Wiley&Sons.

Parameswaran K (2013) Vector quantization, density estimation and outlier detection on cricket dataset. In: *2013 International Conference on Computer Communication and Informatics:* IEEE.

Prais SJ and Mansfield E (1968) Industrial Research and Technological Innovation: An Econometric Analysis. *The Economic Journal* 78(311): 676.

Radhakrishnan J and Chattopadhyay M (2020) Determinants and Barriers of Artificial Intelligence Adoption – A Literature Review. In: pp. 89–99. Springer, Cham.

Rahwan I, Cebrian M, Obradovich N, et al. (2019) Machine behaviour. *Nature* 568(7753): 477–486.

Rai A, Constantinides P and Sarker S (2019) Next Generation Digital Platforms: Toward Human-AI Hybrids. *MIS Quarterly* 43(1): iii–ix.

Raisch S and Krakowski S (2021) Artificial Intelligence and Management: The Automation–Augmentation Paradox. *The Academy of Management Review* 46(1): 192–210.

Ramdani B, Kawalek P and Lorenzo O (2009) Predicting SMEs' adoption of enterprise systems. *Journal of Enterprise Information Management* 22(1/2): 10–24.

Rani P. J, Kulkarni A, Kamath AV, et al. (2020) Prediction of Player Price in IPL Auction Using Machine Learning Regression Algorithms. In: *2020 IEEE International Conference on Electronics, Computing and Communication Technologies (CONECCT):* IEEE.

Ransome Bawack, Samuel Fosso Wamba and Kevin Daniel André Carillo (2019) Artificial Intelligence in Practice: Implications for Information Systems Research. In:

Russel S and Norvig P (2010) *Artificial intelligence a modern approach*.

Schmidt N-H, Erek K, Kolbe LM, et al. (2009) Sustainable Information Systems Management. *Business & Information Systems Engineering* 1(5): 400–402.

Schreurs MA and Steuwer SD (2015) Autonomous Driving - Political, Legal, Social, and Sustainability Dimensions. In: *Autonomes Fahren:* Springer Vieweg, Berlin, Heidelberg, pp. 151–173.

Spiegel O, Abbassi P, Zylka MP, et al. (2016) Business model development, founders' social capital and the success of early stage internet start-ups: a mixed-method study. *Information Systems Journal* 26(5): 421–449.

Steininger DM (2019) Linking information systems and entrepreneurship: A review and agenda for IT-associated and digital entrepreneurship research. *Information Systems Journal* 29(2): 363–407.

Stetter BJ, Ringhof S, Krafft FC, et al. (2019) Estimation of Knee Joint Forces in Sport Movements Using Wearable Sensors and Machine Learning. *Sensors* 19(17): 3690.

Stone P, Brooks R, Brynjolfsson E, et al. (2022) *Artificial Intelligence and Life in 2030: The One Hundred Year Study on Artificial Intelligence*. arXiv.

Thompson VA (1965) Bureaucracy and Innovation. *Administrative Science Quarterly* 10(1): 1.

Tushman M and Nadler D (1986) Organizing for Innovation. *California Management Review* 28(3): 74–92.

Weber M (1979) *Economy and society: An outline of interpretive sociology*. Berkeley, London: University of California Press.

Weber M, Beutter M, Weking J, et al. (2022) AI Startup Business Models. *Business & Information Systems Engineering* 64(1): 91–109.

Yin RK (2009) *Case study research: Design and methods*. Los Angeles, Calif.: SAGE.

Zhu K, Kraemer K and Xu S (2003) Electronic business adoption by European firms: a cross-country assessment of the facilitators and inhibitors. *European Journal of Information Systems* 12(4): 251–268.

Zhu K and Kraemer KL (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.

Zhu K, Kraemer KL and DEDRICK J (2004) Information Technology Payoff in E-Business Environments: An International Perspective on Value Creation of E-Business in the Financial Services Industry. *Journal of Management Information Systems* 21(1): 17–54.

Zhu K, Kraemer KL and Xu S (2006) The Process of Innovation Assimilation by Firms in Different Countries: A Technology Diffusion Perspective on E-Business. *Management Science* 52(10): 1557–1576.

7 Appendix

7.1 Other Publications

Authors	Title	Publication Outlet
Ifland, S., Protschky, D., Schüll, M., Buck, C.	Archetypes of Machine Learning in Professional Sports	North American Society for Sport Management Conference (NASSM 23).
Buck, C., Horbel, C., Ifland, S.	The Triple-Layered Business Model for Professional Team Sports	North American Society for Sport Management Conference (NASSM 23).
Buck, C., Hall, K., Ifland, S., Röttger, J.	Managing the Digital Transformation in Professional European Sport Clubs	Book of Abstracts of the 30th European Sport Management Conference (EASM 2022), pp.572-573.
Ifland, S., Buck, C., Eymann, T., Stähle, P., Thorwarth, H.	Künstliche Intelligenz: Ein theoretisches Werkzeug zur praxisorientierten Konzeption	Energiewirtschaftliche Tagesfragen 72(3), 57-61. 2022
Diel, S., Ifland, S., Wytopil, F., Buck, C.	How Digital Technologies Transform Football: A Structured Literature Review	Proceedings of the 21st Pacific Asia Conference on Information Systems (PACIS 2021)
Urbach, N., Häckel, B., Hofmann, P., Fabri, L., Ifland, S., Karnebogen, P., Krause, S., Lämmermann, L., Protschky, D., Markgraf, M., Willburger, L.	KI-basierte Services intelligent gestalten – Einführung des KI-Service-Canvas.	Projektgruppe Wirtschaftsinformatik des Fraunhofer-Instituts für Angewandte Informationstechnik FIT, Hochschule Augsburg, Universität Bayreuth, Frankfurt University of Applied Sciences, Germany (2021).
Buck, C., Ifland, S., Renz, M.	Value of Star Players in the Digital Age	Proceedings of the 14th International Conference on Business Informatics and Information Systems (WI 2019)
Ifland, S., Buck, C., Renz, M.	Follower and Likes paired with Goals and Tackles – Social Media Brand Value on Football Player Markets	Book of Abstracts of the 27th European Sport Management Conference (EASM 2019), pp-496-497.

7.2 Research Articles and Individual Contributions

Research Article #1: Raiders of the Lost Ark – A Review About the Roots and Application of Artificial Intelligence

Authors:

Christoph Buck – Chair for Information Systems, University of Bayreuth

Sebastian Ifland – Chair for Information Systems, University of Bayreuth

Philipp Stähle – EnBW Energy Baden-Württemberg GmbH

Harald Thorwarth – Chair of Combustion Technology, University of Applied Sciences Rottenburg

Citation:

Buck C, Ifland S, Stähle P, et al. (2021) Raiders of the Lost Ark — A Review About the Roots and Application of Artificial Intelligence. International Journal of Innovation and Technology Management 18(08).

Available at: https://www.worldscientific.com/doi/full/10.1142/S0219877021500450

Extended abstract: Section 3.1.1, pp.19-21

Individual Contribution by Sebastian Ifland

My Co-Authorship is represented by leading the data collection as well as data analysis. Based on that I designed the results of the research project and derived the article's contribution. Throughout the whole article I contributed by drafting text as well as reworking the article according discussed improvements. During the publication process I prepared the article according to the journal's guidelines and escorted the paper development by implementing the reviewers' comments on the article.

Research Article #2: Machine Learning Application Archetypes: Insights From the Complex System of Professional Sports

Authors:

Sebastian Ifland – Chair for Information Systems, University of Bayreuth

Dominik Protschky – Chair for Information Systems, University of Bayreuth

Moritz Schüll – Chair for Information Systems, University of Bayreuth

Christoph Buck – Chair of IT-Entrepreneurship & IT-Innovation Management, University of Applied Sciences Augsburg

Citation:

Ifland S, Protschky D, Schüll M, Buck C (2023) Machine Learning Application Archetypes: Insights From the Complex System of Professional Sports. *Working Paper*. (currently under revision at Journal of Sport Management)

Extended abstract: Section 3.1.2, pp. 21-23

Individual Contribution by Sebastian Ifland

As a co-author I drafted the research idea and contributed to the operational processing via mentoring. I guided my co-authors according to the theoretical alignment and drafted text throughout the whole article. During data collection as well as analysis I continuously brought in my experience to guide the development of the results. By leading the discussion on the contribution of the article I helped to increase the relevance of the article. I also contributed to the submission to the research journal by preparing the manuscript.

Research Article #3: Toward an Enduring Football Economy: A Business Model Taxonomy for Europe's Professional Football Clubs

Authors:

Christoph Buck – Chair for Information Systems, University of Bayreuth

Sebastian Ifland – Chair for Information Systems, University of Bayreuth

Citation:

Buck C, Ifland S (2022) Toward an Enduring Football Economy: A Business Model Taxonomy for Europe's Professional Football Clubs. European Sport Management Quarterly. DOI: 10.1080/16184742.2022.2026448

Available at: https://www.tandfonline.com/doi/abs/10.1080/16184742.2022.2026448

Extended abstract: Section 3.2, pp. 23-24

Individual Contribution by Sebastian Ifland

As a Co-Author, I took over the operative processing of the research project. Under the guidance of my co-author, I developed the research idea, designed the methodological approach, collected and analyzed the data, and drafted the text. During the publication process, I prepared the article for submission and implemented the reviewers' comments in continuous discussion with my co-author.

Research Article #4: Artificial Intelligence Adoption and Management – An Evolution-Theoretical Model

Authors:

Sebastian Ifland – Chair for Information Systems, University of Bayreuth

Christoph Buck – Chair of IT-Entrepreneurship & IT-Innovation Management, University of Applied Sciences Augsburg

Philipp Stähle – EnBW Energy Baden-Württemberg GmbH

Citation:

Ifland S, Buck C, Stähle P (2023) Artificial Intelligence Adoption – An Evolution-Theoretical Model. *Working Paper* (currently under revision at Information & Management).

Available at: Working Paper

Extended abstract: Section 3.3, pp. 25-26

Individual Contribution by Sebastian Ifland

As Lead Author, my authorship appears throughout the ideation, the execution, and preparation for publication of the research project. During the ideation phase I contributed by identifying the research gap, defining the research questions, and designing the methodological approach. During execution I designed and theoretical framing, collected the data through semi structured interviews, as well as analyzed the data. During the article preparation I contributed by drafting and reworking the article as well as managing the submission to the journal. During the research project I took over a leading role, by developing the article direction as well as guiding the research team.